Dynamic Framework to Quantify Thermal Resiliency During Prolonged Cooling Outages in Extreme Hot Climate

Saroj Lamichhane, PE,CEM

213saroj@gmail.com

1400 N Alma School Rd, Chandler, AZ 85224, USA

Corresponding: Saroj Lamichhane (213saroj@gmail.com)

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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 thermal resiliency evaluation methodology do not fully capture passive survivability and recovery components. This study aims to develop a comprehensive dynamic framework to evaluate thermal resiliency of residential units during cooling outage situation in extreme hot season using high-resolution, multi-zone field measured data from 2 apartments in Arizona, USA. The frameworks incorporate thermal exposure, delay component, dynamic component, exponential and sinusoidal models and recovery behavior of the apartments during cooling outage duration of up to 78 hours. Results showed that, immediately after the cooling outage, all the zones exhibited exponential behavior in temperature rise rate followed by harmonic behavior after transient hour. 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. Recovery analysis showed tradeoff between passive survivability during cooling outage and recovery ability.

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 outage.

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 power 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 are a limited number of studies that explore thermal resilience for scenarios of power disruption. The existing research literature on building thermal resiliency is heavily derived from building energy modeling and simulation [7]. The prototype building energy models may not reflect actual building parameters and actual construction scenario [5]. 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] [8].

Resiliency refers to how well a building copes with disruptive events and how quickly it recovers [9]. Most of the existing studies evaluate thermal resiliency during disruptive events [10], and building designers are still seeking metrics that can capture thermal resilience during disruptive as well as recovery phase [11]. 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 Maricopa County, Arizona. The aim of this paper is to develop a comprehensive framework to evaluate building level thermal resiliency by using high-resolution zone level spatial data. The objectives of this study are as follows:

1. Analyze thermal performance and behavior of the apartment during and after power outage in peak summer in Arizona.
2. Evaluate zone level thermal resilience and passive survivability metrics during disruptive and recovery phase.
3. Evaluate apartment level thermal resilience and passive survivability metrics.
4. Develop framework to evaluate apartment level composite thermal resiliency index (CTRI) in hot climatic region during power outage.

2. Literature Review

Heat Wave and Its Impact on Grid

Over the past 30 years, heat has caused more fatalities on average than any other weather-related disaster in the US and many countries across the world [12]. Environmental stressors are among the main causes of power system disturbances worldwide. An increase in average temperature diminishes the ability of the transmission network to meet the demand [7] [13]. In 2019, 34% of all major electric disruptions across US occurred in summer months of June, July and August [14], indicating that the higher outdoor air temperature causes higher cooling loads and strain on grid's ability to meet the demand.

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 [15]. 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 [12].

Extreme hot and cold weather events are becoming more frequent, intense, and longer due to climate change [16] which may lead to indoor overheating [17]. When these events coincide with power 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 [9].

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 [16]. The city recorded 31 consecutive days over 110 °F in 2023 causing record number of heat-related deaths [18].

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. el. [17] 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. el. 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 are heterogenous, and the resource-constrained households may sacrifice more to keep their home comfortable [19].

Brian et. el. [14] 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] [12]. 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 [12].

Severe heat stress can adversely impact basic body functions such as respiration, circulation, mobility, immune response, kidney function and cognition [12] [16] [20]. 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 [17].

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 [8]. 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 [17], 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 [12].

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 [21]. 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 [17]. Among them, the most important models are Fanger's comfort model (predicted mean vote (PMV) and predicted percentage dissatisfied (PPD)), adaptive model [17], and the two-node model [22].

PMV is defined as the index that predicts the mean value of the thermal sensation votes and the scale ranges from -3 to +3 corresponding to the categories: cold, cool, slightly cool, neutral, slightly warm, warm, and hot. The satisfaction of the comfort equation is a condition for optimal thermal comfort of a large group of people, or when most of this group experiences thermal neutrality, and no local discomfort exists [23].

Fanger's PMV and PPD models have been widely adopted in Standards such as ASHRAE 55 and ISO 7730 [15]. Standards ASHRAE 55 and ISO 7730 present methods for predicting the general thermal sensation and degree of discomfort of people exposed to moderate thermal environments based on indoor thermal environmental factors (i.e. temperature, thermal radiation, humidity, air velocity) and personal factors (clothing level and metabolic rate) [22] [23]. PPD model applies the PMV index to estimate the percentage of people in a specific space who find the thermal conditions unsatisfactory [17].

J. Van Hoof et. el. [23] 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 [17].

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 [24].

Adaptive model is gaining popularity over time and is added to ASHRAE 55 (2017,2020) for naturally ventilated buildings as it recognizes that different populations have different preferences for thermal comfort based on physiological, psychological, and behavioral factors [15].

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 [23].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 [17].

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 [26]. 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 [12].

Maggie et. el. [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 [9]. 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 [9] [27].

Hours of safety (HOS) is a metric developed by US environmental Protection Agency (EPA) and the Rocky Institute as a measure of the duration of time a building is able to maintain safe conditions above a predefined temperature threshold during a cold event. Since this study is focused on resiliency in hot climate, HOS isn't considered.

Hong et. el. [9] 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.

Some of the other widely used metrics are wet bulb global temperature (WBGT), hours of exceedance, and overheating degree. Some of the shortcomings of the existing resiliency metrics in literature are that they are not generalized, and they are not representative of long-term resiliency [8].

WBGT is an empirical thermal measurement developed in the 1950s that measures dry-bulb air temperature, natural wet-bulb temperature and black globe temperature [8] [12]. 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

Various research has been done to evaluate thermal resiliency of buildings in hot and cold climates using simulation software and statistical analysis [5] [7] [14] [20] [29] [30] [31]. 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]. These factors are often not fully captured when using simulated software than when using M&V in actual building. Literature reviews have shown that most of the studies done using simulation tools lack measurement and verification of passive habitability in occupied buildings to validate the simulation.

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. el. [12] 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.

Most indoor overheating research relies on outdoor temperature data and has no common indoor heat index for evaluating indoor heat stress [12]. Simplified metrics like HI, passive survivability, thermal autonomy are best applied at zone level and not for whole building [11]. Some metrics have been developed to assess thermal resiliency at building level: Shabnam et. el. [11] 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] [32]. Moreover, the study only considers indoor operative temperature to develop the metric and excludes other important variables like relative humidity.

Thermal resilience is an important attribute for buildings as climate change is causing an increase in the frequency and severity of extreme weather events which can coincide with power outages and challenge the safety of inhabitants [6]. 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 [12] [32].

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 [9]. 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.

