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Developing and Evaluating Metrics for Demand Flexibility in Buildings: Comparing Simulations and Field Data

Jingjing Liu[1], Rongxin Yin[1], Marco Pritoni[1],
Mary Ann Piette[1], and Monica Neukomm[2]

[1]Lawrence Berkeley National Laboratory and
[2]U.S. Department of Energy

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Jingjing Liu, Rongxin Yin, Marco Pritoni, Mary Ann Piette, Lawrence Berkeley National Laboratory
Monica Neukomm, U.S. Department of Energy

ABSTRACT

Building demand flexibility (DF) has attracted significant attention in recent years among researchers, technology developers and control companies, aggregators, utilities, and many others. There are numerous challenges with today's electricity systems such as managing peak demand capacity and integrating variable renewables into the grid. Flexible building loads can provide various grid services to help reduce electricity costs, smooth out renewables intermittency and balance supply and demand. Recognizing this, the US DOE is leading the Grid-interactive Efficient Buildings (GEB) initiative which includes research to evaluate the potential, availability and timing of flexible loads.

In this paper we present load shed metrics for three building types – medium office, large office and retail store – and compare prototype simulation results with measured data from 12 actual buildings that participated in hot summertime utility demand response (DR) events. The DR strategies included varying zone temperature and reducing light levels. The magnitude of a key DF metric, "demand decrease intensity" (or "shed intensity") (W/ft^2), between the simulation results and field data are similar (14-32% differences) for both mean and median values, though the field data show much larger variation among DR events. The coefficient p-values from linear regression model tests showed that outside air temperature is a significant variable for the whole building *shed intensity* when the resetting zone temperature strategy is deployed. These findings support the concept of using prototype building simulation to estimate building DF and expanding future simulation research to additional building types and climate zones.

Introduction

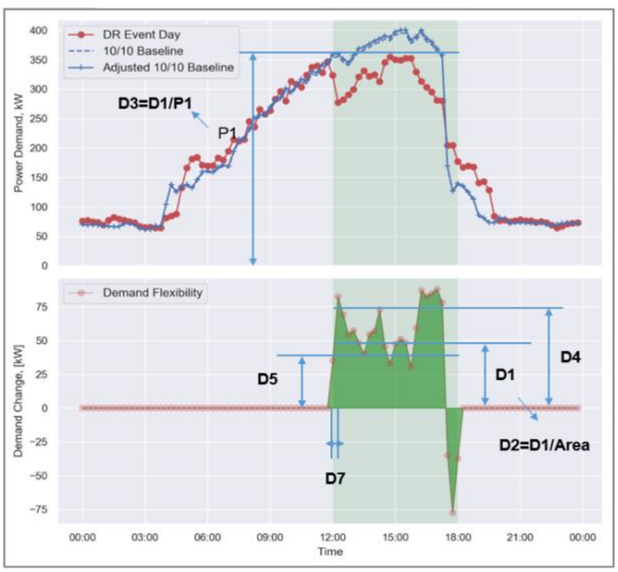
Building Demand Flexibility

The idea of using building "demand flexibility" (DF), also known as "load flexibility" or "energy flexibility" to respond to grid needs, is gaining traction among researchers, technology developers and control companies, aggregators, utilities, and many others. Perhaps the most important driver behind this trend is the growing challenge of maintaining the supply and demand balance on the electrical grid with deeper penetration of variable renewable generations such as wind and solar technologies (Mai et al, 2012). Given the operational constraints in traditional generation sources (e.g. thermal, nuclear, etc.), it is costly to modulate these sources to offset the intermittency of renewables generation and it is important to explore the capabilities of demand side resources to maintain the grid balance (MITEI, 2011). While DF can be provided by many types of buildings, commercial buildings are the focus of this paper. To better study the role of building flexibility, the U.S. Department of Energy (DOE) is leading a major research initiative on this topic named “Grid-interactive Efficient Buildings” (GEB) with a growing portfolio of projects. GEB defines DF as “the capability of DERs to adjust a building’s load profile across different timescales” (DOE EERE, 2019). This paper describes early results from a project to develop a framework to standardize and measure building DF using defined metrics.

Building Demand Flexibility Metrics

The GEB initiative distinguishes five demand side management (DSM) strategies under the GEB framework: “Efficiency”, “Load Shed”, “Load Shift”, “Modulate”, and “Generate” (DOE EERE, 2019). Lawrence Berkeley National Laboratory’s (LBNL) Flexible Loads project primarily focuses on defining metrics for *Shed*[1] and *Shift*[2] (as shown in **Figure 1** and **Figure 2)**. The Shed metrics cover the following aspects of a load shedding event: average depth of demand decrease (“D1-D3”), variability of demand decrease (“D4-D6”), ramping capability (“D7-D9”), and net energy consumption impact (“D10”). The Shift metrics contains a load increase portion in addition to the load decrease (i.e. demand “shed”). The metrics for load increase are similarly structured as those for “shed” in Figure 2. Load increase is considered negative because we use conventions from traditional demand response (DR) programs where load decrease is positive.

