Analyzing Unoccupied Setback Effectiveness and Prevalence

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https://github.com/NeedleInAJayStack/RTEM-Hackathon_2022

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1 Introduction

Energy conservation is a win-win with regards to decarbonization. By improving building energy efficiency, not only is a building's carbon footprint reduced in the short term, but transitioning it to renewable energy sources becomes more feasible. In order to maximize ongoing investments in renewable power generation, there should be simultaneous efforts to implement high-value low-cost energy conservation measures in existing buildings. Whether due to occupancy schedule changes, temperature setpoint overrides, poor ventilation adjustments, or various other issues, many buildings use more energy than necessary during unoccupied hours making unoccupied energy reductions one of the most effective means to reduce total energy consumption.

This document proposes a set of key performance indicators (KPIs) and an analysis framework to identify and prioritize energy reduction through unoccupied setbacks. Nearly every building can significantly reduce energy usage by basic changes to its unoccupied operation, typically by improving occupancy detection or modifying zone air temperature setpoints, minimum discharge air flow setpoints, or lighting status based on occupancy. It is possible to implement these changes on nearly all control systems and the results are extremely cost-effective.

2 Approach

The proposed framework requires only a single whole-building electric consumption point, recorded at hourly frequencies or faster. The energy consumption is then cleaned by removing meter rollover artifacts, aligning time-stamps to a consistent frequency, and interpolating missing values. Next, the values are dis-aggregated if usage is represented by a monotonically increasing counter, and finally the history is passed through a filter to remove outliers. At this point, the data is clean, normalized, and ready for analysis

The cleaned data is split into weekly periods, each of which is passed through a k-means clustering algorithm[1] that identifies 2 nodes: a high-usage cluster and a low-usage cluster. This results in a mapping between each historical observation and whether it belongs in the high or low group, as well as average values for these high and low groups. In general, we interpret the high-usage period to be the occupied time in a building, and the low-usage period to be the unoccupied time.

From these results, two meaningful weekly KPIs can be computed:

1. **Unoccupied Turndown Factor**: The high-usage cluster value divided by the low-usage cluster value. Scaled from 0 to 1, lower values indicate more effective unoccupied setbacks. Lower is better from an energy reduction standpoint.

[1] `https://en.wikipedia.org/wiki/K-means_clustering`

2. **Occupied Duration Factor**: The amount of time the building was in a high-usage state, divided by the total time in the KPI period. Scaled from 0 to 1, lower values indicate more prevalent unoccupied setbacks, in terms of time. Lower is better from an energy reduction standpoint.

This simple approach offers several distinct advantages. First, the data requirements are extremely low; only a single historical point is required. Of the 230 buildings in the New York State Energy Research and Development Authority's Real Time Energy Management (RTEM) dataset, 99 have *Electric Consumption* points, making it the 5th most prevalent point type behind only *Virtual*, *Zone Temperature*, *Outside Air Temperature*, and *Status*. Second, it is widely applicable. The analysis process is not impacted by the type of building, the pattern of occupancy throughout the week, or the type or complexity of the equipment systems within the building. Since no assumptions are made on the time of occupancy, it functions as well on irregularly occupied buildings (like community centers or theaters) as on regularly occupied buildings (like commercial office buildings or retail). Third, it delivers actionable results. Even the most primitive control systems offer features for modifying building operation according to occupancy.

3 Usage

These KPIs alone do not scale according to energy usage, so they are best used as part of a top-down Energy Use Intensity (EUI) based analysis. For example, if comparing buildings within a portfolio, the EUI could be used to determine the worst-performing facilities, and then the KPIs above could be used to determine whether these facilities would benefit from improving the unoccupied operation.

The KPIs suggest different actions:

- A large Unoccupied Turndown Factor suggests that unoccupied operation should be investigated. When unoccupied, zone air temperature setpoint deadbands should widen significantly, minimum discharge airflow setpoints and outside air flow setpoints should be set as low as possible, and lights should be turned off. This KPI may also suggest that there are areas of the building that never enter an unoccupied state.

- A large Occupied Duration Factor suggests that occupancy scheduling and detection systems should be investigated. Of course, unoccupied energy saving measures must conform to each building's unique occupancy patterns. However, if occupancy is based on a schedule, that schedule should be checked to ensure that it matches actual occupancy patterns. If occupancy is detected using a sensor, the sensors should be validated for correct operation.

While a KPI value on a particular building during a particular week is meaningful, KPIs are typically most useful when they are compared between entities or over time. A building with a large KPI value compared to its peers, or with a KPI value that increases over time may provide context on what constitutes a large KPI value.

