# On Modelling of Resiliency Events using Building Performance Simulation: A Multi-Objective Approach

**ABSTRACT**

Climate change brings several challenges to BPS practitioners beyond GHG emission mitigation. Adaptation to grid-outage events, caused by both acute and chronic stresses, requires consideration of how building services can be provided to occupants in a time of need. At the moment, we lack both the tools and processes to quantify key metrics such as thermal resiliency in tandem with annual performance indicators. This paper proposes a multi-objective approach using thermal resiliency, annual net-energy, and life-cycle cost to better quantify building performance during grid-outages. The approach can handle a variety of events, using shortened simulation periods, and consider cost-implications of outages by applying the value of lost load to annual operational costs. The methodology is demonstrated using a case-study and a historical grid-outage from an ice-storm event. Resiliency indicators are improved by two times and the payback of upgrade packages are decreased to 14 years for a single outage event.
*Keywords:* thermal resiliency, adaptation, zero net-energy, life-cycle cost

## 1. Introduction

The infrastructure we build now is not prepared to withstand the shocks of future climate events. Although significant efforts have been placed on rapid decarbonization of the built environment by meeting our 1.5 °C targets [1], it may be prudent to place equal or greater effort on adapting to increased frequency and severity of grid-outages caused by chronic stresses and acute weather events. Events, in as few as the last three years, have required more than $650B USD (0.28% of Gross Domestic Product (GDP)) to recover from [2]. Due to the predicted regularity of outage events, designing infrastructure to survive and potentially thrive during a loss of power may bring health, social/political and economic benefits to owners, operators and occupants. At the moment, we lack the modelling tools needed to evaluate building performance during outages from the earliest conceptual phases of a project.

The novelty and utility of resiliency analysis using building performance tools has been well documented [3–6]. It has been established that a balanced approach is needed: practitioners do not want to focus on resiliency at the expense of other annual indicators of performance such as energy, emissions, and cost. Marjaba and Chidiac (2016) noted a lack of metrics for assessing the resiliency for buildings, particularly in tandem with other sustainability indicators [5]. Clarke (2018) proposed resiliency test procedures where event-specific perturbations are applied to a calibrated model over multiple years [6]. In support of these goals, progress has also been made in developing extreme weather files to evaluate building performance during an event. For example, Pernigotto et al. (2020) developed a procedure for extreme weather events based on EN ISO 15927-4:2005 [7]. Still lacking is a method to conduct resiliency evaluations in concert with other annual indicators. Addressing these limitations may aid the increased prominence of resiliency studies using building performance analysis to future-proof our existing and new building stock.

Quintessential to the problem of resiliency is the temporal thermal performance of occupied spaces during outages. Clearly, both extreme hot and cold can lead to increased morbidity especially in elderly populations [8]. Nevertheless, even small deviations from temperature setpoints have consequences to certain demographics. For example, Lindemann et al., 2014 found significant physical deficiencies in the elderly (mean age of 78) when exposed to moderately cool room temperatures of 15 °C [9]. Furthermore, the exact definition of occupant comfort has not been thoroughly explored during outage events at any demographic segment [10]. Without reliably conditioned shelter, and other basic necessities, we may face the necessity of continued state of emergencies until our infrastructure has been updated to withstand increasingly common utility outage events.

## 2. Literature Review

Resilience has become a critical issue due to the present climate change trend of increased severity and frequency of weather events [11]. In Canada, cold-climate weather events, such as ice storms and snowstorms, have the largest consequences on occupant comfort and people's livelihood [12]. For example, the 1998 Eastern Ontario ice storm caused around $1.2B in losses and over 840,000 insurance claims [13]. Similarly, summer events, such as heat waves in Fort McMurray followed by wildfires, have caused $3.7B in in damages making it the most costly disaster in Canadian history [14]. To address both the adaptation and mitigation aspects of climate change, a 2021 report recommends that Canadian's allocate no fewer than 2–3% of annual GDP to transition to net-zero and adapt to our changing climate by 2050 [15].

Despite the importance of evaluating, quantifying, improving, and optimizing the thermal performance of buildings during outage events, few previous studies have created a flexible framework for assessing thermal resiliency. Flexibility allows for a more generalized approach to assess resiliency, and other related indicators, independent of the specific outage scenario, region or climate.

### 2.1. Defining Resiliency

Resiliency assessment has progressed in various fields, including building performance, earthquake engineering, structural engineering, urban planning, and environmental engineering [16–18]. Resiliency is a system's ability to maintain an acceptable level of performance in the face of external stimuli that can otherwise result in failure. Resiliency has been defined and redefined in literature for over fifty years [19, 20]. Rostami and Bucking presented over ten unique definitions of resiliency and described how interpretations have significant overlap with other definitions such as robustness, reliability and vulnerability. Generally, approaches to resiliency assessment could be categorized into quantitative and qualitative models [22, 23]. However, the concept of resilience applied to building thermal performance assessment using quantitative approaches has only recently started to be addressed [20]. Unsurprisingly, previous studies have defined unique metrics to quantify thermal resiliency, including: (i) peak and mean temperature [24], (ii) number of hours above a defined temperature threshold [25], (iii) number of degree-hours above a defined temperature threshold [26, 27], (iv) maximum predicted mean vote and predicted percentage of dissatisfied, (v) passive habitability or the duration of time a space remains habitable post-outage [28], and (vi) time to reach temperature setpoints [29]. The various proposed metrics for assessing thermal resiliency indicate no convergence in formal definitions [24–27, 29]. The need to develop a flexible resiliency assessment framework using multiple metrics has not been addressed and it is a knowledge gap identified by existing literature in both building environmental assessment and related fields [10, 30, 31].

The first step towards quantifying resiliency is to define a performance function representing how a building responds to an outage event [32]. A quality function, often denoted as $Q(t)$ in literature, quantifies how a system responds to external stimuli [16, 17]. This term was first applied to structural engineering problems [33, 34], but has been later used in various civil engineering fields such as transportation engineering [35], infrastructure management [36], environmental engineering [37], and water resource management [38]. Quality functions are typically unitless and normalized such that a value of one indicates nominal performance whereas a value of zero indicates a failure. A failure is an inoperable state where an item, component or system does not perform as previously specified [39]. Designing to fail safely and adapt from failure has received recent attention in literature. 'Safe-to-fail' broadly describes adaptation scenarios that allow infrastructure to fail, in a controlled manner, ideally minimizing the subsequent consequences of failures [40]. This approach is more cost-effective than over-engineering infrastructure such that failures never occur. To better adapt from failure, Taleb (2012) defines antifragility as an aspiration, beyond resiliency, where systems grow stronger to future events after exposure to an external threat [41].

### 2.2. Relationships between resiliency and life-cycle cost

Associating economic value to resilient infrastructure is difficult as it often requires an estimation of avoided future capital expenditure or loss of economic activity. This problem has been previously solved by electrical engineers who allocated a Value of Lost Load (VoLL) to power blackouts which are at an increased risk due to privatization and the expansion of renewable capacity [42]. Further applications include micro and nanogrids that provide localized utilities during grid-outages [43]. Originally, this solution was applied to critical infrastructure such as hospitals, military bases, water treatment plants, and computer server farms requiring redundancies and where an operator is willing to pay a premium to avoid power disruptions [44]. In 1992, it was estimated that residential VoLL is between $2–10 per kWh whereas the commercial markets see higher values ranging from $5–46 per kWh [45]. A literature review in 2015 points to a considerable increase in VoLL varying between $5–280 per kWh [42]. Regardless of the end-user, VoLL is always understood to be higher than the price of the undelivered energy [43].