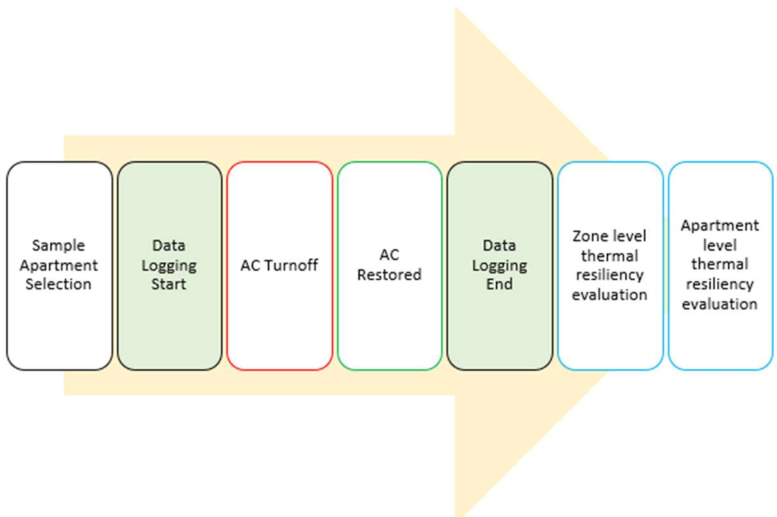

Figure 1 General Methodology Summary

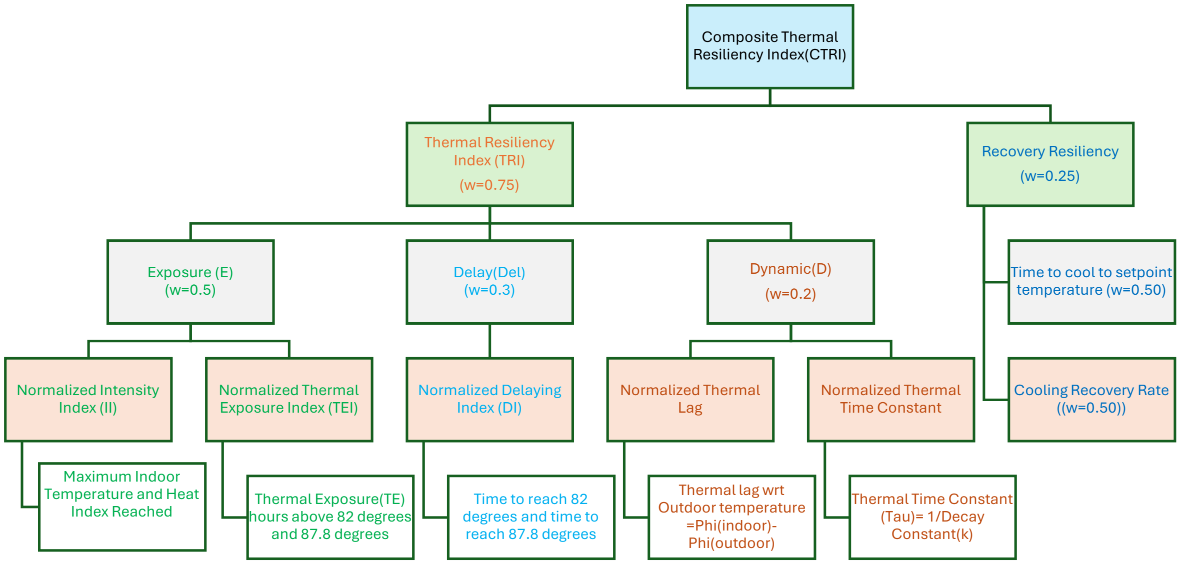

Figure 2 Thermal Resiliency Framework

Data Collection

The collected raw dataset and processed dataset in this study are publicly available in Zenodo repository [33]. 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. One of them is a 700 sq.ft. 1 bed 1 bath apartment located on the top floor of a 2-story building in Chandler, Arizona. Another apartment is a 1,040 sq.ft. 2 bed 2 bath apartment located on second floor of a 2-storied building in Mesa, Arizona. 1BHK apartment is north facing while the 2BHK apartment is east facing. Both apartments lie in very hot and dry climatic zone 2B.

Hobo data loggers were placed at center of the rooms at about 2-3 ft. from floor. Few loggers were also placed on opposite walls, ceiling and near window of each room when applicable, to collect high-resolution spatial room level data. 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 8/14/2205 at 14:30 PM, and it was turned back on 8/17/2025 at 7:50 PM, totaling 77.33 hours of power outage. The average and maximum outdoor air temperature during the power outage duration were 94°F and 108°F respectively. The average and maximum outdoor air relative humidity during the power outage duration were 29% and 77% 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 were kept on until 7/6/2026 8:29AM. 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.

Resiliency Metrics

Several metrics were calculated to formulate an index that captures resiliency during both disruptive as well as recovery phase. Disruptive phase is referred to in this paper as the duration when AC was off, and recovery phase refers to the duration after the AC was turned back on till it reached thermostat setpoint. To measure the resiliency during disruptive events, the resiliency metrics were grouped into three categories: Exposure (E), Delay (Del) and Dynamic (D) 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 weighted average of normalized Thermal Exposure Index (TEI) and normalized Intensity Index (II).

$$E = w1\ x\ (1 - II) + w2\ x\ (1 - II) \qquad \textit{Equation 1}$$

Where w1 and w2 are weights assigned to TEI and II respectively. In this study W1= 25% and w2=75% are used, which gives more priority to exposure hours above threshold than the maximum intensity reached.

Thermal Exposure Index (TEI)

TEI measures the exposure hour above the threshold temperature and heat index. TEI is calculated as:

$$TEI = w1\ x\ [TE82/max\ (TE82)] + w2\ x\ [TE87.8/max\ (TE87{,}8)] \qquad \textit{Equation 2}$$

Where w1=25% and w2=75% to signify that more weight is given to exposure hours for higher threshold temperatures. TE_{82} and $TE_{87.8}$ are normalized thermal exposure (TE) ratio calculated as:

$$TE82 = Total\ observed\ degree\ hours\ above\ 82°F/Total\ AC\ off\ hours \qquad \textit{Equation 3}$$

$$TE87.8 = Total\ observed\ degree\ hours\ above\ 87.8°F/Total\ AC\ off\ hours \qquad \textit{Equation 4}$$

Intensity Index (II)

Intensity Index (II) is calculated as:

$$II = [w1\ x\ maximum\ Heat\ Index\ (HIz)\ reached\ in\ apartment/Critical\ Heat\ Index(HIc)] + [w2\ x\ Maximum\ indoor\ temperature\ reached(Tmaxz)/Critical\ Temperature\ (Tc)] \qquad \textit{Equation 5}$$

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

Heat Index Threshold

As per National Weather Services, Heat Index (HI) can be calculated as [34] :

$$HI = -42.379 + 2.04901523T + 10{:}14333127RH - 0.22475541T\ x\ RH - 6.83783\ x\ 10^{-3} x T^2 - 5.481717\ x\ 10^{-2} x RH^2 + 1.22874\ x\ 10^{-3} x T2\ x\ RH + 8.5282\ x\ 10^{-4} x\ T\ x\ RH^2 - 1.99\ x\ 10^{-6} x\ T2\ x\ RH^2 \qquad \textit{Equation 6}$$

If the calculated HI is less than 80°F, the following formula is used:

$$HI = 0.5\ x\ \{T + 61 + (T - 68)x1.2 + (RHx0.094)\} \qquad \textit{Equation 7}$$

Although the HI was developed for outdoor environments, it is used in this study as an indicator of potential heat stress metrics such as indoor air velocity and mean radiant temperature were not measured to capture and formulate actual indoor heat index.

As per LEED v4.1, the heat index categories and the hazard categories are given in Table 1 [9].

Table 1 Heat Index Categories

Heat Index Range	**Hazard Category**	**Heat Syndrome**
< 27 C (80F)	Safe	None
27 to 32 C (80 to 90 F)	Caution	Fatigue possible
32 to 41 C (90 to 105 F)	Extreme Caution	Sunstroke, heat cramps, heat exhaustion possible
41 to 54 C (105 to 130F)	Danger	Sunstroke, heat cramps, heat exhaustion and heat stroke likely
> 54 C (130F)	Extreme Danger	Heat stroke or sunstroke imminent

Temperature Threshold

ASHRAE has set temperature threshold of 27.2°C (80.96°F) to define heat exposure in old population [35]. However, several studies point out that health risks increase at or above 26°C (78.8°F) [35] 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 [36] [37]. In literature, the threshold of 272.7 C (82°F) is often used as upper limit of acceptable temperature [35]. 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 weighted average time to reach temperature thresholds (82°F and 87.8°F) divided by total ac off hours.

$$DI = [w1\ x\ Time\ to\ reach\ 82°F/Total\ AC\ off\ hours] + [w2\ x\ Time\ to\ reach\ 87.8°F/Total\ AC\ off\ hours] \qquad \textit{Equation 8}$$

If the threshold temperature of 87.8°F is not reached, then the total AC off duration is taken as the time taken to reach the threshold. w1 is taken as 0.25 and w2 is taken as 0.75 to prioritize to higher threshold.