4 Results

See KPI results for each building in Table 1 of the Appendix

5 Example Analysis

5.1 Building 188

Building 188 and Building 165 are identically sized commercial retail spaces with similar occupied electricity consumption. However, Building 188 has an average unoccuiped turndown factor of 0.424 while Building 165 has a value of 0.147. Figure 1 compares the total consumption of these two buildings over a representative week in June 2019 and shows that Building 188 has significantly higher usage during unoccupied times, as predicted by the higher unoccupied turndown KPI value.

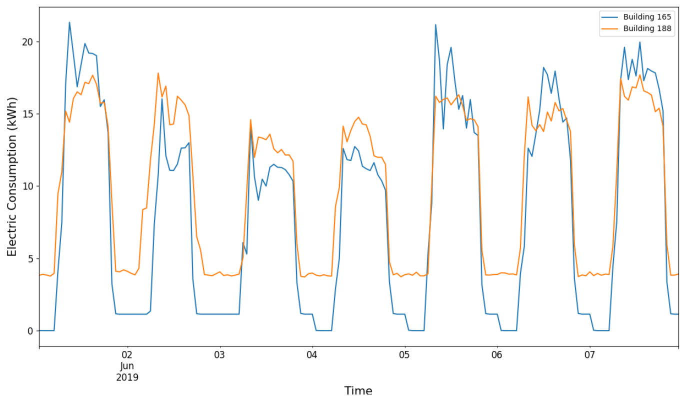

Figure 1: Building 165 and 188 total electric consumption in kilowatt-hours from June 1 to June 7, 2019

Since these facilities have HVAC submetering, we can dis-aggregate the whole-building electricity consumption. Figure 2 shows the submeter HVAC electric consumption for each building over the same time period. The nighttime HVAC consumption in Building 188 is much lower than the total consumption, indicating that it is unrelated to the HVAC equipment and is likely related to light or plug loads.

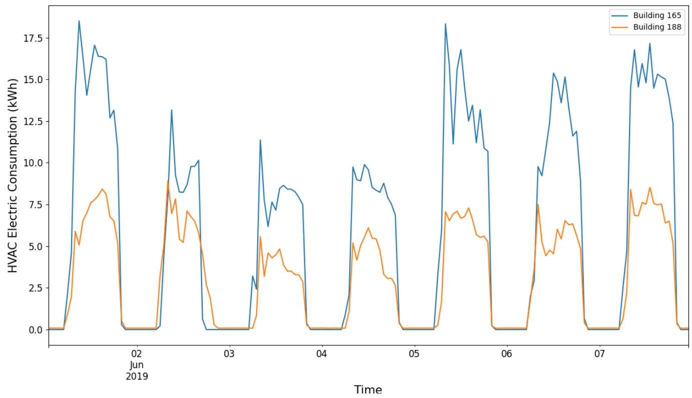

Figure 2: Building 165 and 188 HVAC electric consumption in kilowatt-hours from June 1 to June 7, 2019

If Building 188 is able to achieve a turndown equivalent to that of Building 165, the KPIs suggest that its energy consumption will be reduced by about 11,500 kilowatt-hours (kWh) per year, which is roughly 16% of its total yearly energy usage.

5.2 Building 275

Building 275 and 393 are both large office buildings. Building 393 has more than twice the square footage and three times the occupied electrical consumption of 275. However, with an unoccuiped turndown factor of 0.821, Building 275 has much less effective unoccupied setbacks than Building 393, whose factor is 0.336. Figure 3 shows the total electric consumption for both buildings for a week in early March 2020, and illustrates that Building 275 has much less variance in consumption between daytime to nighttime hours.

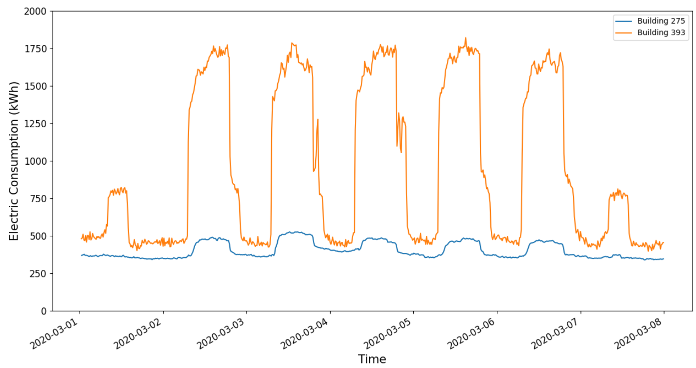

Figure 3: Building 275 and 393 total electric consumption in kilowatt-hours from March 1 to March 7, 2020

If Building 275 was able to achieve the same unoccupied turndown factor as 393, which is not unusual in the commercial office group, it would reduce its total energy use by an estimated 36%. Extrapolating from the 6 months of available energy usage data, this would result in savings of 5,000,000 kWh or $750,000 of reduced consumption charges per year, assuming an average electric rate of 15¢/kWh.