Although the application of VoLL started with grid black-outs, associating intrinsic value to avoiding infrastructure failure has utility. Previous works have also shown how VoLL can be incorporated into life-cycle financial assessments [46, 47]. Nevertheless, VoLL has not been directly applied to assess the economic value of resilient infrastructure.

To address gaps in literature, this paper proposes a quality function to assess the thermal resiliency of a building during a simulated grid-outage. This deterministic approach will evaluate the thermal decay of two designs during a historical ice-storm event: a code-compliant design and a proposed improved design. The new proposed performance metrics for resiliency will be determined in tandem with the annual net-electricity use of the home and the 25 year life-cycle cost establishing a multi-objective approach. To account for the economic benefit of designing for resiliency, the value of lost load will be integrated into the annual operation costs of the building. The methodology is demonstrated using an energy model of a constructed tiny home that includes innovative technologies such as a microgrid compatible building-integrated photovoltaic roof with $21kWh$ of battery storage, highly insulated and air-tight envelope, and advanced control capabilities. All technologies are anticipated to contribute positively to the thermal resiliency of the home.

## 3. Case Study

### 3.1. Northern Nomad Tiny Home

Figure 1 shows the case-study considered in this paper. The Northern Nomad is a 19m$^2$ tiny home that was constructed in 2018 and is located in Ottawa, Canada. The home showcases many innovative features including a thin, highly insulated enclosure using vacuum panels and a 2.34 kW south-facing, roof-integrated PV system with 21kWh of electric battery storage. A 900L tank was integrated into the conditioned space and serves the dual purpose of water storage and optional thermal mass. The water tank affects the thermal decay of the proposed design and is not present in the code-compliant reference design. The case-study was modelled in EnergyPlus using a single thermal zone, a photovoltaic one-diode model and kinematic battery based on the physical electrical configuration.

The Northern Nomad research home is an ideal case-study as it includes several technologies and design approaches that improve resiliency metrics and the magnitude of those improvements can be experimentally validated without disrupting existing occupants. Presently, the home is undergoing experimental studies to ensure it meets its original net-zero energy design goal. Experimental validation of resiliency measures is also planned and is important as design variables which improve resiliency may differ from those which reduce annual energy use. Once experimental validation is complete, an area of future work is to apply these upgrades to a portfolio analysis which may better represent existing building stocks to identify measures that broadly improve the resiliency of buildings.

Table 1 shows the decision variables considered for the case-study. The reference building is a minimal code compliant design as per Ontario Building Code Part 9 [48]. The proposed building is the as-built design. Design parameters not shown in Table 1, such as occupant end-use and thermostat setpoints, were identical in both scenarios.

**Table 1:** Influential Model Variables for Case-Study

| Variable | Description | Units | Reference | As Built |
|---|---|---|---|---|
| wall_ins | Effective resistance of wall insulation | $m^2K/W$ | 3.5 | 6.51 |
| ceil_ins | Effective resistance of ceiling insulation | $m^2K/W$ | 4.23 | 6.51 |
| floor_ins | Effective resistance of floor insulation | $m^2K/W$ | 5.46 | 6.51 |
| infil | Natural infiltration rate | $L/s/m^2$ | 0.302 | 0.076 |
| pv_area | Percent of PV area on roof | % | – | 95 |
| pv_eff | PV efficiency | % | – | 15.8 |
| GT_s | Glazing type, south (also N,E,W) | – | DGLowE | TGLowE |
| batt_size | Battery size for DC-coupled system | $kWh$ | – | 21.12 |

Figure 1b shows an image of the energy model as constructed in EnergyPlus version 9.6 (viewer shown as per OpenStudio SketchUp plugin). The energy modelling approach is backwards compatible with EnergyPlus version 9.0 with minor changes to output variables. Figure 2 shows the electrical configuration used by Northern Nomad tiny house. A DC-coupled configuration was selected to use AC-based loads in the home and enable on-grid/off-grid capabilities via a micro-

**(a)** The Northern Nomad (North Face) **(b)** Energy Model representation

**Figure 1:** Case-study building

grid compatible inverter. These components allowed for the as-built design to grid-disconnect and self-power where as the code-compliant design experienced a complete loss of power during the outage event.

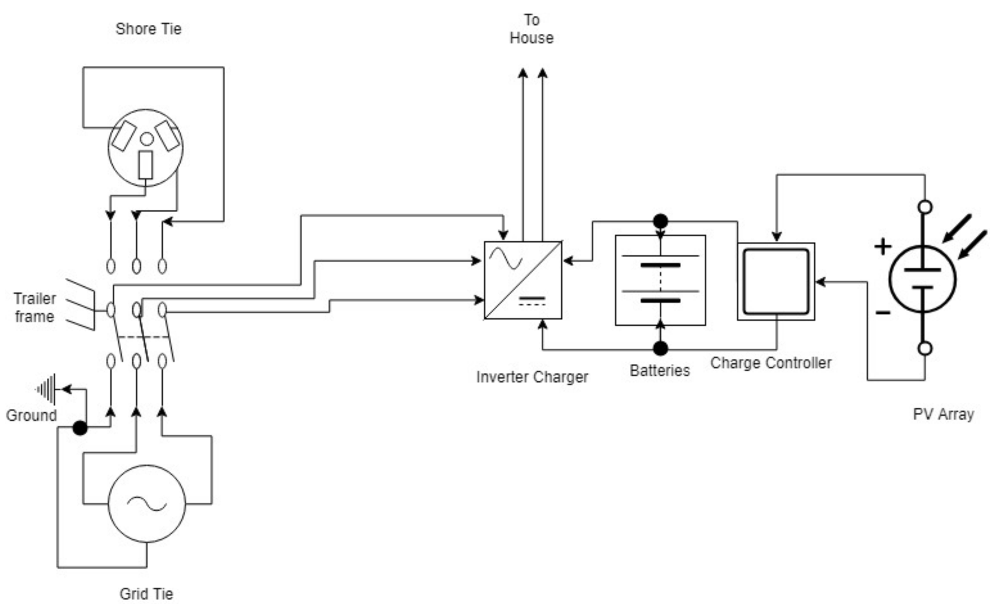


**Figure 2:** Electrical single line diagram of the Northern Nomad's renewable energy system

### 3.2. Selected Resiliency Event

As previously described, resiliency studies may consider acute events such as regional heat waves or symptoms of chronically stressed infrastructure such as brown-outs due to unforeseen demands on power grids. This paper considers an acute event to quantify building performance using a historical outage. Future work will consider predicted outage events using projected climate change trends. The IPCC anticipates that future events will be more severe and longer than historical events [1]. Emphasis in this paper is placed on frequently reoccurring events, 1:10 – 1:30 year events, and not extreme outliers such a 1:100 or 1:200 year event.

