Demonstrating the Reliability of Randomized Measurement and Verification for Switchable Control Retrofits Using a Large Open-Source Dataset

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Conventional measurement and verification (M&V) methods rely on pre- and post- retrofit comparison to estimate energy savings. They are often time-consuming and unreliable, especially when non-routine events including static changes and gradual changes denoted as operational drift occurs during the M&V process. Those events are unrelated to the intervention but significantly affect building energy consumption and thus when the analyst applies conventional M&V suggested by industry guidelines, the results can be largely confounded. In this study, we demonstrated that switchable interventions, such as most control retrofits, can benefit from a new M&V method which randomly samples whether to implement the baseline or the intervention strategy at a fixed interval (e.g., daily). We tested this novel randomized M&V method on a large public dataset covering various climate zones and commercial building types, using a virtual chilled water supply temperature reset based on outdoor weather as the intervention. Our results show that compared to the conventional method, the randomized method provides faster and more accurate savings estimations. Additionally we found that when non-routine events are present, the randomized M&V approach estimates savings that are much closer to the ground-truth savings than the conventional M&V method, demonstrating much improved reliability. We also assessed the impact of dropping samples affected by carryover when switching between strategies, and identify the optimal sampling interval for that scenario using this large dataset.

# 1 Introduction

## 1.1 Conventional M&V

Measurement and Verification (M&V) is the process of quantifying energy savings from energy efficiency projects by comparing actual energy consumption against a baseline, adjusting for factors like weather and occupancy. This process ensures that improvements in energy performance are accurately evaluated. In the United States, practitioners often refer to ASHRAE Guideline 14, the International Performance Measurement and Verification Protocol (IPMVP), and the Federal Energy Management Program (FEMP) for standard guidelines (DOE 2008; Efficiency Valuation Organisation 2012; ASHRAE 2023). These guidelines outline standardized methods for quantifying energy savings, whether through calibrated simulations or monitored measurements for specific equipment or systems (isolation methods) or for entire buildings (whole-building methods). In this study, we will focus on the energy savings quantified at the whole-building level where the measurements are obtained from utility bills or whole-building meters, however the overall conclusions would also apply to isolation methods. Typically, the process begins with baseline measurements taken during the year before implementing the energy-efficiency retrofit, followed by the same measurement procedure during the year after the intervention. After collecting two years of data, an M&V analyst fits an energy prediction model, using variables such as outdoor temperature and time (Mathieu et al. 2011) to project baseline energy consumption in the post-retrofit period. The difference between the counter-factual baseline and the measured intervention period energy consumption represents the energy savings. One of the key drawbacks of this method is its reliance on a two-year timeline to quantify savings, during which baseline measurements can become outdated due to changes in building performance caused by non-routine events unrelated to the intervention. Specifically, an M&V analyst should account for two types of baseline changes: (1) static changes, which are known building operational changes: such as renovation, equipment addition or removal; and (2) gradual changes, which often occur subtly and unknown, such as the incremental adoption of LED lighting or more efficient plug loads. Identifying and quantifying these changes are particularly labor-intensive and challenging. Consequently, those limitations reduce the feasibility of M&V and complicates the quantification of estimation uncertainty, thus impacting the accuracy and timeliness of savings assessments.

## 1.2 Randomized M&V

To address the limitations of conventional M&V methods and the challenges posed by non-routine events, we proposed a M&V method that adopts the randomized crossover design (Raftery et al. 2024), a gold standard from medical, agricultural and online controlled experimental (i.e. A/B testing) studies (Blackston et al. 2019; Duan, Kravitz, and Schmid 2013; Gupta et al. 2019; Mie et al. 2022; Munro, Wager, and Xu 2023; Raseduzzaman and Jensen 2017). An early application of this randomized design to the field of M&V in buildings was first used in (Raftery et al. 2018), which compared the energy performance on two different supply air temperature reset strategies in a building. Subsequent improvements to the M&V method include adding a sequential evaluation framework and defined stopping criteria to end the M&V period early after reaching a target level of uncertainty, among other improvements, such as using blocked randomization by weekday. The full framework is detailed in a previously published study (Raftery et al. 2024) along with a case study application to a real building, and other example use cases. In summary, this method provides M&V analysts with a randomized schedule that alternates between baseline and intervention implementation while ensuring balanced sampling across days of the week and seasons. For example, given a 10-week M&V period for 1 intervention, the balanced randomized schedule would equally sample 5 Mondays with the baseline strategy in operation and 5 Mondays with the intervention strategy in operation. The limitation of this method is that it is only applicable to a subset of retrofit projects where interventions can be easily switched on and off. However, for all applicable use cases, it allows analysts to detect energy savings sequentially shortly after the test begins. In addition, once the desired estimate uncertainty target is achieved, analysts can terminate the M&V study and switch to 100% intervention. The key advantage of randomization is that if control strategies are sampled with equal probability, the influence of other confounding factors such as occupancy change (commonly known as one of the non-routine events) and other more subtle long term changes in building energy use are likely to be evenly distributed among measurements, leading to a more accurate and unbiased assessment of the intervention effect.