5.3 Building 390

Building 390 is a food and beverage facility, with a large occupied duration factor of 0.798. Figure 4 shows the total electrical consumption over a week in July 2019 and indicates that the daily high-usage period typically spans 20 hours, from 4AM to midnight.

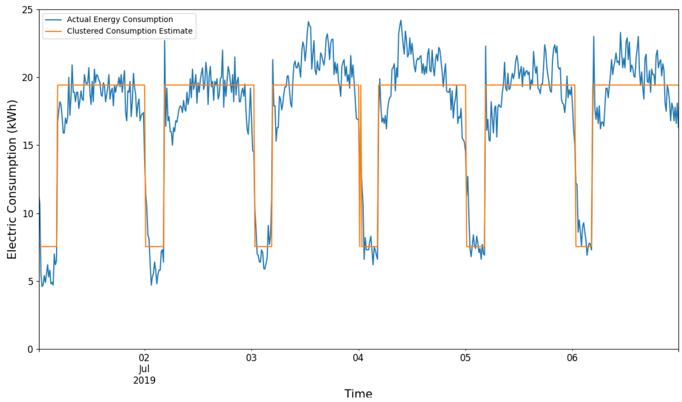

Figure 4: Building 390 actual and clustered electric consumption in kilowatt-hours from July 1 to July 7, 2019. The clustered value shows whether the consumption at a particular timestamp was placed in a high or low usage cluster.

There are certainly food and beverage facilities that keep these hours as staff prepare in the morning and clean at night. However a quick investigation could determine if the consumption profile reflects actual occupancy schedules. If not, and the building could be run in an unoccupied mode even just 2 additional hours each day, modifying the HVAC schedule would save nearly 5% of this building's total energy consumption.

6 Future Growth

As the RTEM dataset expands, these weekly KPIs can be automatically computed on new data. In fact, computing the KPIs for the complete RTEM dataset throughout all time currently takes only a few minutes on commodity hardware. Scripts to compute these KPIs are provided in the linked GitHub repository. By default, these scripts fetch the entire history for a given building, so integrating new data on existing buildings is as simple as re-running the script.

Adding new buildings to the dataset is also easy, but not automatic. Unfortunately, the data modeling of electrical metering within the RTEM dataset is not sophisticated enough to determine which points represent whole-building usage. For example, given a site with multiple electric consumption readings, it is not denoted whether a specific reading is a subset of another or is fully separate. Top level consumption readings are not differentiated from low-level submeters. Due to this, the final list of points used within the analysis was manually revised to determine which points (or collection of points) represented each building as a whole. New buildings must have their whole-building electricity consumption points added to this list.

Project Haystack models metering trees using the `submeterOf`[2] tag, and denotes top-level metering using a `meterScope`[3] tag. Brick Schema models building-level meters with a `Building Meter`[4] class. Adding these concepts into the RTEM ontology would improve future automation efforts.

7 Additional Applications

The clustering approach shown in this document is not specific to whole-building electric energy use. It could potentially be applied to:

Other whole-building utilities Whole-building natural gas, chilled water, or steam consumption also typically have historical profiles correlated to building occupancy. A nearly identical analysis could be performed to determine whether occupancy setbacks produce good turndowns in these other utilities as well.

Submetering If submetering data is available, an unoccupied setback analysis could be performed on each submeter to determine which areas contribute to poor performance at the whole building level. These submeters might cover categories like HVAC, plug, and lighting, or they might cover different tenant zones. The setback analysis approach in this document would apply well to either configuration.

Non-energy points The effectiveness of occupancy setbacks can also be analyzed from low-level non-energy points, such as zone air temperature heating/cooling setpoints, or minimum VAV discharge airflow setpoints. These points may be analyzed via clustering to determine if they change significantly during unoccupied times and for how long. Those results can be used to determine which specific areas of a building contain opportunities for unoccupied setback energy savings.

8 Conclusion

This document presents a strategy for analyzing the effectiveness and prevalence of unoccupied setbacks by using a clustering algorithm on historical whole-building electrical consumption. It outlines the KPIs that can be calculated from

[2] `https://project-haystack.org/doc/lib-phIoT/submeterOf`
[3] `https://project-haystack.org/doc/lib-phIoT/meterScope`
[4] `https://brickschema.org/ontology/1.2/classes/Building_Meter`

the consumption history, and demonstrates how they can be used on real-world data from the RTEM dataset. Finally, it discusses the feasibility of expanding this analysis as the RTEM dataset grows.