This paper uses the 1998 Eastern Ontario ice-storm (January 5–10$^{\text{th}}$, 1998) as an outage event. During the storm, nearly four million utility customers lost power due to an accumulation of up to 7-11cm of ice on trees and power lines. Although the majority of utilities were restored in a matter of days, several rural communities lost power for up to three weeks. This event was selected based on predictions that ice-storm events in Northern climates will occur more frequently due to warmer and more favourable conditions [49]. This paper conservatively uses an outage period of 48 hours with an average outdoor temperature of $-1\,^{\circ}\mathrm{C}$ based on actual meteorological data. For reference, the typical January monthly average in Ottawa is $-10\,^{\circ}\mathrm{C}$ [50]. This is expected as ice-storms are associated with warm, moist air-masses so the 48 hour average temperature is higher than the seasonal temperature.

In practice, we recommend a regional approach using several historical/predicted outage scenarios ideally balanced throughout all seasons. The selection of events is best determined from historical outages and further work is needed to predict the most probable future events. Extreme cold and heat events may be selected if supported by historical precedence or meteorological projections. However, the probability of such an event should overlap with the expected life-span of the building. A diversified approach including both acute and chronic events should yield better outcomes.

The following details were specified for the simulation: (i) the outage event lasted from Jan. 5–7$^{th}$, (ii) historical weather data was translated from NRCan website into EPW format [50], (iii) outage schedules were specified as per Table 2, and (iv) the frequency of the event was set to every 10 years which, regionally, is how often these events occur [13]. Other comparative events include the Houston TX Winter Storm (Feb 10–20$^{th}$, 2021) and the 2009 North American Ice Storm (Jan. 25–30$^{th}$, 2009) [51].

For resiliency studies, the peak value of lost load should be specific to the outage event. For this event, we are particularly concerned about occupant health and the replacement cost to repair the home given a burst frozen pipe (major failure). As such, Figure 3 shows an extreme value of $\$250/kWh$ (at freezing temperatures). Using this peak value, the estimated repair costs due to flooding in the case-study was approximately $5,000 (3% of initial cost). Also implicated in this plot is the health and well-being of the occupant as the probability of hypothermia increases as a core body temperature dips below 37 °C. An exponential relationship demonstrated the occupant's willingness towards action as the average temperature in the occupied space decays towards zero.

Revisiting Taleb's notion of antifragility [41] (see section 2.1), VoLL quantifies the intrinsic economic value of withstanding each event. This approach suggests that economic value can be reinvested back into the system making it more re-

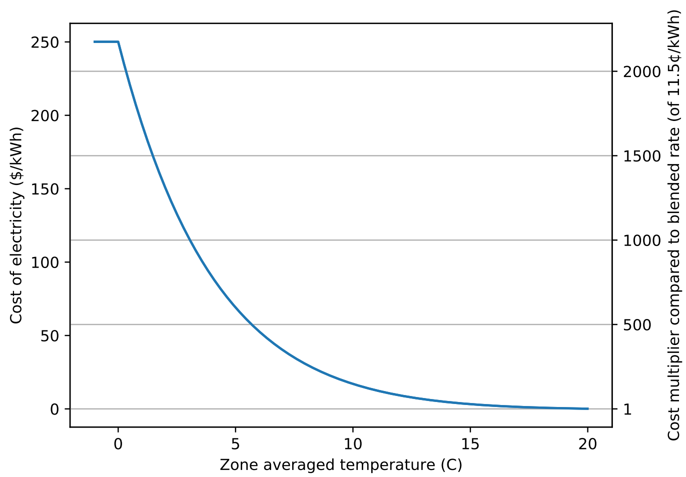


**Figure 3:** Relationship between VoLL and Zone-Averaged Indoor Air Dry-Bulb Temperature

silient to future outage events.

## 4. Methodology

The methodology is presented starting with a flow chart of each major step. Later sections provide additional details regarding model implementation and Key Performance Indicators (KPIs).

### 4.1. Flow Chart for Modelling Annual Simulations and Outage Events

The proposed methodology for modelling resiliency events alongside other annual indicators is described in Figure 4. Major steps include: (i) problem definition, (ii) defining resiliency KPIs, (iii) creating event-specific energy model, (iv) defining cost model parameters, and (v) calculating annual KPIs: net-electricity use and 25 year life-cycle outcomes. Each step is described in this section and is applied to the case-study presented previously in section 3.