## 1.3 BDG2 dataset

To demonstrate and differences between the two M&V methods, the Building Genome Dataset 2 (BGD2) is used, which is an extensive open-access dataset designed to advance research and development in building energy efficiency and control strategies acting as a test-bed for modeling, simulation, and algorithm development (Miller et al. 2020). BGD2 contains over 1000 buildings’ metadata and realistic operational measurements between 2016 and 2017 from across North America and Europe, making it one of the most comprehensive collections of building-related data available for scientific use. The dataset includes various commercial building types such as offices, education facilities, public, and retail buildings, and provides detailed information on their physical characteristics (e.g. energy ratings, heating types and floor area) and hourly measurements of chilled and hot water, electricity, gas usage as well as site outdoor weather conditions. In this study, we mostly use the metered electricity and outdoor weather measurements for running the M&V methods.

## 1.4 Literature review

### 1.4.1 Whole building approach

ASHRAE Guideline 14 and the IPMVP provide options for whole-building M&V use cases. For code compliance using the prescriptive option, 12 months of baseline and 12 months of post-retrofit measurements are required. In addition, the expected savings should be larger than 10% and the baseline model fitting accuracy should have CV(RMSE) lower than 20%. Thus, most research related to M&V for whole-building approach focuses on the accuracy of baseline modeling, exploring model performance from simple regression models to more complex machine learning techniques. One study reviewed various models suitable for M&V applications as well as selected input features (Alrobaie and Krarti 2022) and another study provided a definitive methodology to apply machine learning models for M&V use cases (Gallagher et al. 2018). In addition, a few studies investigated the critical performance metrics to evaluate the developed baseline models (Granderson et al. 2015; Granderson and Price 2014) and compared a variety of models using those metrics (Granderson et al. 2016). These studies made significant contributions by emphasizing the uncertainty associated with the model-fitting process, a key factor in accurately determining energy savings. Furthermore, other researchers addressed this issue by leveraging statistical formulation and inference to improve baseline energy models (Burkhart, Heo, and Zavala 2014; Heo, Choudhary, and Augenbroe 2012; Walter, Price, and Sohn 2014). However, a gap still remains in the literature regarding the rigorous quantification of uncertainties directly associated with calculated savings, for instance, accounting for the potential bias that the baseline model might deteriorate (i.e. become ‘stale’) over the extended period of pre- and post-analysis.

### 1.4.2 Non-routine events impact

Non-routine events in M&V commonly refer to unexpected changes in a building that influence a building’s energy usage and are typically unrelated to the intervention strategy. Current guidelines define non-routine events as ‘static factors’ that needed to be adjusted after projecting baseline in the post-retrofit period (ASHRAE 2023; Efficiency Valuation Organisation 2012). A common non-routine event in energy-saving M&V projects is a change in occupancy or a significant shift in occupant behavior, equipment run time, and operating conditions (e.g. set points, lighting, and ventilation levels). However, current standards or guidelines only provide a general approach for consideration. For example, IPMVP requires the facility owner and the M&V analyst to periodically perform inspections of all equipment and operations during the reporting period, which is labor-intensive and error-prone. ASHRAE guideline 14 recommends performing engineering calculations or computer software simulations to adjust the post-retrofit baseline. Additionally, it is relatively rare to have access to all measurements needed for adjustments such as occupancy, and thus the analyst normally assumes those factors remain unchanged throughout the study. For example, some studies uses linear interpolation to estimate counter-factual baseline for demand response program (Beil, Hiskens, and Backhaus 2015; Keskar et al. 2020). Consequently, one study points out that it is inaccurate to assume no change in the operating conditions during the response period (Huang, Katipamula, and Lutes 2023). Other studies realized such limitation in field study, and emphasized the importance of requiring matched groups to control for exogenous factors beyond weather differences when comparing between baseline and intervention (Demand Side Analytics 2022; Huang, Katipamula, and Lutes 2023).