Energy conservation is the most cost-effective means of decarbonization. Of course, investments should be made in converting fossil fuel-based energy production to renewables. However, in the meantime, we must also make sure that our existing infrastructure is working as efficiently and effectively as possible. Poor unoccupied operation is often the largest opportunity for building energy reduction that does not require a major capital investment. We need automated, visible metrics that ensure that these opportunities are being fulfilled now and will continue to be fulfilled in the future.

9 Appendix

Building ID	Type	Square Footage	Start Date	End Date	Low Cluster Avg	High Cluster Avg	Unoccupied Turndown Factor Avg	Occupied Duration Factor Avg
100	Multifamily	153,750	2019-06-17	2020-10-26	137.66	174.04	0.861	0.567
105	Food/Beverage	56,000	2017-11-20	2019-09-30	2,772.69	6,974.23	0.416	0.328
108			2019-10-28	2020-05-04	11.75	15.63	0.755	0.415
112	Commercial Office	210,000	2017-09-11	2019-03-11	25.64	81.99	0.489	0.475
121	Commercial Office	236,067	2017-11-27	2018-05-28	244.62	591.74	0.416	0.326
122	Food/Beverage	56,000	2017-11-27	2019-09-30	1,901.78	6,605.24	0.324	0.388
123	Commercial Retail	330,000	2017-09-11	2018-09-10	61.12	80.22	0.769	0.371
125	Commercial Retail	8,500	2019-03-11	2020-01-06	1.30	3.38	0.409	0.377
127	Multifamily	789,079	2018-06-25	2018-12-31	21.55	28.69	0.867	0.615
132	Commercial Retail	198,057	2018-08-20	2019-08-19	0.20	0.83	0.272	0.497
135	Commercial Retail	200,000	2018-12-31	2019-12-23	12.85	15.78	0.854	0.544
137	Commercial Office	221,704	2016-12-26	2019-12-09	33.76	76.47	0.463	0.385
139	Food/Beverage	9,000	2019-04-29	2020-02-24	5.02	12.61	0.401	0.855
146	Commercial Office	281,755	2019-02-11	2019-12-30	369.00	746.05	0.500	0.343
147	Commercial Retail	198,057	2018-07-02	2019-07-01	0.37	1.88	0.270	0.362
151	Commercial Retail	198,057	2018-08-20	2018-08-20	0.09	0.87	0.105	0.733
155	Commercial Retail	144,000	2018-08-27	2019-08-26	0.78	2.80	0.268	0.533
157	Food/Beverage	56,000	2017-12-04	2019-09-30	2,133.13	6,906.57	0.332	0.368
158	Food/Beverage	9,000	2019-04-29	2020-02-24	5.46	6.74	0.812	0.532
164	Food/Beverage	56,000	2017-12-04	2019-09-30	1,676.93	4,564.45	0.497	0.459
165	Commercial Retail	144,000	2018-09-17	2019-09-16	0.45	3.05	0.147	0.526
166	Commercial Retail	198,057	2018-07-02	2019-07-01	0.30	2.19	0.192	0.475
167	Commercial Retail	144,000	2018-10-08	2019-10-07	0.26	0.98	0.274	0.262
170	Multifamily	789,079	2018-08-27	2018-08-27	2.01	2.29	0.877	0.986
172	Commercial Retail	198,057	2018-07-16	2019-07-15	0.26	1.80	0.215	0.492
173	Commercial Retail	198,057	2018-08-20	2019-02-18	0.58	1.83	0.427	0.423
175	Commercial Retail	198,057	2018-07-02	2019-07-01	1.17	1.96	0.658	0.495
176	Commercial Retail	150,000	2018-12-31	2019-12-23	33.73	40.35	0.829	0.422
177	Commercial Retail	144,000	2018-09-17	2019-09-16	0.58	4.27	0.136	0.488
179	Food/Beverage	56,000	2017-11-06	2019-09-30	2,261.94	5,714.80	0.419	0.379
187	Commercial Retail	198,057	2018-07-16	2019-07-15	0.42	1.93	0.263	0.557
188	Commercial Retail	144,000	2018-09-03	2019-09-02	1.16	2.88	0.424	0.550
191	Commercial Retail	198,057	2018-07-02	2019-07-01	0.38	1.92	0.248	0.373
194	Commercial Office	1,700,000	2016-12-26	2018-12-10	841.38	1,253.40	0.674	0.486