Dynamic Component

The dynamic component (D) is calculated as weighted average of normalized thermal lag(ϕ_N) and normalized thermal time constant (Tau_N). It can be calculated as:

$D = (w1 \ x \ \phi N) + (w2 \ x \ TauN)$ *Equation 9*

Where w1=0.5 and w2=0.5. Tau_N and ϕ_N are calculated as:

$TauN = Thermal \ time \ constantI \ for \ a \ zone/Max \ thermal \ time \ constant \ among \ zones$ *Equation 10*

$\phi N = Thermal \ lag \ /Maximum \ thermal \ lag \ among \ zones$ *Equation 11*

Thermal lag(ϕ_{lag}) is calculated as:

$\phi lag = \phi zone - \phi outdoor$ *Equation 12*

Where, ϕ_{zone} and $\phi_{outdoor}$ are determined from sinusoidal equation derived from temperature profile of zones from transient hour till the time AC is turned back on. And, Tau is determined from exponential equation observed during initial hours of AC outage until transient time is reached.

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 13*

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.

Performing multivariate regression analysis of Temperature after transient hour gives sinusoidal curve which can be expressed as:

$Tt = C + Mt + B \ sin(\text{ш}t) + Dcos(\text{ш}t)$ *Equation 14*

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 15*

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.

Thermal Resiliency Index

Thermal resiliency index (TRI) for the AC outage duration was calculated using weighted average of Exposure (E), Delay Index (DI) and Dynamic component (D). TRI can be calculated as:

$TRI = \;(w1\;x\;E)\;+\;(w2\;x\;DI)\;+\;(w3\;x\;D)$ *Equation 16*

Where, w1, w2 and w3 are assigned weightages of 0.5, 0.3 and 0.2 respectively. More weightage is given to exposure to prioritize occupant's safety.

Recovery Resiliency Index

Cooling recovery metrics were evaluated using the data after the Ac was turned back on. Time to cool back to setpoint and cooling recovery rate (CRR) were calculated and their weighted average taken to determine Recovery Resiliency Index (RRI). If the setpoint was not reached within the duration of logging, the maximum hour logged was used as the time to reach the setpoint. RRI can be calculated as:

$RRI\; = \;[w1\;x\;(1 - Time\;to\;cool\;back\;to\;setpoint)\;/\;Maximum\;Time\;to\;cool\;back\;to\;setpoint)]\;+\;[w2\;x\;CRR/maximum\;CRR]$ *Equation 17*

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. CTRI can be calculated as:

$CTRI\; = \;(w1\;x\;TRI) + \;(w2\;x\;RRI)$ *Equation 18*

Where, w1=0.75 and w2=0.25. More weightage is given to resiliency during disruptive event 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 [11] [38] and Weightage assigned for each apartment zone is given in table 1.

Table 2 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:

$$\frac{Delta\ T}{delta\ t} = A * exp(-kt)\ , for\ t <= t\ transient \qquad \text{Equation 19}$$

$$T = Ti + M * t + BSin\left(\frac{2\pi t}{24}\right) + DCos\left(\frac{2\pi}{24}\right), for\ T > t\ transient \qquad \text{Equation 20}$$

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:

$$Capt = \sum_{k=0}^{n} \binom{n}{k} w^k C^k \qquad \text{Equation 21}$$

$$Mapt = \sum_{k=0}^{n} \binom{n}{k} w^k M^k \qquad \text{Equation 22}$$

$$Bapt = \sum_{k=0}^{n} \binom{n}{k} w^k B^k \qquad \textit{Equation 23}$$

$$Dapt = \sum_{k=0}^{n} \binom{n}{k} w^k D^k \qquad \textit{Equation 24}$$

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

$$Tapt = Capt + Mapt * t + Bapt * sine(\text{ɯ}t) + Dapt * Cos((\text{ɯ}t) \qquad \textit{Equation 25}$$

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 Validation

Statistical validation was done for the temperature profile equations. For the zone level exponential equation, coefficient of regression (R^2) was noted, and for the sinusoidal model, R^2 and p-values for each coefficient are validated. For the temperature profile of the apartment, RMSE, R^2, CV(RMSE) and mean absolute error (MAE) are calculated to validate the results.

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 does recover 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.

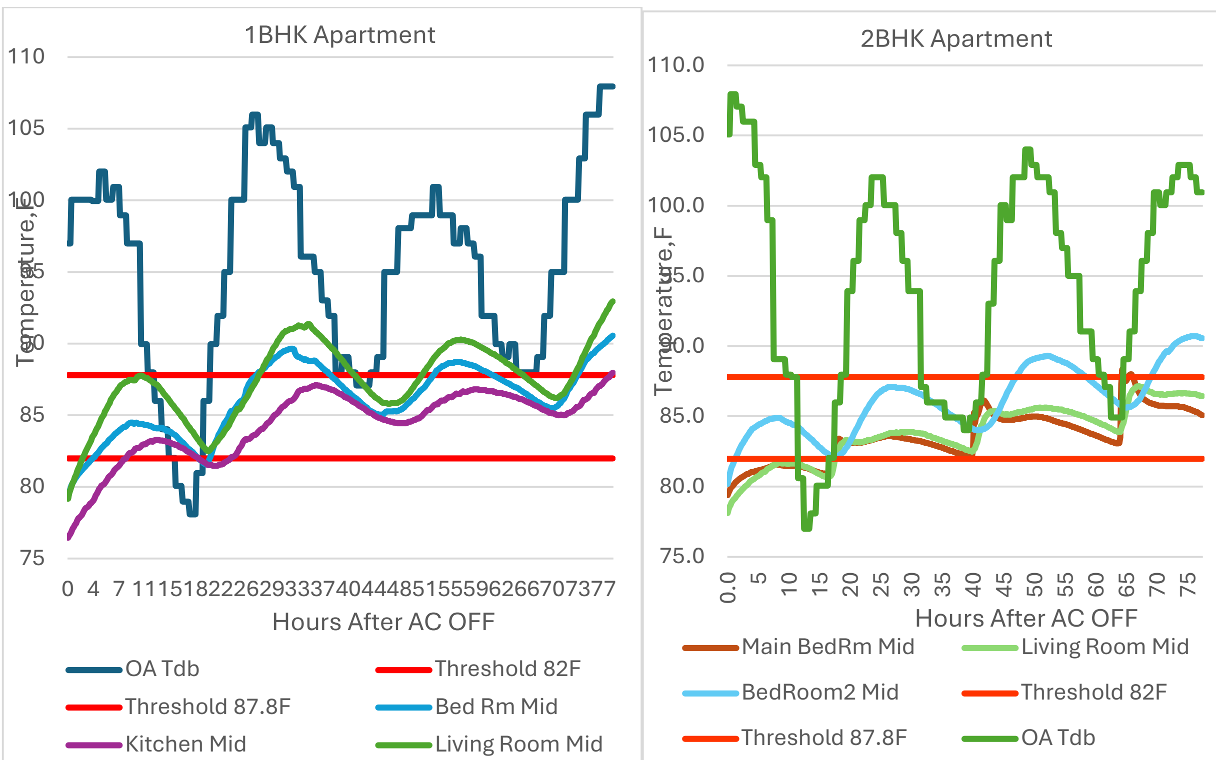

Figure 3 Temperature Profiles After AC Shutdown (Disruptive Phase)