Overall, those non-routine events mostly refer to clearly observable changes, but there are also more gradual and subtle changes in buildings, which are hardly noticed. We define those gradual changes as ‘operational drift’ in this study. One likely encountered operational drift situation is the filter clogging in air handling units due to particle accumulation. This causes supply fans to gradually consume more energy to maintain the required duct static pressure (Feng and Cao 2019; Zhai and Nathaniel Johnson 2017). If M&V analysts are unaware of such changes and lack an appropriate adjustment method (e.g., replacing filters before the intervention begins), the savings could be overestimated as the decreased energy use is incorrectly attributed to the intervention rather than the filter replacement. An operational drift has not been formally defined in the literature or standards, but in this study, we consider it as a special type of non-routine events as it also represents a change in facility operation but in a longer term.

## 1.5 Objectives

As mentioned, the goal of an M&V project is to determine the effect, typically energy savings, of some intervention in the building. In this study, we focus on switchable interventions and an example of such an intervention is a control strategy that adjusts the chilled water plant’s supply water temperature, which can be commonly found in the literature (Duarte et al. 2023; K.-P. Lee and Cheng 2012; Qiu et al. 2022; Jin, Du, and Xiao 2007; Taylor 2012). In our case, we make it even simpler by adjusting the setpoint based on outdoor weather conditions with more description shown in Section 2.2. By conducting such an analysis, we aim to:

1. Determine, using a large sample of buildings, how much more accurately the randomized M&V method would estimate the savings of the proposed intervention compared to the conventional M&V, and how much more quickly it would reach a result.
2. Determine how much more robust the randomized method is compared to the conventional method when static non-routine events and operational drift are present in the dataset. The BDG2 dataset contains real-world building energy usage data collected over two years, inherently contains varying degrees of usage changes. By virtually introducing intervention effects into the existing dataset, we can calculate the ground-truth energy savings, which serve as a reference point for method comparison.
3. Open-source implementation of the proposed randomized M&V method. We ensured the reproducibility of the method by making the analysis code open source including randomized schedule generation, sequential statistical analysis, energy modeling and normalized saving calculation. In addition, we also included code for extended use cases of the randomized method, such as changing sampling ratio and sampling intervals. Using the available open resources, building analysts should be able to seamlessly integrate and apply them in their own M&V projects.

# 2 Method

We outlined the methodology of the study in Figure 2.1 and extended several key components in this section.

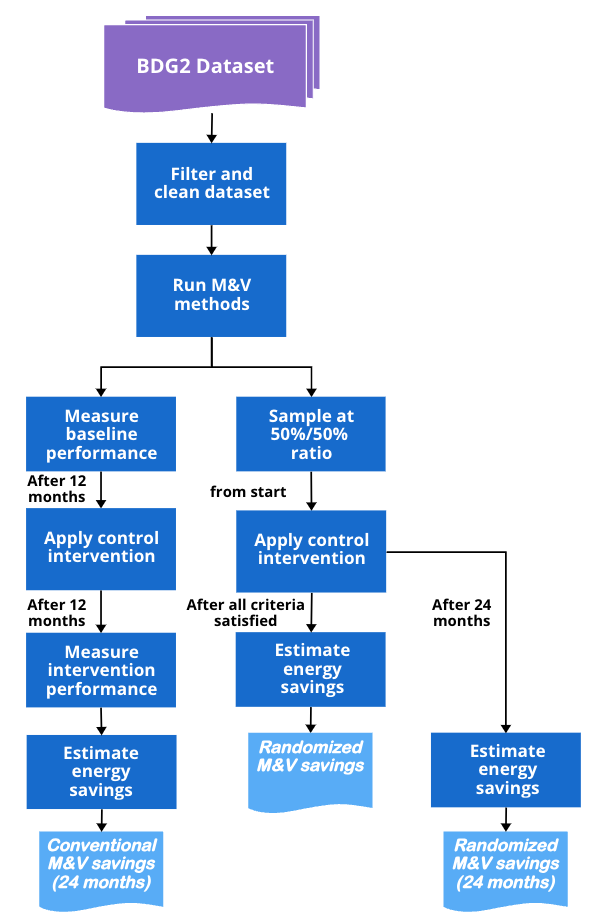


Figure 2.1: Flow chart showing the methodology for comparing the estimated savings of randomized M&V with the conventional M&V