This paper focuses on Load Shed because it has been used in the field in utility DR programs and field data are available to compare with simulation data. In this paper, we focus on the D2 “demand decrease intensity [W/ft^2]” (or “*shed intensity*”) metric, which is defined as the average kW demand reduction during a shed event (or defined shedding period) normalized by the building floor area. The area normalization allows comparison of shed metrics across buildings of different sizes or types.



Metrics	Unit	Value
#D1: Demand Decrease	kW	47
#D2: Demand Decrease Intensity	W/ft^2	0.58
#D3: Demand Decrease Percentage	%	13%
#D4: 75% Demand Decrease	kW	74
#D5: 25% Demand Decrease	kW	44
#D6: Demand Decrease Standard Deviation	kW	51
#D7: Decrease Ramp Rate	kW/min	2.34
#D8: Decrease Ramp Time	mins	< 30
#D9: Response Time	mins	< 5
#D10: Demand Decrease – Spinning Reserve (in 10 minutes)	kW	35
#D11: Net Building Consumption Change Percentage (24 hours)	%	-2.1%

Figure 1. Proposed demand flexibility metrics for Load Shed with an example from an actual building DR event.

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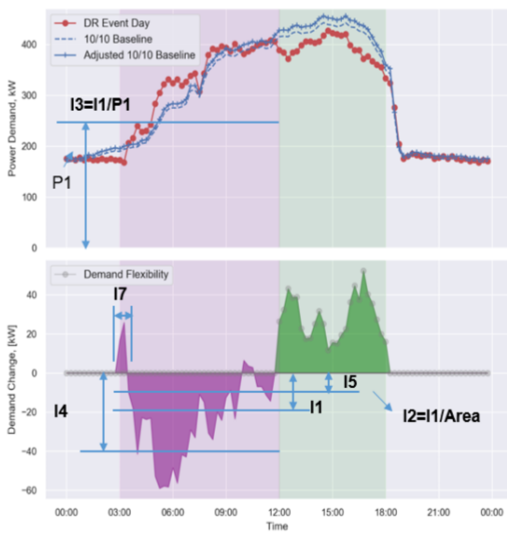
[1] Load Shed: the ability to reduce electricity use for a short time period and typically on short notice. Shedding is typically dispatched during peak demand periods and during emergencies (DOE EERE, 2019).
[2] Load Shift: the ability to change the timing of electricity use. In some situations, a shift may lead to changing the amount of electricity that is consumed.



Demand Decrease		
Metrics	**Unit**	**Value**
#D1: Demand Decrease	kW	41
#D2: Demand Decrease Intensity	W/ft²	0.39
#D3: Demand Decrease %	%	9.5%
#D4: 75% Demand Decrease	kW	51
#D5: 25% Demand Decrease	kW	31
#D6: Demand Decrease Std. Dev.	kW	33
#D7: Decrease Ramp Rate	kW/min	2.58
#D8: Decrease Ramp Time	mins	< 15
#D9: Response Time	mins	< 5

Demand Increase		
Metrics	**Unit**	**Value**
#I1: Demand Increase	kW	-23
#I2: Demand Increase Intensity	W/ft²	-0.22
#I3: Demand Increase %	%	-5.2%
#I4: 25% Demand Increase	kW	-38
#I5: 75% Demand Increase	kW	-9
#I6: Demand Increase Std. Dev.	kW	36
#I7: Increase Ramp Rate	kW/min	-0.30
#I8: Increase Ramp Time	mins	< 30
#I9: Decreased Energy / Increased Energy	%	85.5%
#I10: Net Building Consumption Change % (24 hours)	%	0.23%

Figure 2. Proposed demand flexibility metrics for Load Shift with an example from an actual building DR event.

There are several approaches to evaluate the *shed intensity* in commercial buildings. Measured data from utility DR events can be collected to evaluate *shed intensity*, but these data are often scarce. We can use prototype simulations to evaluate *shed intensity* from various building types, but we need to understand how well these prototypes represent the actual building stock. We can also use building scale testbeds such as FLEXLAB®[3] to conduct controlled experiments to evaluate the variability of *shed intensity* with changes in building systems and conditions.

Demand Response and Demand Flexibility

DR is often mentioned when the industry discusses DF. So what is the relationship between the two? A group of GEB researchers articulates that "like DR, DF is characterized by active load management on timescales consistent with utility system and grid needs. Unlike energy efficiency (EE) and DR, DF is not a resource in the traditional sense, but a potential that the utility or system operator can utilize to provide reliable electricity service. From the system operator's perspective, EE and DR are what you have in your portfolio and DF is what you can do with the resources you have" (Gerke et al, 2020).