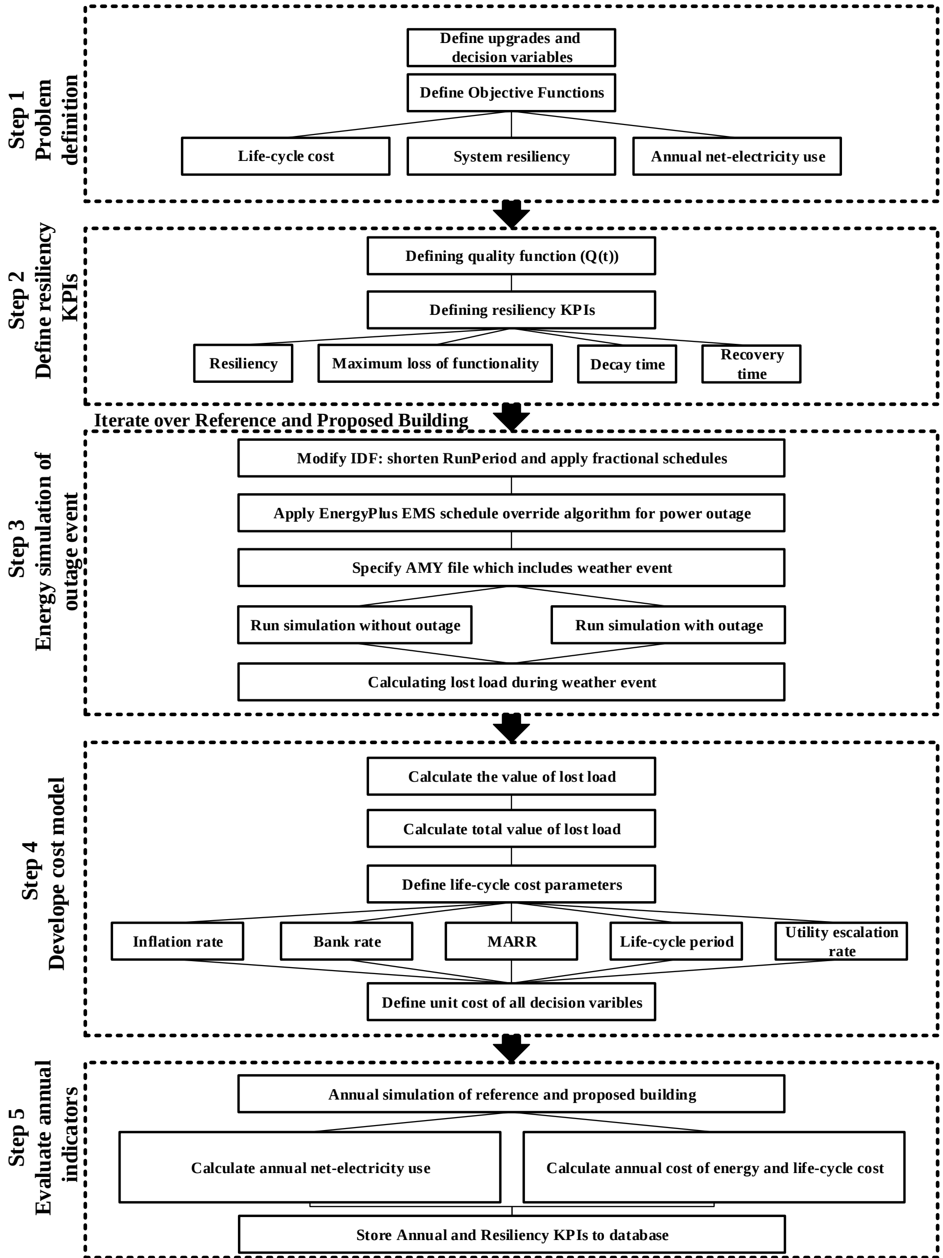


**Figure 4:** Research framework for multi-objective resiliency studies

The approach requires a model of the infrastructure to be tested. For this paper, the case study was modelled using EnergyPlus via the Input Description File (IDF) format [52]. Upgrades were automated using a Python scripting process as determined by user-specified decision variables for both a reference and proposed design, previously presented in Table 1. The event was defined using historical actual meteorological year (AMY) weather data and an estimated frequency of the event. Annual indicators, such as net-electricity use, life-cycle cost over a 25 year period, and event-specific system resiliency KPIs were defined to evaluate building performance. All annual indicators were determined using typical meteorological year climate data that did not include the AMY resiliency events. Resiliency KPIs are defined in section 4.2.

To evaluate the resiliency KPIs, the energy model must be modified. First, the simulation run period is shortened to start two weeks before the event and end one day after the event. This gives enough time for the model to converge before and after the outage event. Larger buildings may require a longer convergence and recovery period. Heating and cooling setpoints were modified to a constant temperature during outage event (20 °C for case-study).

The resiliency event is simulated twice: with and without the grid-outage. EnergyPlus' behaviour was modified to allow for a temporary loss of power if a battery is not present or is insufficiently charged, as described in section 4.3. The lost load is the energy difference between a building that meets its specified end-use loads and setpoints and the actual performance during an outage event. The lost load estimates the energy implications of improved technology and determines the value of lost load in the cost analysis. During an outage event, the energy difference between these two scenarios would be zero if the building had sufficient generation and storage to meet all loads. As a quality assurance process, we recommend that both temperature profiles be plotted to ensure that setpoints are met. This is especially important during the non-outage event as it implies that the subsequent lost load estimate is fully quantified. To ensure the building experiences a full loss-of-power, we recommend plotting the energy use of the building, PV generation, and the battery's state of charge. Several outage events can be modelled by iterating over this process and calculating the VoLL for each event.

The temperature profile of the building during the outage event defined the quality function for resiliency KPIs and the value of lost load. The cost curve, shown in Figure 3, was multiplied by the extracted temperatures to determine the hourly cost of energy during the outage event. This cost is multiplied by the lost load energy difference at each timestep to quantify the VoLL. The resiliency KPIs in section 4.2 were calculated using the zone-averaged temperature profiles and the subsequent quality function of the outage event.

Annual performance KPIs, such as the energy use intensity and life-cycle cost, were calculated next. The VoLL was applied onto annual operational costs and was normalized by the frequency of the event (e.g. for a 1:10 year event, a \$10,000 VoLL would result in an increase of \$1,000 per year in operational expenses). This approach allows for the VoLL of multiple events to be superimposed onto annual operational costs.

### 4.2. Resiliency Key Performance Indicators

Quality functions, denoted as $Q(t)$, allow for the quantification of infrastructure resiliency. For this paper, we mathematically defined the quality of interior environments using equation 1. Note, it is customary to write $Q(t)$ as a function of time and not strictly as a function of temperature.

$$Q(t) = \begin{cases} 1 & \text{if } T(t) \geq T_\gamma \\ 0 & \text{if } T(t) \leq T_\alpha \\ \frac{T(t)}{T_\gamma - T_\alpha} & \text{otherwise} \end{cases} \tag{1}$$

Where: $T(t)$ is the hourly zone-averaged dry-bulb temperature, $T_\alpha = 0\,^\circ\text{C}$, and $T_\gamma = 20\,^\circ\text{C}$ and Q(t) is a linear interpolation between acceptable values when $T_\alpha < T(t) < T_\gamma$.

Using this quality function, a failure occurs when $\alpha = Q(T(t) \leq T_\alpha) = 0$, and an acceptable recovery is defined as $\gamma = Q(T(t) \geq T_\gamma) = 1$.

Thermal resiliency is defined by equation 2.

$$\text{Res}(t) = 1 - \sum_{i=1}^{n} \frac{\int_{t_{1',i}}^{t_{2',i}} \gamma(t) \cdot dt - \int_{t_{1',i}}^{t_{2',i}} Q(t) \cdot dt}{t_{2',i} - t_{1',i}} \tag{2}$$

Visually, this is the area under the acceptable performance curve shown in Figure 5. Since the acceptable recovery rate is $\gamma = Q(T(t) \geq T_\gamma) = 1$, we can simplify equations such that $t_{1',i} = t_s$ and $t_{2',i} = t_f$ which are the start and stop times of the outage event(s).

The maximum loss of function, equation 3, describes the maximum vulnerability of the interior environment.

$$LoF_{max} = 1 - min(Q(t)) \tag{3}$$

The decay and recovery times ($t_{decay}$, $t_{recov}$) are defined with respect to $LoF_{max}$ for the event as shown in Figure 6. Although several thermal decays and recoveries may occur during an outage, only the decay and recovery times from $LoF_{max}$

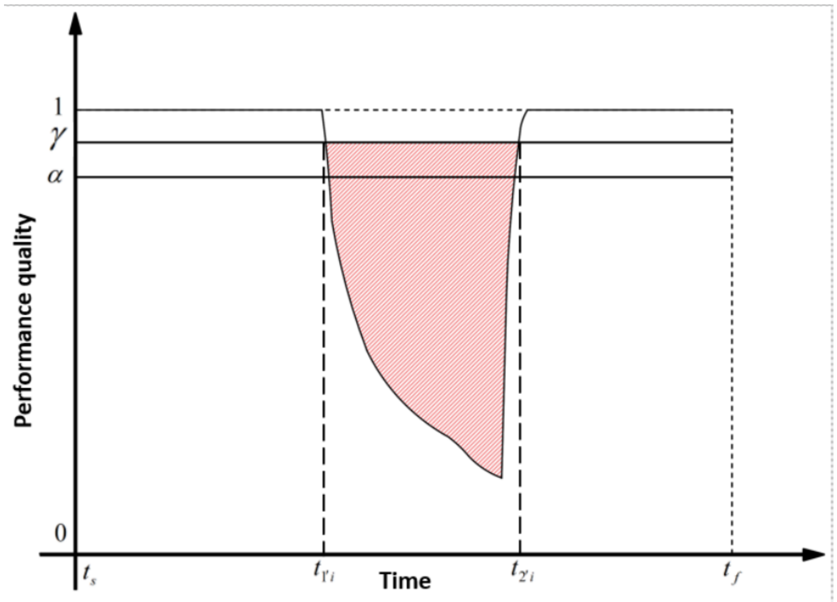


**Figure 5:** Visual Definition of Resiliency

are recorded. This ensured that the longest decay and recovery times are quantified. The decay time could be used as a performance metric as it quantifies the passive habitability of a space as defined by Kesik et al. (2020) [28]. This is possible only if an appropriate alpha value is selected to quantify when occupants can no longer tolerate interior temperatures (ie. a failure).