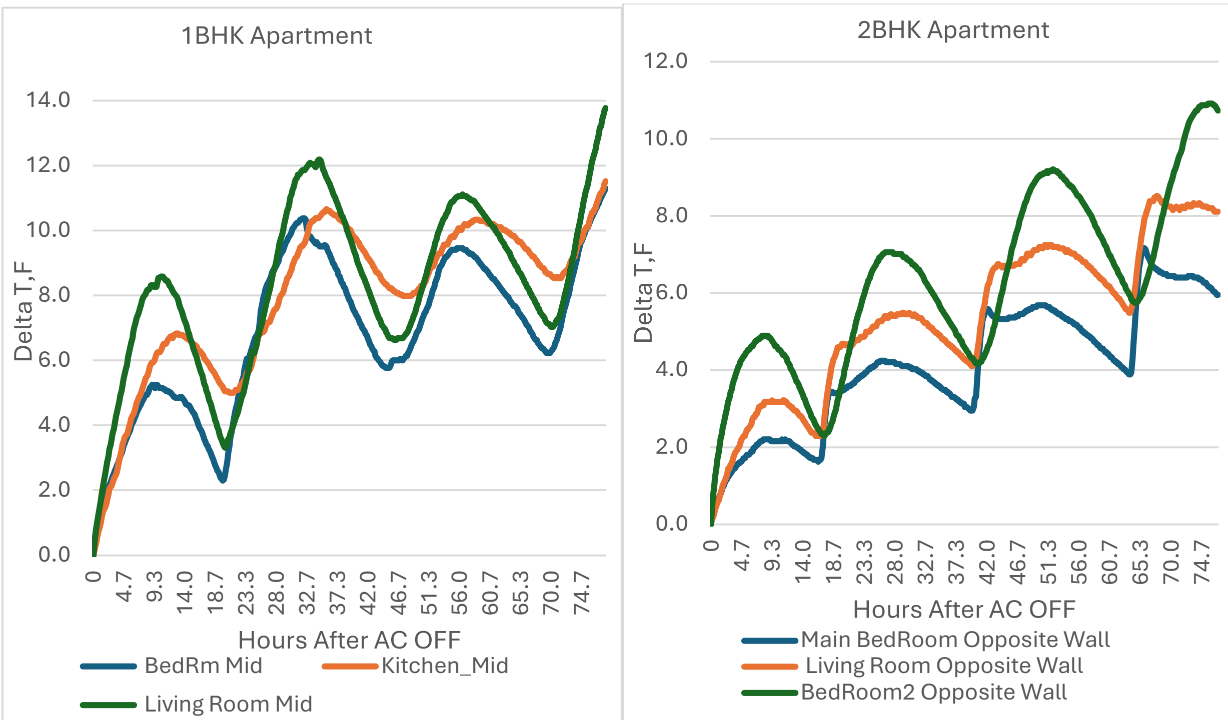

Figure 4 Temperature Rise Profiles

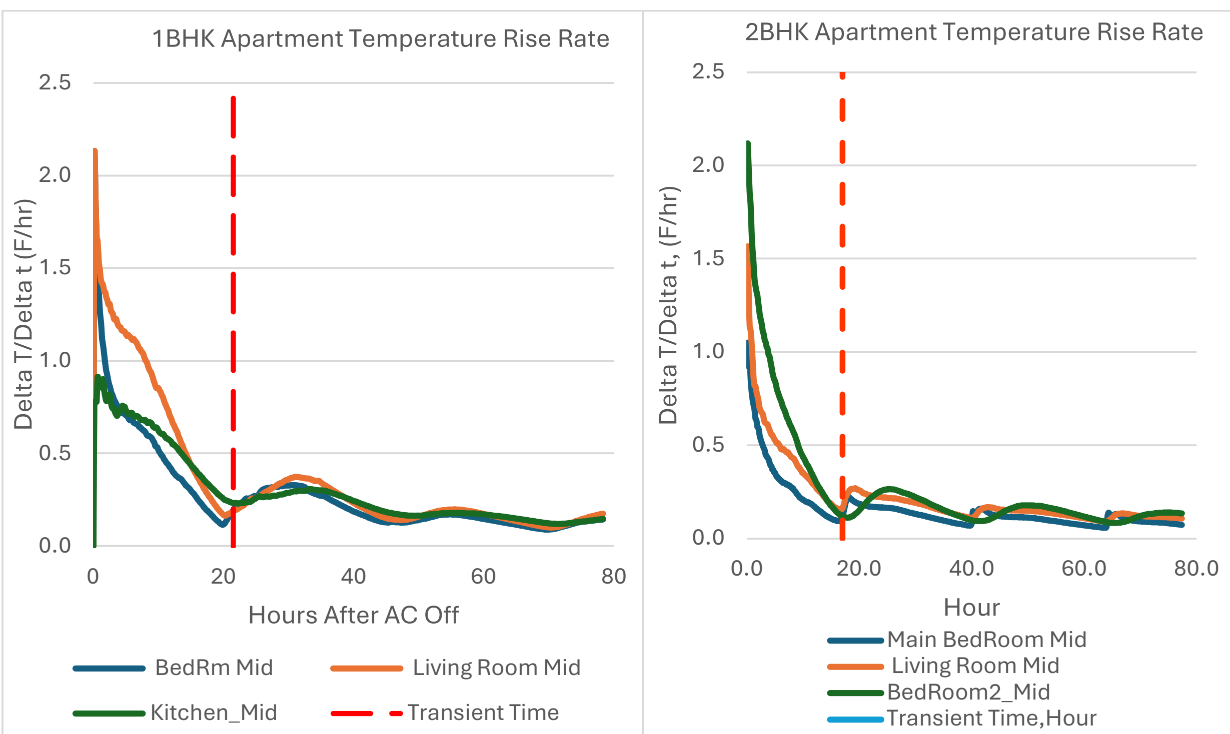

Figure 5 Temperature Rise Rate Profile

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 explained by 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