The meaning of DR has also evolved. In the traditional definition, DR refers to shedding loads when the customer receives a price or dispatch signal from their utilities or the grid (FERC, 2007). In this paper, we use the term "DR" to refer to such traditional DR programs because we extract data from such programs for the analysis presented. However, it is worth noting that more recent definitions of DR recognized by the utility industry are much broader than the traditional definition. For example, LBNL's *2025 California DR Potential Study* (Alstone et al, 2017) defined four DR service types – "Shape", "Shift", "Shed", and "Shimmy" to include reshaping load profile through long-run price response (e.g. time of use rates), shifting load from one time

[3] FLEXLAB® located at LBNL's Berkeley site is the first testbed in the world that can evaluate the energy efficiency of major building systems, as an integrated system, under real-world conditions.

to another (often of the same day), and dynamically adjusting load. The Smart Electric Power Alliance (SEPA) defines today's DR development (i.e. DR 3.0), under which DR would function as a component of distributed energy resources (DERs) in providing various grid services (SEPA, 2017). These two recent DR definitions by LBNL and SEPA are not mutually-exclusive.

Objectives

An important goal of our research is to answer the question – which and how much building load can shed or shift at any given time of the day or year? In this paper, we provide a framework to begin to answer this question by quantifying and interpreting a *Shed* metric using two data sources: (1) energy simulations and (2) field DR performance data. Our main hypothesis is that the ***shed intensity*** (W/ft^2) calculated using an energy simulation prototype with EnergyPlus[4] can represent typical buildings of the same type on the **average** magnitude although we expect the **range and variability** of field data to be larger. We are also evaluating whether the *shed intensity* from implementing global zone temperature adjustment (GTA) strategy[5], a common HVAC control strategy used in today's DR programs, is correlated to outside air temperature (OAT). This trend has been observed in previous studies (Piette et al., 2006; Yin et al., 2008; Coughlin et al., 2009; Mathieu et al., 2011). In this paper we present initial data from office and retail buildings to compare *shed intensity* data between field data and prototype simulations.

Methodology

We created prototype simulation models for three building types (medium office, large office and retail) using the "Commercial Reference Buildings"[6] and "Commercial Prototype Building Models"[7] for buildings built before and after 2004, respectively. The prototype model inputs were kept unchanged in our simulation; only DR strategy was added to the models.

We used kW demand shed results in a previous study (Yin et al., 2008) to calculate the *shed intensity* for the medium office buildings. In addition, we also collected 15-minute whole building electricity usage data from one large office building and two retail sites that participated in DR programs to calculate *shed intensity* for these sites. The medium office sites and retail sites are located in California cities that belong to the ASHRAE Warm-Dry (3B) climate zone[8]; the large office site belongs to the Warm-Marine (3C) climate zone. To calculate *shed intensity* for the retail sites, we used a "10/10" baseline[9] with morning adjustment factor and no upper limit

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[4] EnergyPlus™ is a whole-building energy modeling software. https://www.energy.gov/eere/buildings/downloads/energyplus-0. Prototype models are developed by national labs to represent typical buildings and are often used to evaluate energy-saving strategies.

[5] Raising zone temperature setpoints "globally" across a number of zones in the building during a *Shed* event. It is common for buildings to couple it with "pre-cooling" by lowering the zone temperature setpoint for some time before the *Shed* in order to achieve deeper demand shed and provide better comfort during the event.

[6] https://www.energy.gov/eere/buildings/commercial-reference-buildings

[7] https://www.energycodes.gov/development/commercial/prototype_models

[8] See ANSI/ASHRAE Standard 169-2013, Climatic Data for Building Design Standards

[9] 10/10 baseline: the average demand during the same DR event hours over the previous 10 eligible baseline days (excluding weekends, holidays, DR event days, and none-operation days).

(Piette et al., 2006; Goldberg et al., 2013), which is also consistent with the baseline method used for the office buildings in the earlier study.

To examine the correlation between *shed intensity* and outside air temperature, we performed F-tests using both daily peak OAT and the average OAT during events as the single independent variable in linear models. The correlation is tested significant at 95% level when p-values are smaller than 0.05. We also compared the regression line slopes between the field and simulation data for the same predictors and reported R^2 values.

Medium Office

We used a group of 9 medium-size office buildings to compare *shed intensity* calculated from field data with prototype simulation results. **Table 1** summarizes the general building information of the selected buildings.

Table 1. A Group of Nine Medium Offices Participated in Actual DR Events and the Prototype Simulation Model for Comparison

Site ID	Building Use	Floor Area (ft^2)	Year Built	Construction	HVAC System	DR Strategy
A	Office	68,955	1990	Concrete	RTU + VAV	Pre-cooling+GTA
B	Office	62,800	1988	Concrete	RTU + VAV	GTA
C	Office	38,808	1988	Concrete	RTU + VAV	Pre-cooling+GTA
D	Office	73,730	1988	Concrete	RTU + VAV	GTA
E	Office	70,069	1993	Steel	RTU + VAV	GTA
F	Office+Classroom	80,750	2001	Steel	RTU + VAV	Pre-cooling+GTA
G	Office+Data Center	104,501	2005	Steel	RTU + VAV	Pre-cooling+GTA
H	Office+Classroom	119,035	2002	Steel	RTU + VAV	Pre-cooling+GTA
I	Office+Auditorium	81,079	1994	Concrete	RTU + VAV	GTA
Model	Office	53,628	Post-1980	Concrete	RTU + VAV	GTA