### 4.3. Energy Model Resiliency Implementation

Resiliency events were modelled using EnergyPlus' Energy Management System (EMS) which allows for custom routines and controls. EnergyPlus' default behaviour is to meet specified loads regardless if energy resources are available. This means EnergyPlus is not inherently capable of capturing the thermal and energy dynamics of resiliency events without user modification (as of Version 9.6). Our first attempt to model the outage involved a grid-connected trans-

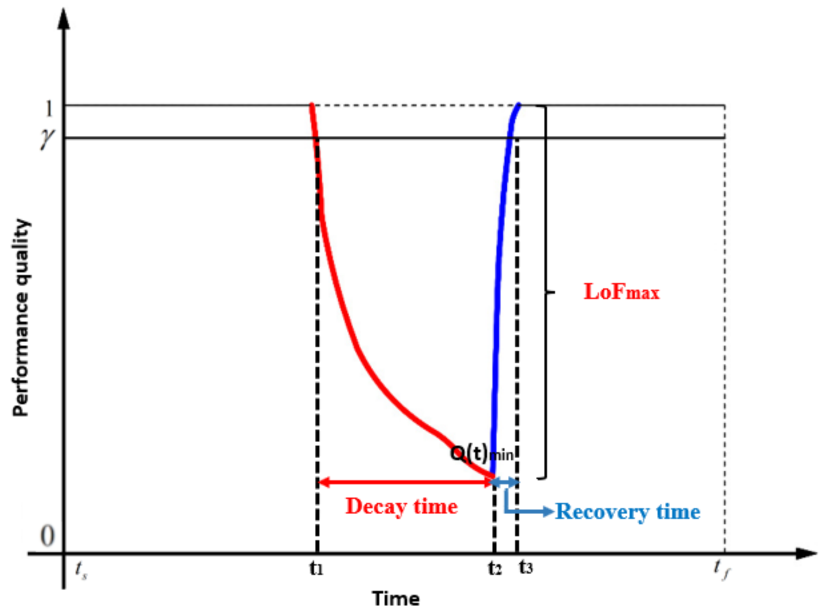

**Figure 6:** Visual Definition of $LoF_{max}$ and $t_{decay}$–$t_{recov}$

former for the entire facility with an availability schedule set to 'OFF' during the grid-outage. However, a core feature of EnergyPlus is to meet loads and thermostat setpoints by whatever means possible. As such, to model grid-outage events, one must override schedules for every load in the building by directly setting them to zero during the outage. The control logic, shown in Algorithm 1, demonstrates the pseudo-code for this schedule override (generalized to any simulation tool). Note that loads can be met during an outage if an appropriate charge is present in a battery or if sufficient generation is present on-site.

The fractional load logic depends on the load type considered. The building will not use electricity if all schedule fractions are set to zero. For the case study considered, the EMS schedule fractions are shown in Table 2. Note, the DHW system was unavailable during the outage event to provide HVAC systems sufficient resources to meet setpoints (and prioritize improving thermal resiliency

**Algorithm 1** Schedule Override Algorithm for Power Outages

**Precondition: objs** is a collection energy model objects that are being modified
**Precondition: S** are user defined schedule types (eg. *lights, plug-load, HVAC, DHW*)

```
function OVERRIDESCHEDULES(objs, S)
    mod_objs ← objs                                   ▷ Energy model objects to be modified
    minSoC ← 0.1                                      ▷ Min tolerable state of charge in battery (kWh). 'minSoC'
                                                        is compared to battery SoC at each timestep.
    mod_objs ← addRecovOutageSchedules(mod_objs)      ▷ Add grid 'avail' and 'recov' schedules
                                                      ▷ avail = 0 during grid-outage. recov = 1 when outage event is over.
    i ← 0
    for s in S do                                     ▷ For each schedule in schedules. Schedule types shown in Table 2
        o ← getUserOverrides(s)                       ▷ Get user specified schedule overrides (as per Table 2)
        mod_objs ← addSensorActuator(mod_objs, s)     ▷ Add sensor objects for battery state and
                                                        Actuator overrides for Schedules.
        if SoC ≤ minSoC & avail = 0 then              ▷ Scenario: Outage and no battery charge
            scheOverride ← 0
        else if SoC > minSoC & avail = 0 then         ▷ Scenario: Outage and battery charge
            scheOverride ← o[i]['batt']               ▷ User specified schedule behaviour
        else if avail = 0 & recov = 0 then            ▷ Scenario: Outage and battery charge
            scheOverride ← o[i]['recov']              ▷ User specified schedule behaviour
        else pass                                     ▷ Scenario: Before outage event.
                                                        Use default schedule
        i ← i + 1
    return mod_objs
```

over providing hot-water to occupants). Other utility outages, such as natural gas and propane, are not considered but they could be implemented into the methodology via additional availability and recovery schedules.

Modelling outages using EnergyPlus involves several intricacies. A limitation of the proposed algorithm is that an end-user must specify fractional loads for when the building recovers from an outage. As implemented, EnergyPlus' schedule objects have been overridden by user EMS inputs. These could be restored by outputting annual schedules to a comma separated file during a pre-simulation and reading them back into the model at every timestep during and after the resiliency event. By default, fractional loads are equivalent for both resiliency simulations (with and without the grid-outage). This implies that specifying fractional loads has no consequence on VoLL calculations. It does impact heat gains in the spaces and subsequent occupant comfort post-event which is not

**Table 2:** Schedule fractions throughout entirety of resiliency event

| Schedule Type | Description | Pre-Event[a] | During Event | Post-Event |
|---|---|---|---|---|
| HVAC Availability | HVAC system availability to meet temperature setpoints | — | 1.00 | 1.00 |
| Lighting Availability | Fraction of lighting power density schedule | — | 0.25 | 1.00 |
| Plug-Load Availability | Fraction of plug-load power density schedule | — | 0.50 | 1.00 |
| DHW Setpoint | DHW system temperature setpoint | — | 0 | 60 °C |

*a*: as specified by EnergyPlus schedule;

explicitly studied.