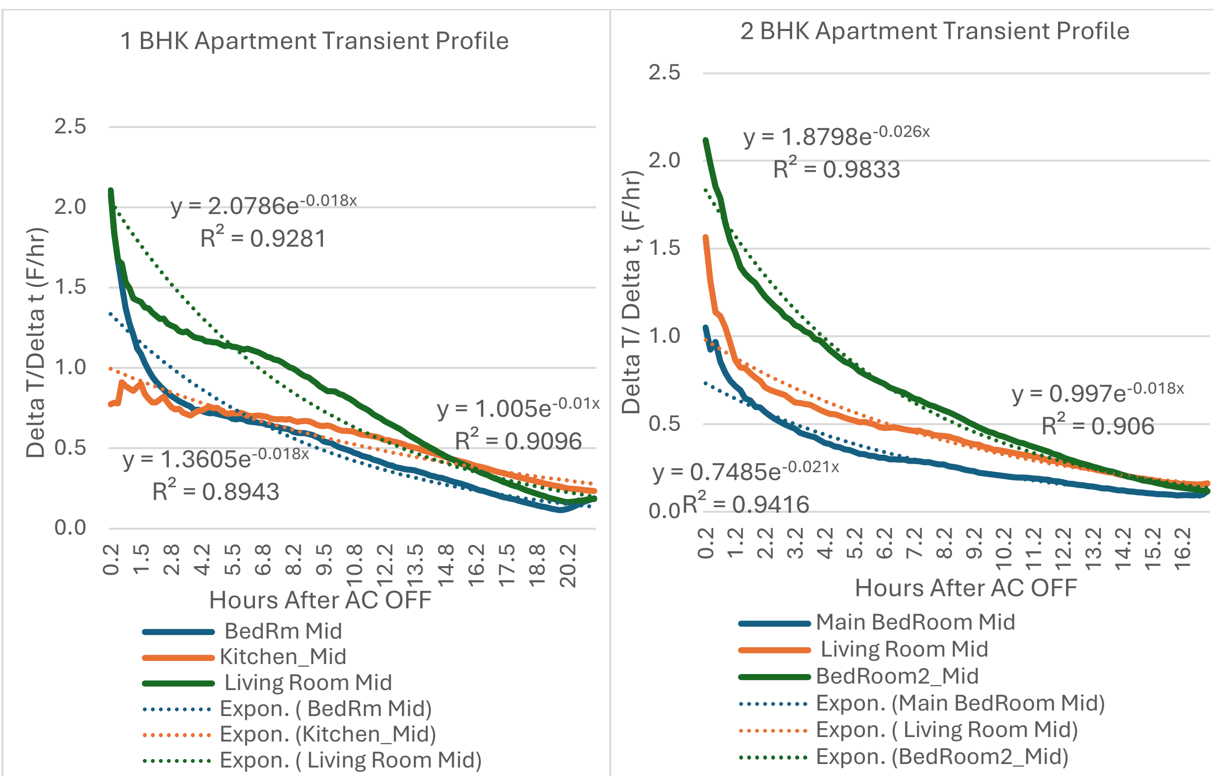

Figure 7 Transient Profiles

Transient profile of temperature rise rate is exponential curve 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 located farthest from outdoor air conditions; thus, it has lowest TRR.

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, can be explained by 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 indicating that 2BHK apartment has better passive buffering during initial outage period. Findings from both apartments demonstrate that TRR or k alone isn't a good indicator of resiliency and determining resiliency requires comprehensive approach which includes multiple resiliency indicators.

	1BHK Apartment	BedRm Mid	Kitchen_Mid	Living Room Mid	Building	Outdoor
Sinusoidal Model: Tin(t)= C + Mt + Bsin(wt)+Dcos(wt)	C (Intercept/Baseline zone temperature)	86.7	84.4	87.5	86.6	94.0
	Delta T/hr (f/hr)	0.022	0.046	0.035	0.0	0.0
	B (Sine coefficient)	0.459	-0.695	-0.055	0.1	1.2
	D(Cosine coefficient)	-2.0	-1.3	-2.7	-2.1	-8.6
	Daily Peak to Peak Oscillation, F	4.07	2.92	5.31	4.3	17.30
	Thermal Damping Ratio	0.24	0.17	0.31	0.3	
	Thermal Lag (Phi (indoor) -Phi (outdoor), (hour)	0.3	9.6	3.0	2.6	
	Normalized Thermal Lag (Phi-N)	0.04	1.0	0.3	0.3	

	2BHK Apartment	Main Bedroom Mid	Living Room Mid	Bedroom2 Mid	Building	Outdoor
Sinusoidal Model: Tin(t)= C + Mt + Bsin(wt)+Dcos(wt)	C (Intercept/Baseline zone temperature)	82.585	82.61	84.42	83.32	91.26
	Delta T/hr (f/hr)	0.053	0.07	0.08	0.07	0.08
	B (Sine coefficient)	0.848	0.68	0.37	0.62	6.68
	D(Cosine coefficient)	0.128	-0.40	-2.08	-0.86	-5.68
	Daily Peak to Peak Oscillation, F	1.72	1.58	4.23	2.70	
	Thermal Damping Ratio	0.0979	0.090	0.241	0.15	
	Thermal Lag (Phi (indoor) -Phi (outdoor), (hour)	3.2643	0.68	2.90	2.60	
	Normalized Thermal Lag(Phi-N)	1.0	0.2	0.9	**0.80**	

Figure 8 Harmonic Phase Profile

After the transient duration, indoor temperature displays cyclic behavior driven by outdoor diurnal temperature fluctuations, solar gains, heat transfer, and thermal mass effect. Figure 8 provides details on the sinusoidal model coefficients for each room in both apartments. Coefficient C intercept) indicates the baseline average temperature 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 Bedroom 2 and lowest in main bedroom.

Highest daily peak to peak deviation is observed in Living room (5.31°F), and Bedroom (4.07 °F) in 1BHK apartment, and bedroom 2(4.23°F) in 2BHK apartment, both of which have the highest exposed surface wall area. Indoor to Outdoor temperature amplitude (Thermal damping ratio) is highest in Livingroom (0.307) and lowest in Kitchen (0.169) in 1BHk apartment. In 2BHK apartment, thermal damping ratio is highest in Bedroom 2 (0.241) and lowest in Livingroom (0.09). It indicates that Living room and bedroom of 1BHK apartment and bedroom 2 of 2BHk apartment are most influenced by outdoor air conditions than other zones. While kitchen (83%) in 1 BHK apartment and living room (81%) and main bedroom (90%) in 2 BHK apartment have higher buffer against outdoor daily temperature fluctuations. The results also point out that 2BHK apartment (0.15) has better thermal damping ratio compared to 1BHK apartment (0.3) apartments.

The thermal lag represents the delay between daily outdoor temperature cycle and indoor harmonic response after the apartment has passed the transient duration. The thermal lag data shows that Kitchen in 1 BHK apartment (9.58 hours) and main bedroom in 2BHK apartment (3.26 hours) has the highest delayed penetration of outdoor temperature fluctuations.

4.2 Statistical Validation

The coefficient of regression (R^2) value for the exponential model and sinusoidal model during cyclic phase for the apartment zones is given in Table 3. 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 3 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 apartment level sinusoidal model developed using weighted average zone level parameters successfully passed statistical validation. The statistical validation for the sinusoidal model of apartments is given in Table 4. The sinusoidal model for both apartments displayed strong capability with R^2 values of 0.877 and 0.752 for 1BHK and 2BHK apartment respectively. The RMSE, MAE and CV(RMSE) are 0.56, 0.48 and 0.2% respectively for 1BHk apartment. For 2BHK apartment, RMSE, MAE and CV(RMSE) are 0.66, 0.59 and 0.2% respectively.

Table 4 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	0.877	21.5	0.56	0.48	0.2
2 BHK Apartment	0.752	17	0.66	0.59	0.2

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

4.3Thermal Resiliency Metrics

4.3.1 Disruptive Phase (AC Outage)

Thermal resiliency metrics for zone level and apartment level are given in Figure 9 for 1BHK apartment and Figure 10 for 2 BHK apartment. Results show that all zones crossed higher temperature threshold of 87.8 °F in 1BHK apartment. Living room mid sensor recorded highest temperature and heat index of 93 °F and 89 °F respectively while comparing mid zone sensors only. The range of Intensity Index (II) across different zones is very small and ranges from 0.88 to 0.92. However, Thermal Exposure Index (TEI) shows big range in values ranging from 0.12 to 0.44. Results from 2BHK also show similar data-II ranges from 0.857 to 0.90 but TEI ranges from 0.083 to 0.438. It indicates that all zones can reach similar levels of maximum indoor exposure level, but they can have varied level of exposure duration. Thus, both maximum exposure level as well as duration of exposure should be included in capturing indoor thermal exposure.