These office buildings share the same HVAC system type as in the prototype model – Packaged rooftop units (RTU) with variable air volume (VAV) system. Each office building deployed global temperature adjustment during DR events raising the thermostat setpoint above the normal setpoint (77ºF) by 2ºF from 12:00PM to 3:00PM and 3ºF from 3:00PM to 6:00PM. Several sites deployed a moderate precooling strategy (lower setpoint by 2ºF) in the morning. For these sites, the average kW demand shed during each 3-hour DR event was available in a previous study (Yin et al., 2008).

Large Office

One large office site in California (see **Table 2**) was used for similar comparisons conducted for medium offices. This site is an 323,000-square-foot typical large office building in San Francisco, California. It uses two 420-ton water-cooled chiller as the cooling plant and single-duct VAV air handling units (AHUs) for the air conditioning. The prototype large office building model uses two water-cooled chillers as the default cooling source, which matches the site’s system type.

Table 2. Large Office Participated in Actual DR Events and the Prototype Simulation Model for Comparison

Site	Floor Area (ft^2)	Year Built	Construction	HVAC Type	DR Strategy
Field site	323,000	1987	Concrete	Water-cooled Chiller + VAV	GTA
Reference Model	498,588	Post-1980	Concrete	Water-cooled Chiller + VAV	GTA

This site was normally operated at a constant setpoint of 74°F during the startup and occupied hours. GTA strategy was implemented by raising the thermostat setpoint to 78°F during the 4-hour DR events (2:00-6:00PM). Additionally, this site implemented the precooling strategy by reducing the thermostat setpoint to 72°F from 10:00AM to 2:00PM.

Retail

Two retail stores were also included in the analysis. We collected whole building electric data for 19 DR events in 2017 and 2018. 10 of the 19 DR events started at 3:00PM and ended at 7:00PM. For the remaining 9 events, one-third of the events started at 4:00PM, 5:00PM, and 6:00PM respectively, and they all ended at 7:00PM. As shown in **Table 3**, these two sites have similar concrete construction and packaged RTUs with VAV fans.

Table 3. Two Retail Stores Participated in Actual DR Events and the Prototype Simulation Model for Comparison

Site	Building Use	Floor Area (ft^2)	Year Built	Construction	HVAC Type	DR Strategy
#1	Retail	108,900	2004	Concrete	Packaged RTUs	GTA & Lighting
#2	Retail	130,179	n/a	Concrete	Packaged RTUs	GTA & Lighting
Reference Model	Retail	5,500	90.1-2004	Concrete	Packaged RTUs	GTA & Lighting

Two types of DR strategies were implemented at both sites: (1) GTA: the sites raised thermostat setpoint for a large portion of the RTUs from 74ºF to 80-81ºF (i.e. by ~6 ºF); (2) Switch off every other light (i.e. 50% of the lights) for a large portion of the sales area.

It is important to mention that we have not done a more thorough comparison between the characteristics of the actual and simulated buildings and differences such as envelope characteristics, occupant density, lighting power density, or other factors that could influence DF. We had limited access to the building characteristics from the utility DR program data. We simulated the implemented DR strategies using prototype models with typical meteorological year (TMY3) weather data.

Comparing Shed Intensity between Simulation and Field Data

Medium Office

Figure 3 shows the *shed intensity* comparison between the field events and simulated results. The blue and orange bars represent the mean values across the sites and the mean of simulated 15-min values, respectively; the black lines represent standard deviation ranges. The left-side of the figure is organized by individual shed events, ranked by daily peak outside air temperatures and the right-side combines all events. The same figure style is also used for the other two building types below.

We found that the mean shed intensities for the 9 sites are similar to the simulated intensities, but the simulated *shed intensity* about one-third less than the field data. However, the field data shows a much larger variability evidenced by both a much wider range in each event and a much larger overall standard deviation in comparison with the simulation. Larger variability in field data is always expected because many other factors can influence DF to various extents whereas simulation assumes the building parameters unchanged across all events.