### 4.4. Cost Model

VoLL was calculated by multiplying the energy difference between each resiliency event (with and without a grid connection) at every timestep to the values shown in Figure 3 (which is based on the hourly zone-averaged dry-bulb temperature). The VoLL, divided by the frequency of the event in question, was applied to the annual utility costs. Although it is not immediately intuitive, this approach implies that a consumer is indirectly spending more to operate their building if it performs poorly during an outage event. As such, VoLL should be event specific and determined from repair costs to damaged components and services. An end-user can also consider health and well-being implications and subsequent actions to condition spaces in the event of an emergency. This proposed approach allows for resiliency design features to carry a cost benefit for improving performance and accelerates the payback of technology packages. Studying multiple outage events (for example 3–5 events in the life-cycle of the building) is recommended to better capture a full spectrum of outage events and should further accelerate paybacks.

For the life-cycle economic analysis, it was assumed that a long-term inflation target of 2% is met over the 25 year period studied. An expected marginal rate of return (MARR) of 2.8% takes into consideration a guaranteed investment alternative with a 0.8% growth rate [53]. Utility prices are expected to increase annually over the life-cycle at a rate of 3%.

The utility rates are shown in Table 3 [54]. Note that technologies were not controlled to take advantage of reduced overnight rates. The battery is programmed to charge the module if a surplus of electricity is available, otherwise any stored charge is used at the following timestep. The battery module could be programmed to charge overnight and discharge during the day when peak rates occur resulting in 8.8¢/kWh of savings. This simplification ensured that we are studying accelerated paybacks from modelling resiliency events in isolation and not the savings from a difference in overnight utility rates.

**Table 3:** Time of use billing schedule (Winter 2021) [54]

| Pricing Schedule | Hours | TOU | Price (¢/kWh) |
|---|---|---|---|
| Summer Weekdays | 19:00–07:00 | off-peak | 8.2 |
| | 07:00–11:00 | mid-peak | 11.3 |
| | 11:00–17:00 | on-peak | 17.0 |
| | 17:00–19:00 | mid-peak | 11.3 |
| Winter Weekdays | 19:00–07:00 | off-peak | 8.2 |
| | 07:00–11:00 | on-peak | 17.0 |
| | 11:00–17:00 | mid-peak | 11.3 |
| | 17:00–19:00 | on-peak | 17.0 |
| Weekends and Holidays | 00:00–24:00 | off-peak | 8.2 |

A microgrid compatible inverter and an automatic transfer switch allowed the home to disconnect from the grid and self-power during an outage. This configuration enabled the home to import and export electricity throughout the year while still maintaining off-grid capabilities. Microgrid compatible configurations do carry significant cost premiums. For this paper, it was assumed that PV was roof integrated (ie. replacing a finished surface) for $1.5/W and microgrid compatible components carried a 25% total cost premium (applied to PV, inverter and battery capital expenditures). The 21kWh battery back was purchased for $9,000 CAD ($425/kWh). As microgrid compatible components become more common, this cost premium may decrease in the future.

To explore a policy implication of improved resiliency, the proposed cost methodology explores reductions in insurance payments to further accelerate payback. Naturally, buildings that can withstand outage events are less likely to make claims on their insurance policies. As such, we studied a 10% reduction in annual insurance premiums (savings of $100/year for the case-study).

A Monte Carlo analysis was conducted on cost parameters to better understand their influence on economic payback. An ensemble of parameters were sampled 300 times using a normal distribution and a standard deviation of 1–5% of its nominal value based on the confidence of there assumed values. The resulting values were simulated and fit to a linear regression model to rank variables by p-values. All sampled values and subsequent outcomes were reported with a 95% confidence interval. The analysis was conducted multiple times to eliminate non-influential cost parameters and to avoid over-parameterization of the regression model.

## 5. Results and Discussion

Results are organized into the following subsections: (i) key performance indicators, (ii) temporal performance during simulated outage event, (iii) pathway analysis, and (iv) Monte Carlo economic analysis.

### Key Performance Indicators

The performance metrics of the study are summarized in Table 4.

**Table 4:** Performance metrics for Reference and Proposed Designs

| KPI | Description | Units | Reference | As Built |
|---|---|---|---|---|
| Annual: Net-EUI | Net Energy use Intensity | $kWh/m^2$ | 368 | 11 |
| Annual: LCC Payback | Life-cycle payback of upgrade packages | years | – | 14.2 ± 3.2 |
| Initial Cost Premium | Initial cost premium relative to reference | $ | – | 27,500± 5,100 |
| Event: Energy Deficit | Unmet energy demand during outage (determines VoLL) | kWh | 48 | 5 |
| Event: VoLL Cost | Value of Lost Load during outage | $ | 4,600 ± 500 | 20 ± 2 |
| Event: Resiliency | Resiliency KPI, see equation 2 | – | 0.40 | 0.83 |
| Event: $\text{LoF}_{\text{max}}$ | Maximum Loss of Function, see equation 3 | – | 0.94 | 0.27 |
| Event: $t_{decay}$ | Decay time to $\text{LoF}_{\text{max}}$ | hours | 48 | 16 |
| Event: $t_{recov}$ | Recovery time from $\text{LoF}_{\text{max}}$ to $Q(t) = 1$ | hours | 6.0 | 3.0 |

Note that the original target of NZE is not met in the proposed design. This is due to power conversion losses within the PV/battery system which were not originally accounted for. Accounting for these losses, approximately 400kWh/yr or 15kWh/$m^2$, the proposed design would have surplus net-electricity generation over a typical meteorological year.

Technology payback (including all upgrades presented in Table 1) was reduced from a non-payback scenario, to 14.2 ± 3.2 years for a single ice-storm event. The non-payback scenario, where resiliency VoLL is ignored, is partially attributed to the round-trip energy penalty for operating battery storage (approximately 10% of gross energy production). As such, batteries did not have life-cycle payback based solely on annual indicators due to increased energy use accompanied with a significant cost-premium. Future studies will consider multiple events where some events may occur simultaneously which is anticipated to further accelerate paybacks. Designing for resiliency required a cost premium of $27,500, which is approximately 20% to the initial cost of the project.

The difference in VoLL was significant when comparing the reference and proposed designs. The code-minimal reference design experienced near-freezing temperatures within 12 hours of the event resulting in an accumulation of $4,600±500 in VoLL (or $460 per year given the 1:10 year frequency). The proposed Northern Nomad design accumulated $20±2 in VoLL during the same period.

From a policy perspective, decreasing insurance rates by 10% accounted for nearly 20% of savings relative to the annual VoLL metric. Although this policy outcome was not as significant as other cost parameters, this result shows promise that policies can influence the payback of resiliency measures.

**Temporal Performance during Simulated Outage Event**

Figure 7 shows the power and temperature/Q(t) profiles for the reference design. The shaded block on the x-axis indicates the beginning and end of the outage event. A rebound energy demand, of approximately 1.5kW, in the 'No Outage-Power' plot is present as the home recovers from the outage. This is due to delayed DHW demands (i.e. that were scheduled 'OFF' during the event) being met post-recovery. To ensure we estimated lost-load accurately, the rebound effect is present both in the non-outage and outage scenarios. However, power requirements are more pronounced in the reference building outage scenario as the building meets both setpoints and DHW demands simultaneously post-recovery.