205	Food/Beverage	8,500	2019-04-29	2020-02-24	5.49	6.72	0.814	0.512
206	Multifamily	789,079	2018-06-25	2018-12-03	21.19	26.24	0.852	0.539
210	Commercial Retail	198,057	2018-07-30	2019-07-29	0.14	0.70	0.246	0.409
217	Commercial Office	229,154	2019-12-09	2021-12-06	31.67	85.35	0.491	0.515
220	Commercial Retail	198,057	2018-07-16	2019-07-15	0.20	2.13	0.093	0.458
225	Commercial Retail	198,057	2018-07-02	2019-07-01	0.31	0.98	0.311	0.411
226	Commercial Retail	144,000	2018-09-17	2019-09-16	0.42	1.58	0.270	0.344
236	Commercial Retail	144,000	2018-09-03	2019-09-09	0.42	1.59	0.339	0.522
248	Multifamily	127,000	2019-04-08	2019-10-07	58.97	78.77	0.747	0.438
249	Commercial Retail	120,000	2018-12-31	2020-06-08	12.32	15.01	0.848	0.414
250	Multifamily	120,721	2019-02-25	2019-08-26	105.21	123.03	0.855	0.345
252	Commercial Retail	198,057	2018-08-20	2019-08-19	0.40	2.37	0.259	0.505
253	Multifamily	789,079	2018-06-25	2019-01-14	14.18	15.69	0.911	0.685
260	Commercial Retail	144,000	2018-09-03	2019-09-02	0.07	0.43	0.491	0.564
264	Commercial Retail	144,000	2018-11-19	2019-11-18	0.40	1.53	0.353	0.363
265			2019-09-23	2020-05-04	3.43	6.18	0.617	0.551
274	Commercial Retail	144,000	2018-09-17	2019-09-16	0.58	4.27	0.136	0.488
275	Commercial Office	522,000	2019-10-28	2020-04-27	366.20	448.35	0.821	0.337
277	Commercial Retail	198,057	2018-07-16	2019-07-15	0.26	1.47	0.252	0.299
282	Food/Beverage	56,000	2017-12-18	2019-09-30	1,143.91	5,270.35	0.384	0.439
285	Commercial Retail	198,057	2018-08-20	2019-08-19	0.28	1.01	0.354	0.494
294	Commercial Retail	144,000	2018-09-10	2019-09-09	0.42	1.87	0.215	0.407
297	Commercial Retail	198,057	2018-07-16	2019-07-15	0.46	1.48	0.327	0.451
307	Food/Beverage	56,000	2017-12-18	2019-09-30	2,476.87	5,782.70	0.481	0.380
316	Commercial Retail	144,000	2017-03-20	2019-03-18	2.01	8.78	0.237	0.523
322	Commercial Retail	198,057	2018-07-16	2019-07-15	0.29	2.84	0.113	0.458
327	Commercial Retail	198,057	2018-08-20	2019-08-19	0.11	0.29	0.375	0.583
332	Commercial Retail	120,000	2019-08-19	2020-02-24	54.45	65.96	0.845	0.390
350	Commercial Retail	198,057	2018-07-16	2019-07-15	0.37	1.79	0.399	0.324
353	Commercial Retail	198,057	2018-07-16	2019-07-01	0.28	1.99	0.201	0.449
372	Commercial Retail	198,057	2018-07-16	2019-07-15	0.20	0.90	0.266	0.509
373	Multifamily	127,577	2019-11-25	2020-06-01	20.36	23.56	0.864	0.559
380	Food/Beverage	56,000	2017-11-27	2019-09-30	3,213.26	7,497.76	0.552	0.467
386	Commercial Retail	198,057	2018-12-03	2019-12-02	0.03	0.03	0.988	0.470
390	Food/Beverage	8,500	2019-04-29	2020-02-24	6.73	15.71	0.429	0.798
393	Commercial Office	1,100,000	2019-07-29	2020-07-27	508.76	1,620.37	0.336	0.404
394	Commercial Office	725,000	2018-01-01	2018-12-31	3.52	11.92	0.445	0.496
420	Healthcare	236,000	2018-04-09	2018-12-31	144.76	227.08	0.723	0.527
423	Multifamily	119,710	2019-12-30	2020-11-30	2,922,233.79	6,979,961.45	0.613	0.665
426	Hospitality	80,000	2017-12-04	2020-11-30	7.99	12.36	0.692	0.439
440	Commercial Office	268,000	2020-09-28	2021-09-27	64.43	183.73	0.400	0.242
442	Multifamily	205,000	2020-12-28	2021-05-10	29.94	62.07	0.480	0.665

Table 1: Buildings with associated KPI values computed across the building's entire historical dataset