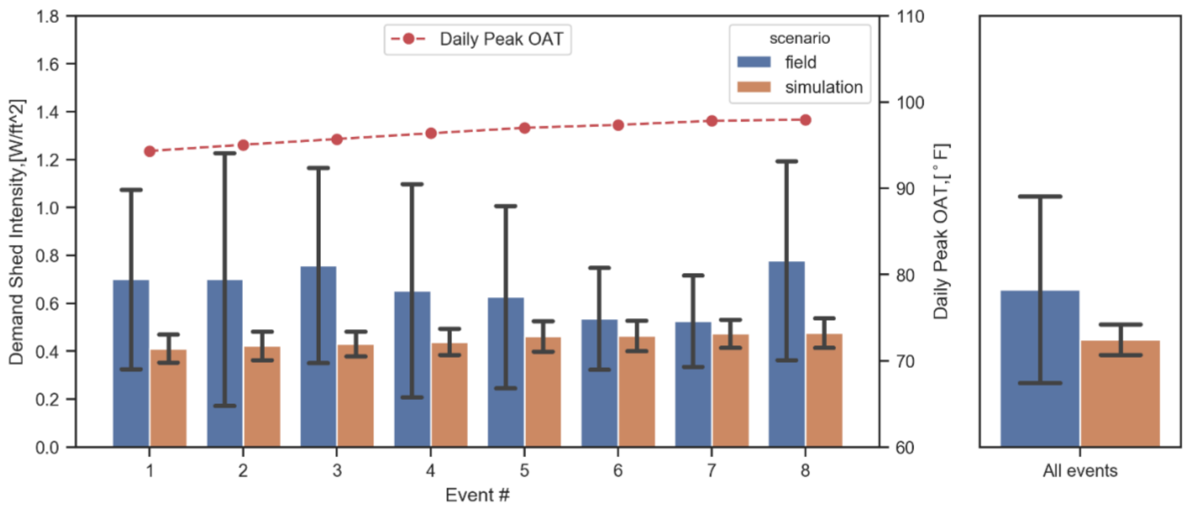

Figure 3: Mean and Standard Deviation of Demand Shed Intensity [W/ft^2] Calculated from Field Event Data and Prototype Simulation for 9 Medium Offices

Note that the daily peak OAT on those eight event days fell in a narrow range between 95-98ºF, which made it difficult to observe correlation with *shed intensity* in the field results beyond the noise from other unknown factors' influence.

Large Office

For the example large office, there were 12 shed events across wide weather conditions from cool to warm. As shown in **Figure 4**, the *shed intensity* reached the highest value on the day when the outside air temperature reached 90ºF, and it was lower on a cooler event day of 65ºF. The figure also reveals that the mean for all events combined are similar (< 10% difference) between field and simulated results and within the range of the standard deviation.

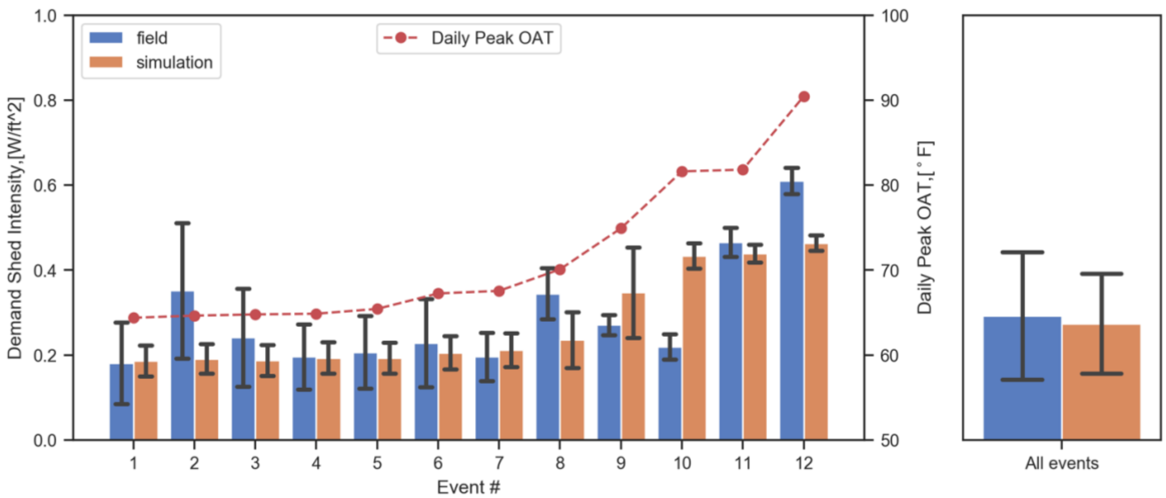

Figure 4: Mean and Standard Deviation of Demand Shed Intensity [W/ft^2] Calculated from Field Event Data and Prototype Simulation for a Large Office