## 2.1 Filter and clean dataset

We extracted the electricity measurements from the BDG2 dataset and filter out all qualified buildings based on the following criteria:

1. Missing values < 1000: given the hourly resolution of all measurements, this is equivalent to 1.5 months of missing days.
2. Mean electricity usage > 0 kWh: target buildings should have active electricity usage.
3. : any increase or decrease in building electricity usage in the second year should be less than 25% of that in the first year.
4. Electric EUI < 750 kWh/: excludes buildings at the top 5% of electrical energy usage intensity according to the statistics provided by the Building Performance Database (Lawrence Berkeley National Lab, n.d.; Mathew et al. 2015).
5. Warehouse and parking types are excluded: target buildings have less demand flexibility to implement a chilled water set point reset control.

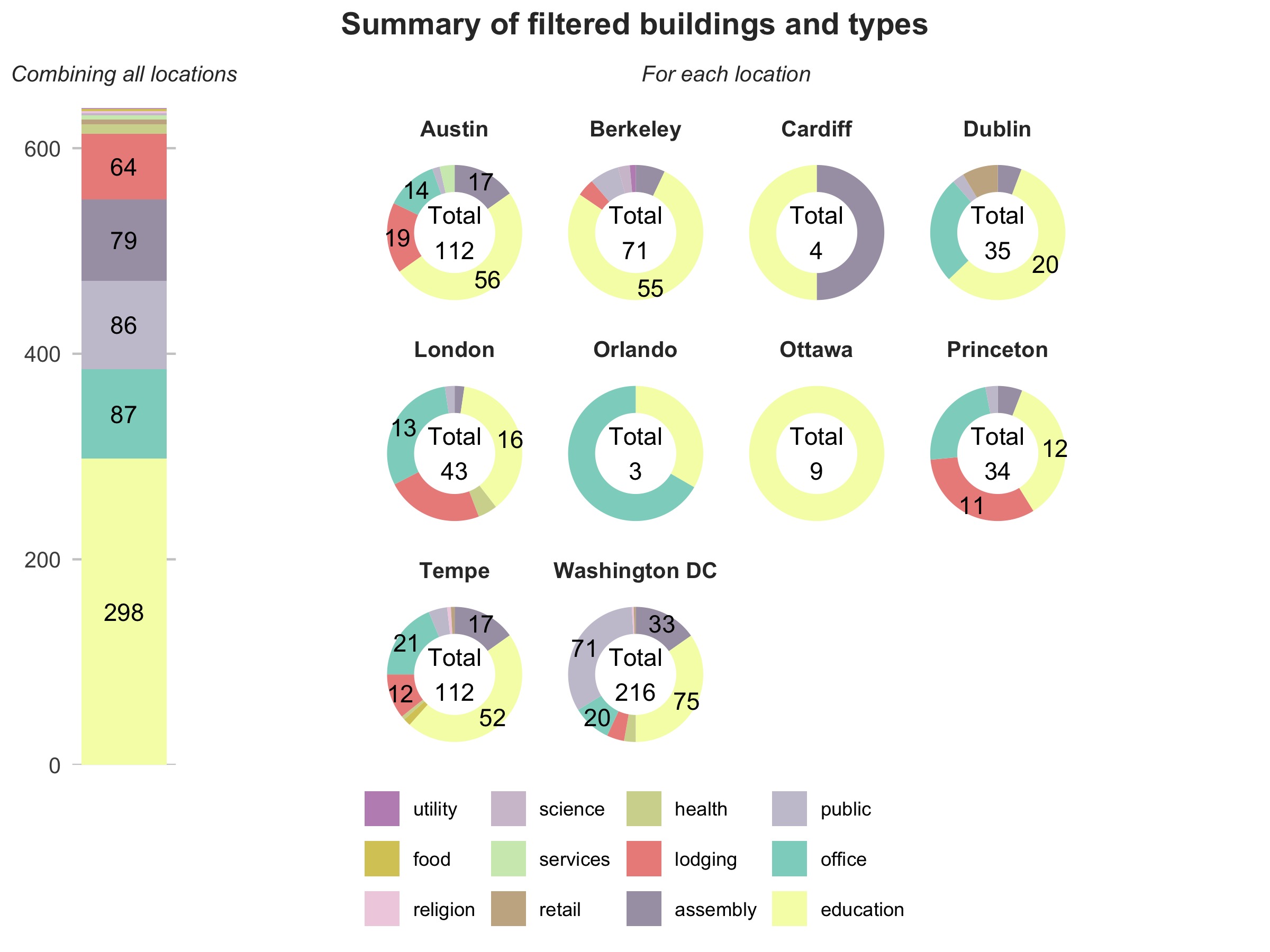


Figure 2.2: Site summary of the filtered buildings from BDG2 dataset (counts < 10 are omitted for visualization; left: aggregated counts of buildings for each type; right: breakdown building counts for each building type at each location)

For all qualified buildings, we further added one more stringent criterion to explore all buildings with very stable electricity usage between the two years:

1. No statistically significant difference (P-value > 0.05) between the two-year electricity usage, which are sometimes assumed to be the case for whole-building measurement and verification.

As a result, there are only 66 buildings were labeled in this ‘stable’ subset (out of total of 600 buildings) implying that the assumption that buildings are typically stable over the timeframe involved in conventional M&V is rarely true. As mentioned in Section 1.4.2, such variability is largely associated with non-routine events, especially operational drifts since the assessment last for two years. And according to the statistics shown here, it is a typical case observed in real buildings applications.

## 2.2 Apply virtue intervention

Figure 2.3 shows the algorithm for the proposed control intervention that reset the chiller supply temperature based on the outdoor weather conditions, which can be commonly found in the literature (Y. J. Lee et al. 2022; Čongradac and Kulić 2012). For both strategies, we assume that the chiller operates when the outdoor temperature exceeds 10°C. The baseline strategy, representing the existing measurements from the dataset, operates with a constant water supply temperature. The intervention strategy, as illustrated in the figure, adjusts the water supply temperature dynamically, resetting it from 7°C to 12°C.