Delaying Index (DI) which is calculated using weighted average of time to reach 82 °F and time to reach 87.8 °F shows that it is important to include multiple threshold temperature in calculating passive survivability metrics and not rely on just one threshold. In 1BHK apartment, it took bedroom 3.7 hours to reach 82°F but it took 27.2 hours to reach 87.8 °F. It took living Room 2.2 hours to reach 82°F but it took 25.5 hours to reach 87.8°F. If only one threshold was used, it would not have captured the dynamics totally. Normalized DI for both the bedroom and the living room is 0.27, which wouldn't have been the case had only one threshold used to calculate DI. Interestingly, thermal decay constant (k) as discussed in section 4.1 showed same value (0.018) for 1BHk apartment bedroom and living room, and for the kitchen it was lower (0.01). Thus, the thermal decay constantly developed from the exponential model can be a good estimator of the passive survivability metric. For 2BHK apartment, DI for main bedroom, living room and bedroom2 are 0.68, 0.81 and 0.46 respectively. Apartment level DI for 1BHK apartment is 0.3 while that for 2BHk apartment is 0.62. Indicating that the 2BHK apartment is in general more resilient than 1BHK apartment in terms of passive survivability. This could be explained by larger floor area and volume, and location, and less exposed surface area. Although 2BHk apartment has higher fenestration area, it also has higher thermal mass and volume but less exposed surface wall and roof.

		BedRm Mid	Kitchen_Mid	Living Room Mid	Bedroom-South Ceiling	Living Room-Ceiling-above glass door	Bedroom Window-Eastwall	Living room-Glass Door Northwall	Bedroom Opposite Wall	Bedroom North Wall	Building	Outdoor
:one Condition	Initial Zone Temperature, F	79.3	76.5	79.2	81.0	79.2	88.0	77.0	78.0	78.5	78.8	97.0
	Initial Zone Relative Humidity,%	42.8	50.7	43.6	43.5	43.6	34.6	47.1	45.1	44.2	44.3	6
Time Period Above Threshold Heat Index (HI)	<80	1	5	1	0	1	6	4	2	2	2	5
	80-90 (Caution)	78	73	78	79	78	72	74	77	77	77	26
	90-103 (Extreme Caution)	0	0	0	0	0	0	0	0	0	0	47.5
	103-124 (Danger)	0	0	0	0	0	0	0	0	0	0	0
	>125 (Extreme Danger)	0	0	0	0	0	0	0	0	0	0	0
Time Period Above Threhold Temperature (Hour)	<78.8 F (26C)	0	3	0	0	0	4	2	0	0	0	1
	78.8F-82F	5	10	2	2	2	3	10	5	5	5	1
	82F-87.8F(31C)	49	65	42	45	42	32	59	49	48	49	3
	87.8(31C)-95F (35C)	24	0	34	32	34	40	7	24	26	24	6
	>95F (>35C)	0	0	0	0	0	0	0	0	0	0	21
Thermal Exposure(TE) Hour, (F hr)	>82F	327.3	210.1	428.2	383.2	428.2	483.4	255.2	325.0	336.4	345.0	
	>87.8F	23.9	0.0	66.7	49.4	66.7	139.5	1.9	21.9	28.2	35.3	
Thermal Exposure Index (TEI)-Normalized	TE82, degrees (TE/Total hour)	4.2	2.7	5.5	4.9	5.5	6.2	3.3	4.1	4.3	4.4	
	TE87.8,degrees (TE/Total hour)	0.3	0.0	0.9	0.6	0.9	1.8	0.0	0.3	0.4	0.5	
	TEI(W82=0.2, W87.8=0.8)	0.26	0.12	0.44	0.36	0.44	0.44	0.13	0.20	0.21	0.3	
Intensity	Maximum Indoor Temperature Reached	91	88	93	92	93	94	89	90	91	91	
	Maximum Indoor Heat Index Reached	87	85	89	88	89	90	86	87	87	87	
	Intensity Index (II)	0.90	0.88	0.92	0.91	0.92	0.93	0.88	0.90	0.90	0.9	
Passive Survivability	Time to reach 82 degrees,hr	3.7	8.5	2.2	1.3	2.2	0.0	6.7	4.3	4.0	3.9	
	Time to reach 87.8 degrees,hr	27.2	78.2	27.5	25.2	27.5	0.0	33.3	27.5	27.3	34.9	
	Maximum rate of temperature rise, delta T/Delta Time (F/hr)	2.1	0.9	2.1	2.1	2.1	2.7	1.6	3.7	2.1	1.9	
	Maximum Temperature Rise, F	11.3	11.5	13.8	10.9	13.8	6.3	12.0	12.4	12.0	12.2	
	Exposure Time Fraction <82F	7%	0%	4%	0%	0%	6%	3%	0%	0%	5%	
	Exposure Time Fraction 82F-87.8F	63%	57%	96%	60%	57%	45%	89%	69%	68%	74%	
	Delaying Index (DI) Normalized-Time to reach threshold temperature/Total Ac off time	0.27	0.78	0.27	0.25	0.27	0.00	0.34	0.28	0.27	0.3	

Figure 9 Thermal Resiliency Metrics During Disruptive Phase-1BHK Apartment

		Main Bedroom Opposite Wall	Living Room Opposite Wall	Bedroom 2 Opposite Wall	**Main Bedroom Mid**	**Living Room Mid**	**Bedroom2 Mid**	Main Bedroom Glass Door	Living Room Glass Door	Main Bedroom Ceiling-Above Glass Door	Living room Ceiling-Above Glass Door	Bedroom 2 Ceiling-Above Window	Building	Outdoor
Zone Condition	Initial Zone Temperature, F	78.9	78.6	79.7	**79.4**	**78.1**	**80.2**	86.8	85.8	82.0	81.9	83.9	79.5	105
	Initial Zone Relative Humidity,%	41.2	46.6	45.0	**41.4**	**47.3**	**43.7**	35.2	37.3	37.8	42.0	39.0	43.5	20
Heat Index (HI)	<80	4	3	0	2	3	0	0	0	0	0	0	1	6
	80-90 (Caution)	74	74	77	76	74	77	77	78	78	41	78	76	31
	90-103 (Extreme Caution)	0	0	0	0	0	0	0	0	0	0	0	0	41
	103-124 (Danger)	0	0	0	0	0	0	0	0	0	0	0	0	0
	>125 (Extreme Danger)	0	0	0	0	0	0	0	0	0	0	0	0	0
Time Period Above Threhold Temperature (Hour)	<78.8 F (26C)	0	1	0	0	1	0	0	0	0	0	0	0	2
	78.8F-82F	20	17	2	17	17	1	4	4	4	4	0	11	3
	82F-87.8F(31C)	58	60	57	59	60	56	35	39	72	38	36	58	15
	87.8(31C)-95F (35C)	0	0	19	1	0	20	38	34	2	0	42	8	17
	>95F (>35C)	0	0	0	0	0	0	0	0	0	0	0	0	41
Thermal Exposure(TE) Hour, (F.hr)	>82F	103	168	310	140	162	321	432	419	242	81	471	217	
	>87.8F	0	0	25	0	0	29	86	78	2	0	106	12	
Thermal Exposure Index (TEI)-Normalized	TE82, degrees (TE/Total hour)	1.3	2.2	4.0	1.8	2.1	4.2	5.6	5.4	3	1	6	3	
	TE87.8,degrees (TE/Total hour)	0.00	0.00	0.3	0.0	0.0	0.4	1.1	1.0	0	0	1	0	
	TEI(W82=0.2, W87.8=0.8)	0.083	0.136	0.438	0.110	0.126	0.438	0.155	0.148	0.132	0.043	0.438	0.24	
Intensity	Maximum Indoor Temperature Reached	86	87	91	88	87	91	96	92	90	86	93	89	108
	Maximum Indoor Heat Index Reached	83	84	87	85	84	87	91	88	86	83	89	86	99
	Intensity Index (II)	0.857	0.867	0.900	0.879	0.868	0.901	0.946	0.912	0.891	0.856	0.923	1	
Passive Survivability	Time to reach 82 degrees,hr	17.8	17.8	1.7	17.3	17.7	1.3	0.0	0.0	0.2	0.5	0.0	11.0	0.0
	Time to reach 87.8 degrees,hr	>77.333	>77.333	47.3	64.3	>77.333	47.0	1.7	21.8	64.8	>77.333	2.7		0.0
	Maximum rate of temperature rise, delta T/Delta Time (F/hr)	0.8	0.8	2.1	1.0	1.6	2.1	1.4	1.4	1.3	0.8	3.8	1.6	
	Maximum Temperature Rise, F	7.2	8.5	10.9	9.0	9.0	10.5	8.9	6.1	7.7	4.1	9.3	9.6	
	Exposure Time Fraction <82F	26%	23%	2%	22%	23%	2%	5%	6%	5%	9%	0%	14%	
	Exposure Time Fraction <87.8F	100%	100%	75%	98%	100%	74%	51%	56%	97%	100%	46%	89%	
	Delaying Index (DI) Normalized-Time to reach threshold temperature/Total Ac off time	0.81	0.81	0.46	68%	81%	46%	2%	21%	63%	75%	3%	62%	