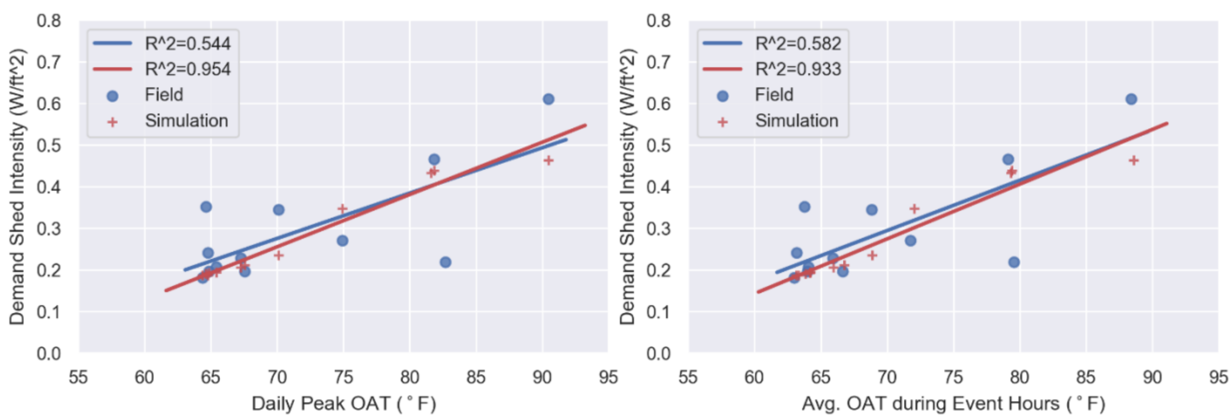

Figure 5: Relationship between Demand Shed Intensity [W/ft^2] and Daily Peak OAT (left) and Average OAT During Events (right) in a Large Office, Calculated from Field DR Event Data and Prototype Simulation

To test correlation with OAT, we calculated coefficient p-values of regression variable daily peak OAT and average OAT during events, respectively, using the field data – they were 0.006 and 0.004 (< 0.05). This result indicates that the correlation between *shed intensity* and both OAT related independent variables are statistically significant at the 95% confidence level. **Figure 5** shows linear regression model fits between *shed intensity* and the two OAT related independent variables, respectively. As shown, the regression line slopes are similar between the field and simulation data, and the field data exhibit more scatter as expected. It should be noted that the number of sites is very limited for this building type.

Retail

Similar to the analysis for office buildings, a pair of boxplot and bar-plot was made for each of the two retail sites.

Retail Site #1

The results in **Figure 6** indicate that the mean are very close (< 5% difference) between the field and simulation results for retail site #1. The field data shows a larger variability (the standard deviation is about 15% larger) in comparison with the simulation.

The mean *shed intensity* from field data and simulation in **Figure 6** were similar for the majority of the individual events. The correlation between *shed intensity* and the outside temperature is moderate.

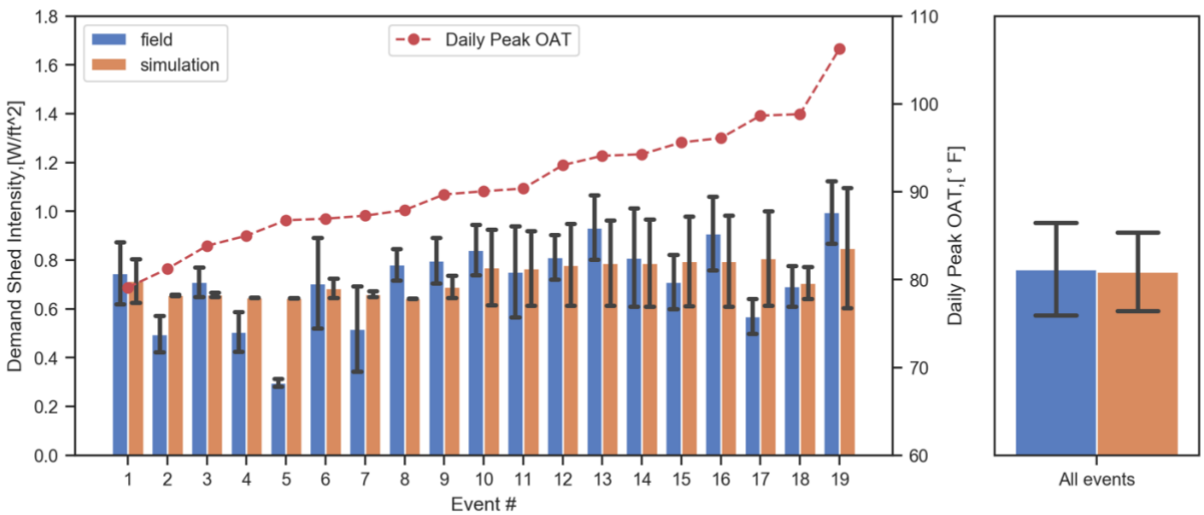

Figure 6: Barplot of the Mean and Standard Deviation of Demand Shed Intensity [W/ft^2] Calculated from Field Event Data and Prototype Simulation for Retail Site #1 (Left: Event by Event; Right: All Events Combined)

Retail Site#2

The results in **Figure 7** show that the mean *shed intensity* values are similar (< 10% difference) although the standard deviations are different between the field and simulation results for retail site #2. Again, the field data shows a much larger variability in comparison with the simulation. The mean *shed intensity* from field data and simulation show larger differences on the individual event level as compared to the retail site#1. The correlation between *shed intensity* and outside temperature is less obvious. Note that the site showed a low *shed intensity* during event #15, #16, and #17; the performance during event #6 and #8 substantially exceeds the levels of the neighboring events in the similar daily peak OAT range.