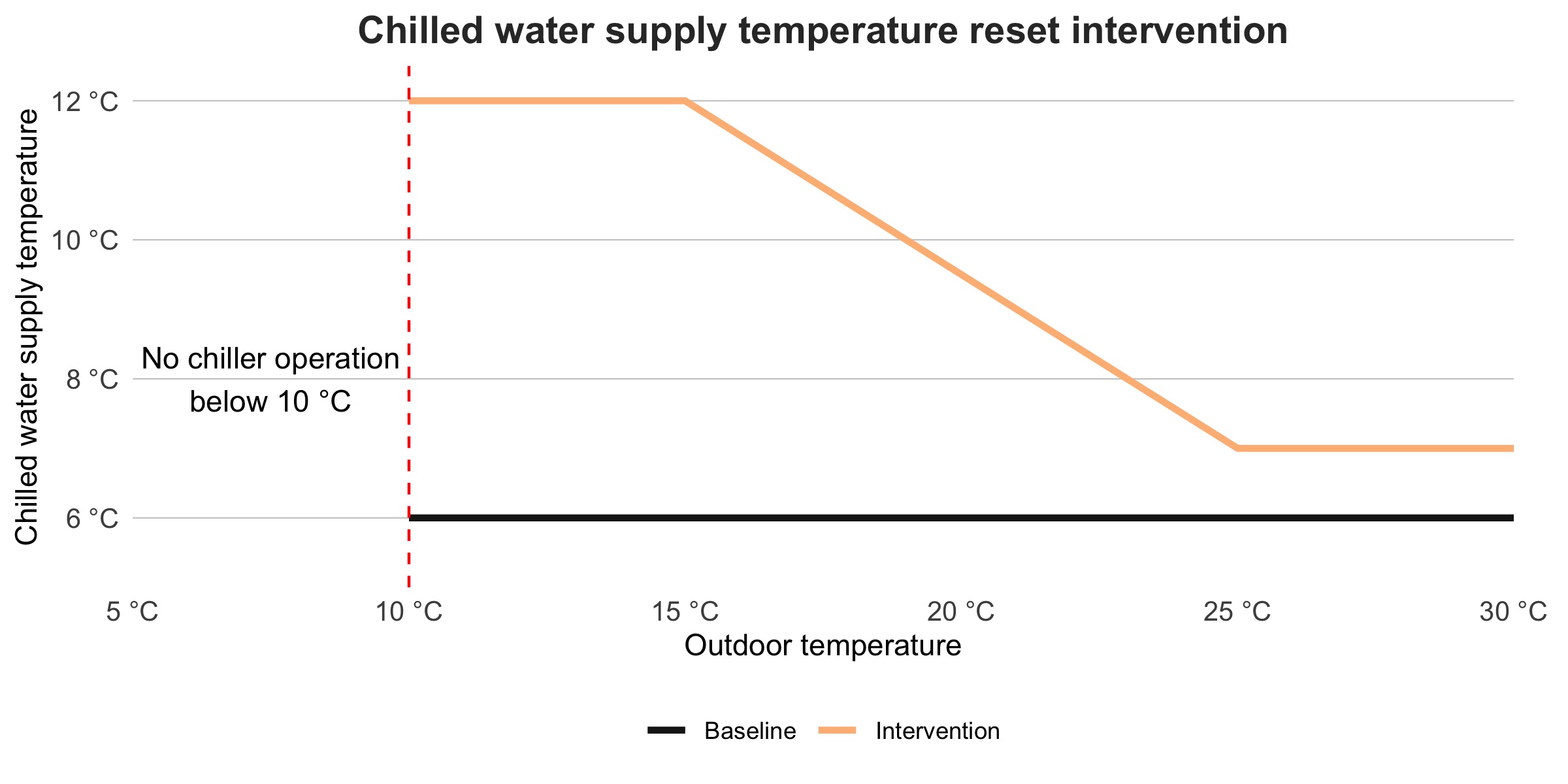


Figure 2.3: Proposed intervention strategy: chilled water supply temperature reset based on outdoor temperature.

We used a simple relationship to map the chilled water supply temperature reset to the electrical energy savings:

We assume on average, HVAC systems account for approximately 50% of a building’s total electricity consumption, and the chilled water plant further consumes around 50% of the HVAC electricity. While this assumption largely simplifies the diverse energy usage across various building types, for the scope of this paper, we assume that 25% of the total building electricity is used by the chilled water plant, (Administration 2012). Typically, the savings from an intervention are not proportional to the building’s hourly electricity usage, which is generally the challenge for M&V. To address this, we mapped the resulting electricity savings as a percentage of the plant’s normal operation, calculated as its mean electricity usage over the two-year period. This percentage is influenced by factors such as outdoor temperature (), intervention supply water temperature (), baseline supply water temperature () and hour of the day (, binary indicator whether during peak hours from 9 AM to 4 PM).

Parameters and their pre-defined values are summarized in the table below. For simplicity, those parameters were not rigorously calibrated for each building and were applied uniformly in the filtered dataset. Interested readers can also change the parameters in our open-source code to simulate different scenarios.