Figure 10 Thermal Resiliency Metrics During Disruptive Phase-2BHK Apartment

4.3.2 Recovery Phase

Table 5 provides details on the recovery phase metric for both apartments. The results show that living room in 1BHK apartment and main bedroom in 2BHK apartment has the lowest cooling recovery. Overall, 2BHK apartment has a higher recovery rate but takes longest to cool back to setpoint. While 2BH apartment performed better during AC outage, 1BHK apartment has better recovery resiliency than 2BHK apartment. This points out that thermal mass, floor area and volume play a critical role in delaying overheating during AC outage but also delays the cooling recovery once AC is restored. Thus, passive survivability and post-outage recovery represent distinct resilience characteristics.

Table 5 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
Time to cool back to setpoint, hour	4.2	4.5	10.5	6.4	22.17	9.5	>77.33	41.7
Cooling Recovery Rate (°F/hr)	2.97	2.79	3.09	2.98	2.28	3.43	4.63	3.45

Recovery Resiliency Index (RRI)	0.78	0.74	0.50	0.677	0.25	0.66	0.50	0.43

4.3.3 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, the combined thermal resiliency index (CTRI) is developed to calculate comprehensive resiliency index by incorporating exposure, delay, dynamic response and recovery characteristics of the apartment. Summary of CTRI metrics are given in Table 6.

Table 6 Composite Thermal Resiliency Index

Room	Exposure (E)	Delay (Del)	Dynamic(D)	TRI	RRI	CTRI
1BHK-Bedroom	0.705	0.741	0.669	0.49	0.78	0.57
1BHK-Kitchen	0.27	0.78	0.27	0.80	0.74	0.80
1BHK-Living Room	0.30	1.00	0.43	0.50	0.50	0.50
1BHK-Apartment	**0.698**	**0.35**	**0.45**	**0.54**	**0.677**	**0.58**
2BHK Main Bedroom	0.786	0.68	0.93	0.78	0.25	0.65
2BHK-Living Room	0.789	0.81	0.60	0.76	0.66	0.73
2BHK-Bedroom 2	0.788	0.46	0.24	0.58	0.50	0.56
2BHK-Apartment	**0.787**	**0.617**	**0.588**	**0.697**	**0.43**	**0.63**

The results show that 1 BHK apartment has lower exposure, delay and dynamic components than 2BHK apartment. Thus, TRI which is derived from these 3 components is lower in 1BHK apartment (0.54) than in 2BHK apartment (0.697). However, RRI was better in 1BHK apartment (0.677) compared to 2BHk apartment (0.43). Higher TRI represents higher passive survivability during prolonged cooling outage. Higher RRI represents

Overall CTRI is better in 2BHK apartment (0.63) compared to 1BHK apartment (0.58). If resiliency was determined by performance during disruptive events only, then 1 BHK apartment would be determined to have 34.9% less resiliency than 1BHK apartment. However, after including the recovery performance, 1BHK apartment has only 8.6% less resiliency than 2BHK apartment. This signifies the trade off between passive survivability and recovery resiliency.

4.4 Spatial Variability

The results displayed that thermal resiliency is strongly influenced by zone specific envelope exposure. It shows that thermal resiliency varies significantly from zone to zone and even within different locations of the zone. For example, from Figure 7 in section 4.3.1 for 1BHK apartment, TEI is 0.26 in bedroom mid, 0.20 in bedroom opposite wall, 0.36 near ceiling and 0.44 near window. In the living room, TEI is 0.44 in the middle and 0.14 in the north 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 (TRI=0.78) and living room displayed the worst passive survivability (TRI=0.39). In 2BHK apartment, main bedroom displayed the best passive survivability ability (TRI=0.74) while bedroom 2 displayed the worst passive survivability ability (0.41). RRI is highest in bedroom (0.78) and lowest in living room (0.50) in 1BHK apartment. In 2BHK apartment, living room has the highest RRI (0.66) and main bedroom has the lowest RRI (0.25). This means that during cooling outage, kitchen of 1BHK apartment and main bedroom of 2BHK apartment, both of which have the least amount of exposed surface area to outdoors are the safest area. During recovery phase, bedroom in 1BHK apartment and living room in 2BHK apartment are the safest area.

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. Limited AC outage duration: This study measured the single AC outage duration of up to single 78 hours. However, it doesn't capture the thermal response of the building under repeated interrupted outages occurred in different times of day and weather conditions.
3. 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 the results especially near threshold values. Future studies could incorporate sensor calibration and verification to quantify the influence of measurement uncertainty.
4. 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.
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. Heat Index (HI) was calculated as approximation using NOAA formulation which is best for outdoor air conditions. Indoor space has limited air movement and radiation compared to outdoors thus it might not provide accurate results. Future studies can incorporate air velocity and mean radiant temperature to develop thermal resiliency models.
7. 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 significantly. 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 dynamic framework integrating exposure, delay, transient and harmonic behavior and recovery characteristics was developed to quantify building thermal resiliency.

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 spatial zone results displayed that thermal resiliency varies significantly from zone to zone and even within different locations of the zone primarily influenced by zone specific envelope exposure and thermal mass.

Recovery behavior demonstrated that there is a tradeoff between passive survivability and recovery. The 2BHK apartment had better performance during AC outage, but 1BHK apartment had better recovery resiliency than 2BHK apartment. Based on the results, it can be stated that exposed surface area, fenestration area, zone volume, thermal mass, and location within apartment plays the most significant role in determining thermal resiliency.

The proposed composite thermal resiliency index which incorporates exposure, delay, dynamic as well as recovery components provides a comprehensive approach for evaluating thermal resiliency of buildings.

References

[1] W. Liu, J. An, C. Wang and S. Hu, "Comparative Study on Outdoor Heatwave Indicators for Indoor Overheating Evaluation," *Buildings,* vol. 15, no. 14, p. 2461, 2025.

[2] D. Aviv, S. Mathiyazhagan, S. F. Jacoby, M. Jiang, N. Bagby and J. Klaris, "Heat Stress and Urban Resilience: Alternative Cooling Strategies to Combat Extreme Heat in the Urban Environment," Kleinman Center for Energy Policy, Philadelphia,USA, 2026.

[3] V. Serrano, S. M. and N. G., "The Global Threat of Drying lands: regional and global aridity trends and future projections," UNCCD, Bonn,Ge rmany, 2024.

[4] K. Sun, M. Specian and T. Hong, "Nexus of Thermal Resilience and Energy Efficiency in Buildings: A case study of a nursing home," Berkeley lab, 2020.

[5] L. M. White and G. S. Wright, "ASSESSING RESILIENCY AND PASSIVE SURVIVABILITY IN MULTIFAMILY BUILDINGS," in *2020 Building Performance Analysis Conference and* , 2020.