Figure 8 shows the energy and temperature/Q(t) profiles for proposed design. This Figure shows that the energy model behaves as expected. At the beginning of the outage event, the proposed building uses battery charge and on-

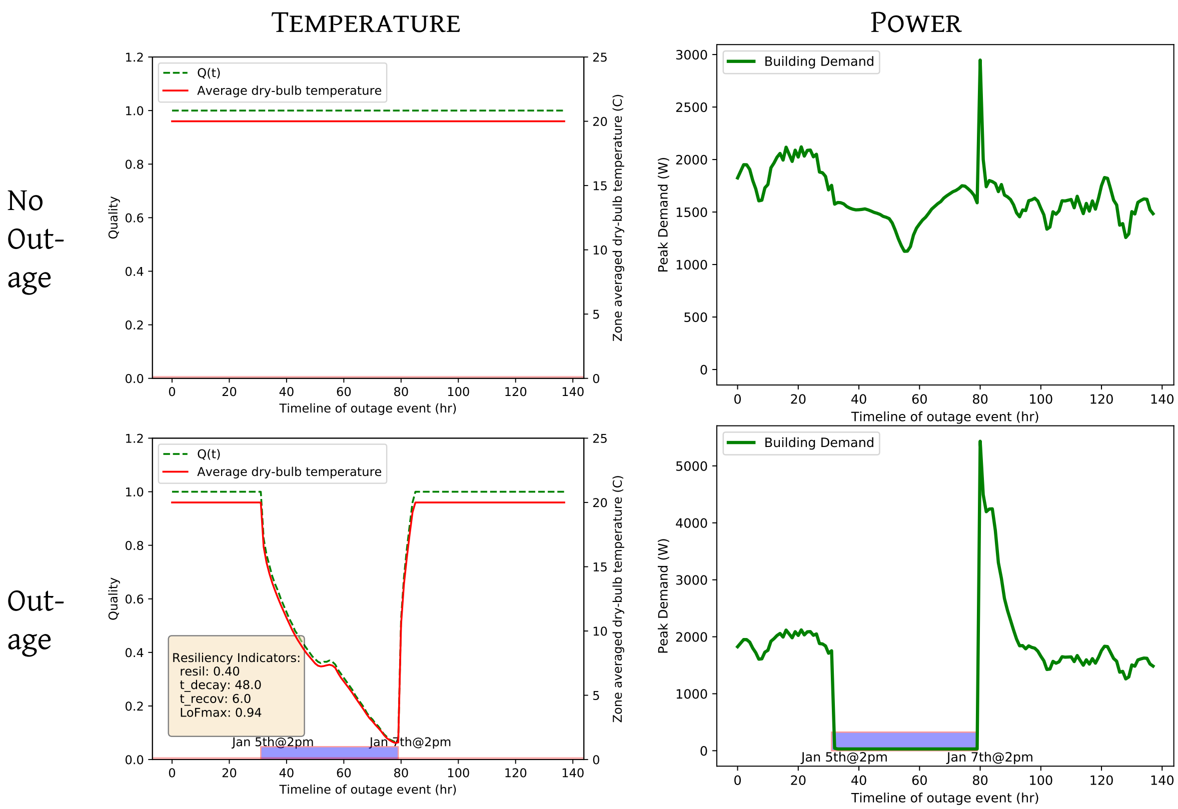


**Figure 7:** Reference Building Resiliency KPIs

site generation to maintain space conditioning. When the charge is depleted, the space will thermally decay until power is restored or additional on-site generation resumes. Clearly, passive and active solar design strategies (insulation, airtightness, thermal mass and generation/storage) improve the resiliency of the proposed building. A feature of using resiliency simulation is that the proposed methodology allows for the quantification of what that relative improvement is with respect to the studied outage event.

The characteristics of the temperature decay shown in Figures 7–8 is significantly affected by the decision parameters, described in Table 1, showing that

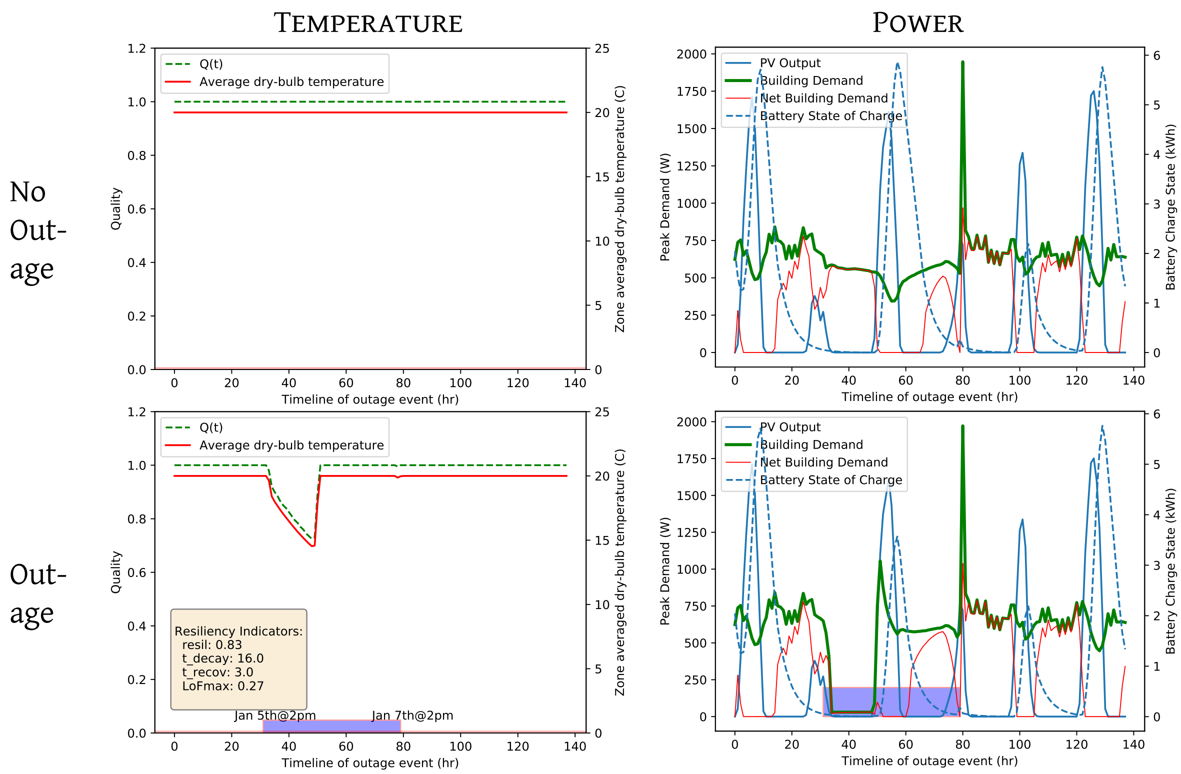


**Figure 8:** Proposed Building Resiliency KPIs

resiliency can be quantified and designed for. The resiliency performance metrics show that the proposed design thermally decays for a shorter period of time and recovers faster than the code-minimal building. Furthermore, the maximum loss of function ($LoF_{max}$) is decreased by 70% for a two-day outage. The resiliency performance indicator, as defined by Equation 2, is two times better in the proposed design compared with the reference design.