Table 1. Parameters for calculating the intervention savings.

|  |  |  |
| --- | --- | --- |
| Parameter | Description | Value |
|  | % savings from setting 1 °C higher than | 0.08 |
|  | % savings adjustment during occupied hours | 1.2 |
|  | % savings adjustment during unoccupied hours | 0.8 |

## 2.3 Run M&V methods

We described in detail the workflow of both conventional and randomized M&V methods in the previous study (Raftery et al. 2024). The conventional method is a pre- and post- comparison on a 12-month baseline and 12-month intervention timeline. The randomized method defines sampling requirements as:

* Use a daily sampling interval with the sampling time at midnight each day.
* Block by day of the week with a block period of 12 weeks.

and stopping criteria as:

* A minimum and maximum of 12 and 108 weeks respectively. The randomized schedule covers the entire two-year period but stopping criteria enables an early stop at the end of the satisfied blocking period.
* At least 80% of the dry-bulb temperature range in the annual TMY data sampled by both strategies.
* No carryover effect using a t-test with a p-value not exceeding a defined significance threshold of 0.05.
* 90% confidence that energy savings exceed or do not exceed 0% using the SPRT test. Medium effect size (d = 0.5) quantified by cohen’s d and calculated SPRT statistics either falls below the lower threshold or exceeds the upper threshold.
* Sample strategies at an equal sampling ratio (50% baseline, 50% intervention).