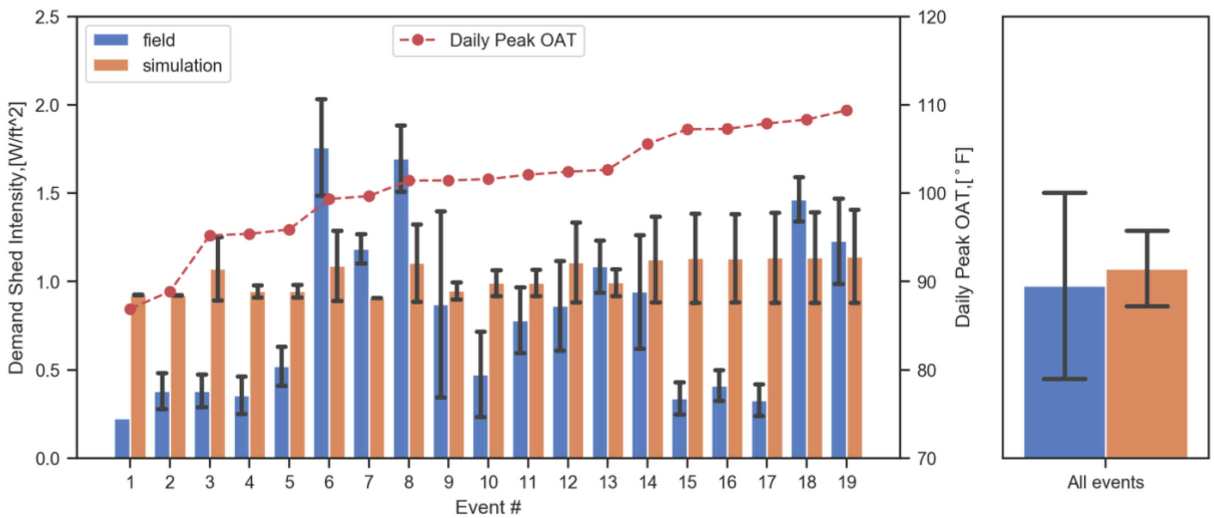

Figure 7: Mean and Standard Deviation of Demand Shed Intensity [W/ft^2] Calculated from Field Event Data and Prototype Simulation for Retail Site #2 (Left: Event by Event; Right: All Events Combined)

Again, to test correlation with OAT, the p-values of regression variable daily peak OAT and average OAT during events are 0.047 and 0.013, respectively, using field data. Considering that the p-values are smaller than 0.05, both OAT related independent variables are statistically significant for *shed intensity*. **Figure 8** shows linear regression model fits using these two OAT related independent variables, respectively. We observe that the regression line slopes are similar between field and simulation data in both plots, and the field data exhibit more scatter (low R^2). To improve understanding of what other factors contributed to the variability, we will need better knowledge of the strategy used during each event and building characteristics.

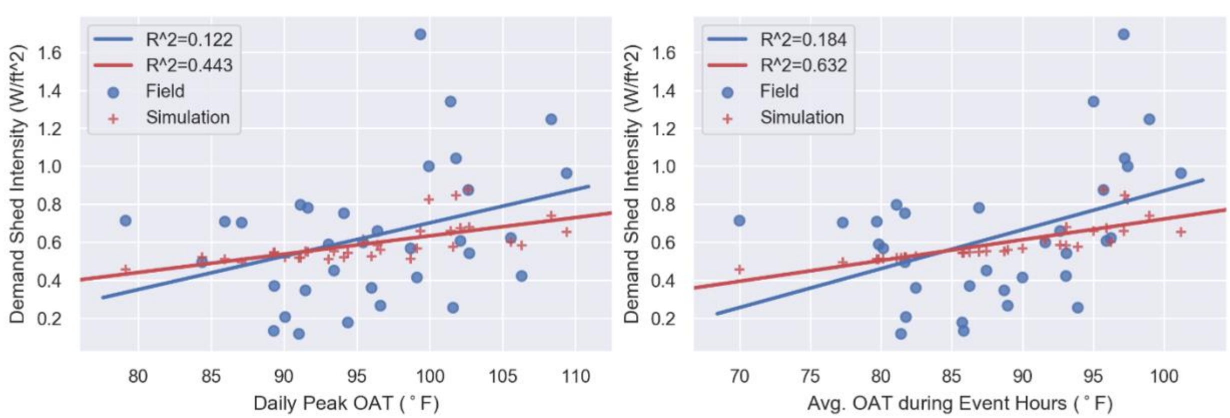

Figure 8: Relationship between Demand Shed Intensity [W/ft^2] and Daily Peak OAT (left) and Average OAT During Events (right) in Retail Stores, Calculated from Field DR Event Data and Prototype Simulation

Key Findings

We compare *shed intensity* calculated from a total of 122 DR events at 12 sites (including offices and retails) and compared it with EnergyPlus prototype simulation results. The results are summarized in **Table 4**, which show the comparison of *shed intensity's* variations for three building types – medium office, large office and retail. Based on these results, we found that:

Table 4. Key Findings in Prototype Simulation and Field DR Event Data Comparison - Demand Shed Intensity [W/ft^2]