[6] T. Kesik, L. O'Brien and A. Ozkan, "Thermal Resilience Design Guide," University of Toronto, 2019.

[7] M. Sheng, M. Reiner, K. Sun and T. Hong, "Assessing thermal resilience of an assisted living facility during heat waves and cold snaps with power outages," Berkeley Lab, 2023.

[8] A. F. Krelling, Y. Wu, J. Malik, M. Wei, C. Perry, R. Lamberts, D. Yan and T. Hong, "Thermal Resilience of Buildings and Communities:A Multistakeholder Review of Metrics and Approaches," *Annual Review of Environment and Resources,* vol. 50, pp. 681-708, September 2025.

[9] T. Hong, J. Malik, A. Krelling, W. O'Briend, R. Lamberts and M. Wei, "Ten questions concerning thermal resilience of buildings and occupants for climate adaption," *Building and Environment,* vol. 244, 2023.

[10] D. R. Liyanage, K. Hewage, M. Ghobadi and R. Sadiq, "Thermal Resiliency of single-family housing stock under extreme hot and cold conditions," *Energy & Buildings,* vol. 323, 2024.

[11] S. Homaei and M. Hamdy, "Thermal resilient buildings: How to be quantified? A novel benchmarking framework and labelling metric," *Building and Environment,* vol. 201, no. 108022, 2021.

[12] S. H. Holmes, T. Phlillips and A. Wilson, "Overheating and passive habitability: indoor health and heat indices," *Building Research & Information,* vol. 44, no. 1, pp. 1-19, 2016.

[13] K. J. Skolfield, A. R. Escobedo and J. R. Vergara, "Transmission and Capacity Expansion Planning Against Rising Temperatures; A Case Study in Arizona," in *2021 IISE Annual Conference*, 2021.

[14] B. J. Stone, E. Mallen, M. Rajput, A. Broadbent, S. E. Krayenhoff, G. Augenbroe and M. Georgescu, "Climate change and infrastructure risk: Indoor heat exposure during a

concurrent heat wave and blackout event in Phoenix, Arizona," *Urban Climate,* vol. 36, 2021.

[15] S. Lamichhane, R. Mostafa, B. Gopalakrishnan and D. G. Devaru, "eQUEST BasedBuilding Energy Modeling Analysis for Energy Efficiency of Buildings," *Energy Engineering,* vol. 121, no. 10, pp. 2743-2767, 2024.

[16] S. E. Kirkpatrick, C. H. Gregory, J. K. Vanos, J. W. Bladwin, H. Staudmyer, G. G. Echavarria and O. Jay, "Deadly heat stress conditions are already occuring," *Nature communications,* vol. 17, no. 2590, 2026.

[17] C. C. Hampo, L. H. Schinasi and S. Hoque, "Surviving indoor heat stress in United States: A comprehensive review exploring the impact of overheating on the thermal comfort, health, and social economic factors of occupants," *Heliyon,* vol. 10, 2024.

[18] S. Trego, S. Meerow, L. Keith and D. M. Hondula, "Heat mitigation and management in the City of Phoenix, Arizona: A case study of America's hottest large city," *Journal of Urban Affairs,* pp. 1-12, 2025.

[19] M. K. Wright, D. M. Hondula, P. M. Chakalian and L. C. Kurtz, "Social and behavioral determinants of indoor temperatures in air-conditioned homes," *Building and Environment,* vol. 183, no. 107187, 2020.

[20] A. Baniassadi, D. J. Sailor, S. E. Krayenhoff, A. M. Broadbent and M. Georgescu, "Passive survivability of buildings under changing urban climates across eight US cities," *Environmental Research Letters,* 2019.

[21] Maricopa County, "2024 Heat-Related Deaths Report," Maricopa County Department of Public Health, 2025.

[22] bigladder software, "Occupant Thermal Comfort," [Online]. Available: https://bigladdersoftware.com/epx/docs/8-7/engineering-reference/occupant-thermal-comfort.html. [Accessed 30 06 2026].

[23] J. V. Hoof, "Forty years of Fanger's model of thermal comfort: comfort for all?," *Indoor Air,* vol. 18, pp. 182-201, 2008.

[24] ANSI/ASHRAE standard 55-2023, "Thermal Environmental Conditions for Human Occupancy," ASHRAE, 2023.

[25] K. Dolaana, K. O. Berk, H. Hanne, G. Ida, W. B. P., T. Jorn and B. O. W., "Critical review of standards for indoor thermal environment and air quality," *Energy and Buildings,* vol. 213, no. 109819, 2020.

[26] T. Kesik, W. O'Brien and A. Ozkan, "TOWARDS A STANDARDIZED FRAMEWORK FOR THERMAL RESILIENCE MODELING AND ANALYSIS," in *2020 Building Performance Analysis Conference and sIMbUILD*, 2020.

[27] X. Luo, T. Hong and K. Sun, "Simulating thermal resilience of buildings and their influence by urban microclimate using," in *17th IBPSA Conference*, Belgium, 2021.

[28] A. Mitchell, G. S. Wright and M. Heidarinejad, "Thermal resilience in passive buildings: metrics, modleing methods, tool development, and evaluation of passive and mixed mode responses," *Joournal of Building Performance Simulation,* pp. 1940-1493, 2025.

[29] S. Wijesuriya, R. A. KIshore, M. V. Bianchi and C. Booten, "Enhancing thermal resilience of US residential homes in hot humid climates during extreme temperature events," *Cell Reports Physical Science,* vol. 5, no. 101986, 2024.

[30] C. J. Lin, D. B. Crawley, M. Coudert, D. Niyogi and Z. Nagy, "From comfort to survival: Indoor heat vulnerability during extreme events," *Building and Environment,* vol. 289, no. 114070, 2026.

[31] M. P. Tootkaboni, I. Ballarini and V. Corrado, "Towards climate resilient and energy-efficient buildings: A sensitivity analysis on building components and cooling strategies," *Building and Environment,* vol. 270, 2025.

[32] C. Y. Siu, W. O'Brien, T. Marianne, M. Armstrong, A. Laouadi, A. Gaur, Z. Jandaghian and I. Macdonald, "Evaluating thermal resilience of building designs using building performance simulation – A review of existing practices," *Building and Environment,* vol. 234, no. 15, 2023.

[33] S. Lamichhane, "Dynamic Framework to Quantify Thermal Resiliency and Passive Survivability During Prolonged Air Conditioning Outages in Extreme Hot Climate: Arizona Case Study," [Online]. Available: https://doi.org/10.5281/zenodo.21696738. [Accessed 01 07 2026].

[34] National Weather Service , "National Weather Service Weather Prediction Center," NOAA, [Online]. Available:

https://www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml. [Accessed 01 07 2026].

[35] J. R. Edwards, A. J. D. Roos, C. C. Hampo, W. Huang, E. Lincoln, S. Hoque and L. H. Schinasi, "Residential indoor temperatures and health: A scoping review of observational studies," *Science of Total Environment,* vol. 979, no. 179377, 2025.

[36] Health Canada, "Guidance on Upper Indoor Temperature Limits: Protecting the Health of Older Adults," Health Canada, Ottawa, 2026.

[37] S. K. Beckman, M. Hiete and C. Beck, "Threshold temperatures for subjective heat stress in urban apartments-Analysing nocturnal bedroom temperatures during a heat wave in Germany," *Climate Risk Management,* vol. 32, no. 100286, 2021.

[38] L. Ji, C. Shu, A. Laouadi, M. Lacasse and L. L. Wang, "Quantifying improvement of building and zone level thermal resilience by cooling retrofits against summertime heat events," *Building and Environment,* vol. 229, 2023.