## Pathway Analysis

A pathway analysis was conducted to understand the relative importance of each upgrade as reported in Table 1. Figure 9 shows each incremental upgrade applied to the reference design resulting in the proposed design. The $LoF_{max}$

KPI quantified system performance during the simulated outage event. To ensure that upgrades are ordered by significance, all options are analyzed starting with the reference design, and the one with the largest improvement is selected. After eliminating the selected variable, this process is repeated until each parameter from the reference design is changed to match the proposed design. The magnitude of each incremental improvement is inherently non-linear and cannot be determined as a superposition of each incremental improvement. The three most-significant upgrades were related to air-tightness, on-site generation and thermal/electrical storage. Thermal and electrical storage have a relatively small, or even negative, impact on annual performance but aid significantly in improving thermal resiliency.

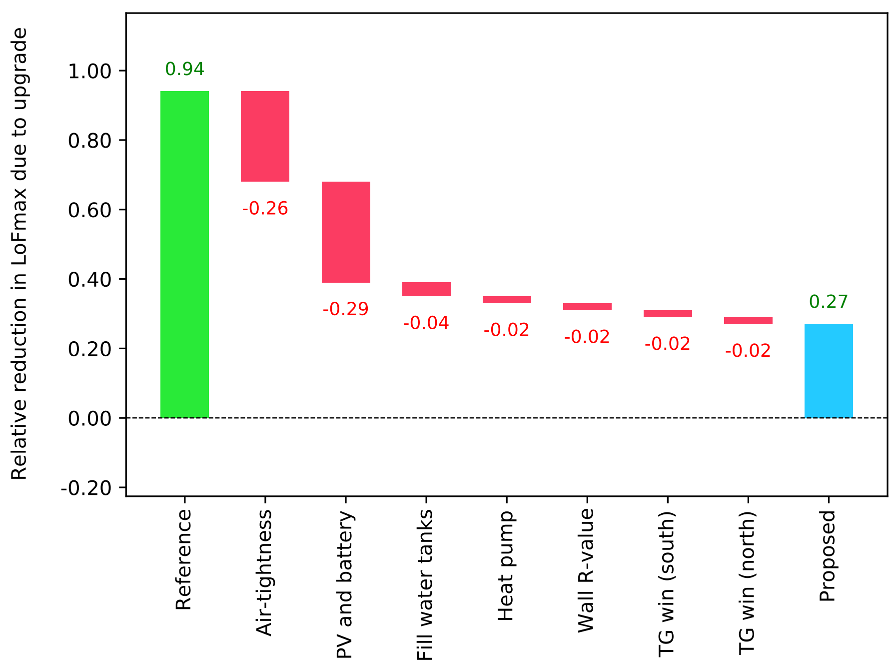


**Figure 9:** Pathway analysis from reference to proposed design using the maximum loss of functionality ($LoF_{max}$)

### Monte Carlo Economic Analysis

The Monte Carlo analysis varied 22 cost parameters and found 8 were highly-significant, as reported in Table 5. Notably, the duration of the outage event was less significant than the costs associated to key upgrades such as PV, batteries and heat pump upgrades. Both the inflation rate and energy escalation rates were unrelated to the outage event but had influence over the life-cycle analysis. The event frequency and VoLL also significantly affected payback. Additional research is need to be better understand the expected frequency of climate change events, rather then rely solely on historical data.

**Table 5:** Variables with a highly-significant influence on the Cost Model

| Description | Value | Units |
|---|---|---|
| Energy Escal. rate | 3.00 ± 0.43 | % |
| Inflation Rate | 2.00 ± 0.21 | % |
| VoLL | 250 ± 36 | $/kWh |
| Event frequency | 10.0 ± 1.3 | yrs |
| Battery Cost | 425.0 ± 88 | $/kWh |
| Micro-grid Multi | 1.15 ± 0.06 | – |
| PV Roof Cost | 1500 ± 290 | $/kW |
| Heat Pump | 1150 ± 120 | $/kW |

## 6. Conclusion and Future Work

This paper deterministically quantifies resilience KPIs using a simulated outage event. The energy difference between two simulations evaluates the lost load and the value of lost load is determined by applying a cost curve to hourly zone-averaged temperature profiles during the outage event. The value of lost load, normalized by the frequency of the outage event, is added to operational costs in the life-cycle analysis. A multi-objective approach quantifies building performance using annual net-energy demands, life-cycle cost and resilience KPIs. The methodology is demonstrated using a case-study where a single ice-storm event reduced economic payback of resiliency measures to 14.2 ± 3.2 years. The proposed design deviated 5 °C below setpoints whereas the code-compliant design suffered a near failure with temperatures approaching 0 °C over a 48 hour outage period.

The novel contributions of this paper include the: (i) methodology for evaluating resiliency events in a popular BPS tool (flow chart presented in Figure 4); (ii) proposed algorithm as an augmented BPS feature that allows for resiliency simulation (see Algorithm 1); (iii) proposed KPIs for resiliency evaluation applicable to thermal performance and integration of those KPIs into LCC considerations using VoLL; and (iv) case-study outcomes which include quantification of resiliency KPIs and paybacks.

The results presented in this paper are intuitive in the sense that improving values shown in Table 1 should improve resiliency performance metrics. In fact, these parameters reflect a subset of what is commonly considered good passive solar design. However, the proposed approach quantifies exactly what the relative impact of those changes are for specific outage events, and with additional work, can recommend optimal values for specific combinations of regional events. As additional outage events are considered, the consideration of VoLL may encourage more stringent insulation, storage and air-tightness targets beyond what was previously considered optimal values for a specific climate. Furthermore, battery storage becomes a more attractive investment if building owners and operators can better understand the economic benefits of the technology.

The limitations of this proposed work are: (i) the results reflected the case-study and the climate event presented and cannot be generalized to other geographies/events; (ii) additional experimental studies are needed to better quantify decay and recovery times as the time constant of the building was not calibrated for; and (iii) outcomes presented are for a particular outage event only occurring every 10 years. It is anticipated that the cost benefits and KPIs will improve if multiple events are considered.

The extrapolation of simulation results from this paper to larger homes and buildings should be approached with caution. The case-study's heat loss characteristics and high sensitivity to infiltration is likely a consequence of the tiny home's large surface area to volume ratio. However, if the tiny home archetype were treated as a refuge space within a larger building, as recommended by Kesik et al. (2020) [28], the results may be broadly applicable to other case studies assuming an extended outage where surrounding zone temperatures approach exterior conditions. A refuge space could be thermally isolated from the surrounding buffer zones and independently self-power. This simulation study could aid in determining required photovoltaic panel areas and battery size for similar climate zones.

Future work includes the additional consideration of complementary seasonal events. These could include summer heat waves or more ambiguous grid-outages due to failed transmission lines, repairs or accidents. We anticipate that 3–5 outage events over the life-cycle of the building should give better coverage to future unknown events, however, this should be studied explicitly in various regions before further conclusions are drawn.

Based on the outcomes of this paper, we recommend that developers and practitioners consider the value-added to clients by including resiliency capabilities into existing workflows and BPS tools. Native support of this feature, combined with databases of historical and predicted regional events, may help BPS practitioners make recommendations to help buildings better adapt to future climate change events.

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