Building Type	# of Sites	# of Events	Comparison	Mean	Std. Dev.	Min	25th Percentile	Median	75th Percentile	Max
Large Office	1	12	Measured	0.29	0.15	0.10	0.17	0.24	0.40	0.67
			Simulated	0.27	0.12	0.14	0.17	0.23	0.43	0.50
			Difference (%)	-7%	-20%	40%	0%	-4%	7%	-25%
Medium Office	9	72	Measured	0.66	0.39	0.22	0.36	0.60	0.79	1.80
			Simulated	0.45	0.06	0.31	0.40	0.45	0.49	0.57
			Difference (%)	-32%	-84%	41%	12%	-24%	-38%	-69%
Retail	2	38	Measured	0.86	0.40	0.20	0.58	0.81	1.02	2.25
			Simulated	0.74	0.17	0.53	0.64	0.67	0.78	1.33
			Difference (%)	-14%	-57%	164%	11%	-16%	-24%	-41%

The *shed intensity* metric in the prototype simulations and DR field results are similar (14-32% differences) based on the mean and median values for each of the three building types. The standard deviation is larger in field data which could be attributed to variations in operating conditions such as occupancy and other factors for which we lack knowledge. Note that the 25th and 75th percentiles in **Table 4** are aggregated statistics across multiple sites of the same building type, which is differentiated from metric "D4" and "D5" in **Figure 1**.

When global temperature reset is used as one of the key DF strategies, *shed intensity* is correlated to the outside air temperature as shown for large office and retail stores, using either "daily peak temperature" or "average temperature during event" as the independent variable (or predictor). We used p-values to determine that such correlations are significant at the 95% confidence level. We also tested fitting the data with linear regression lines and observed that the slopes are similar between simulation and field data using both predictors. However, given the limitations of the existing dataset, such conclusions cannot be extended to beyond the dataset. Expanding the dataset and gaining more site- and event- specific information will be desirable in the future. From the building physics standpoint, this can be explained by buildings' shed capability generally increases with outdoor temperature because the potentially curtailable baseline cooling loads are greater on warmer days, until the HVAC capacity is saturated beyond its designed capacity on extreme hot days.

These preliminary findings provided initial support to validating our two hypotheses stated upfront and therefore supports our project DF simulation framework. We recognize that this is a limited dataset and we have little site-specific details on factors that could impact accuracy or further explain the variations in the results. Therefore, definitive conclusions would not be possible without more field data with granular time series data and site specific details.

Discussion

In this paper we conducted a preliminary comparison of ***shed intensity*** between a limited set of field measured data and prototype simulation results on three building types. The results suggest that prototype simulation using EnergyPlus can give a reasonable estimate of the mean and median. The field data showed a larger variability across the three building types and we have limited information to explain the variability. However, there are several known factors that could have led to the greater variability in the field measured results, which include but not limited to:

(a) Selection of baseline method and its accuracy. In simulation, the baseline is determined by running the model with DR strategies disabled. However, with actual buildings, baselines are more complex because the building's operation without shedding load on the exact same event day cannot be recreated in reality is estimated using baseline models that have known limitations.

(b) Limited site specific information. The prototype simulation results are outputs varying only a small number of inputs related to building vintage (which is a proxy for a number of characteristics), climate location, and DF strategy details. However, there are a great deal of variations in an actual building's geometry, construction, window-to-wall ratio, thermal mass, internal load, occupancy, HVAC system configuration and operation, efficiency and control settings, and many other building characteristics. These discrepancies between the prototype simulation model and a specific actual building can also lead to significant differences in the results.

(c) Uncertainties in the DR control sequences. There is known and unknown variation in the DF strategies implemented at the sites in this dataset. For example, some medium offices implemented GTA while others coupled it with moderate pre-cooling. In addition, it was observed that for a given site the same DF strategy performed well on some event days but worse on other days. Since we do not have trend logs of the actual site's control sequences and parameters on each event day, it is difficult to diagnose any operational behavior in the DF performance. For example, did the building operator actually change the temperature setpoint equally in all the zones during all events? or some VAV terminals didn't respond to the temperature setpoint reset due to the stuck dampers.

Summary and Next Steps

This paper has presented initial field data and simulation results which demonstrate that simulation output for DF can be similar to what has been observed in field data. Future work will explore both a broad set of simulation output and a broader set of field data to explore the questions: which and how much building load can shed or shifted at any given time of day or year? We are trying to better understand how various factors and attributes influence a building's DF such as building characteristics, outdoor environmental conditions, set points for the DF control strategies, timing of the DF strategy deployment, and so on. We will use simulation to test DF sensitivity to these building attributes and event characteristics. We will also compare additional field data with simulation data to improve our understanding of the capabilities and limitations of EnergyPlus in evaluating DF. Finally, our work will also include comparing these data sets with controlled laboratory testing in in FLEXLAB®. In such a lab testing environment, the impacts from single parameters can be evaluated more accurately by minimizing or removing the uncertainties from other factors.

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