# 3 Results

The accuracy () is calculated as:

where indicates true electricity usage and indicates the estimated electricity usage either through the conventional method or the new randomized method. We present the distribution of savings estimation accuracy using boxen plots, also known as letter plots, which is an advanced variation of the box plot designed to extend beyond the interquartile range (IQR) by progressively dividing the data into smaller percentiles, revealing more detail in the tails of the distribution. We set the division parameter to k = 4, meaning the entire box area represents the data distribution from 6.25% to 93.75%. As the steps move closer to the center line (50% median), the distribution range progressively narrows with the next step representing 12.5% to 87.5%, followed by 25% to 75%. In addition, for each boxen plot, we also showed the mean value of the distribution on top for reference.

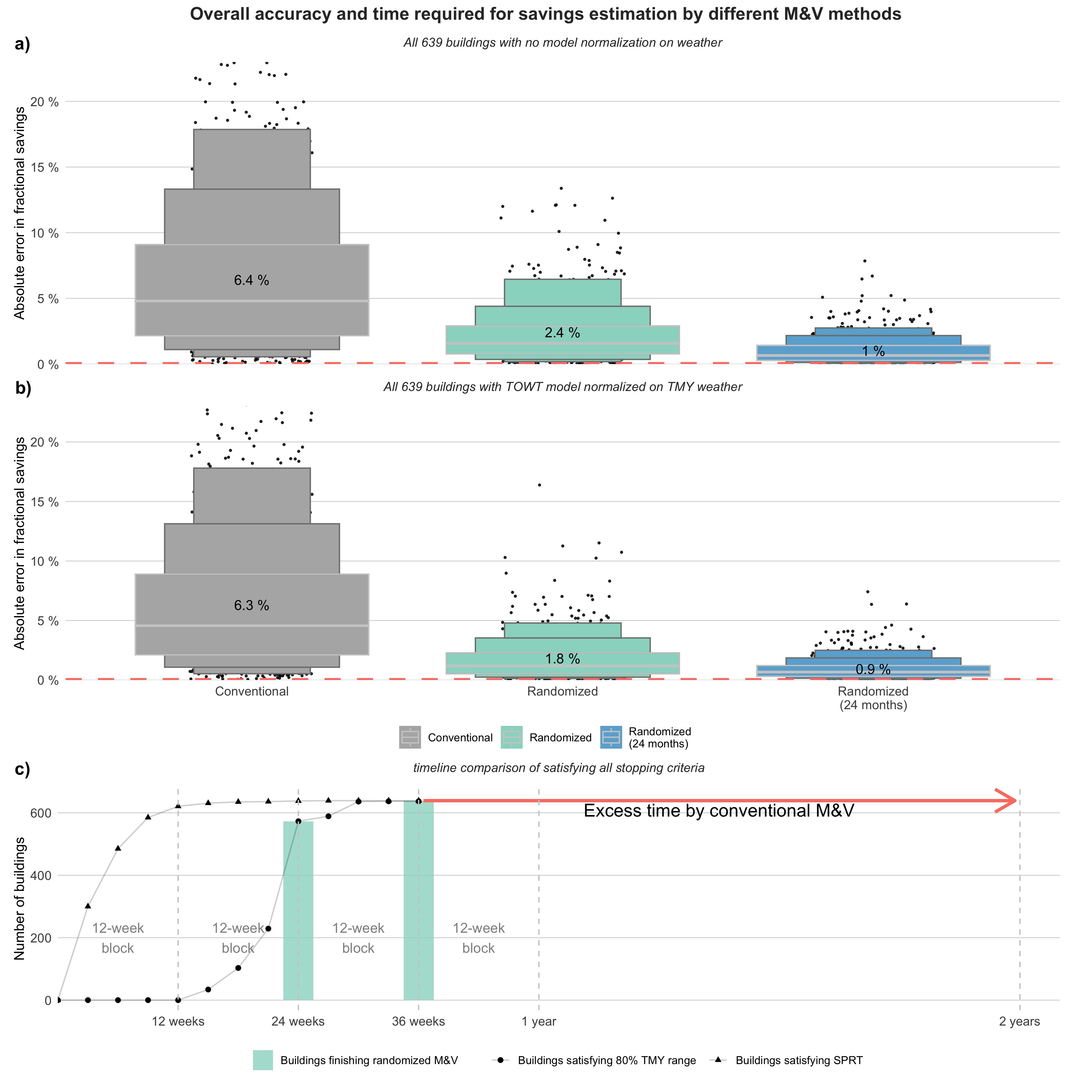


Figure 3.1: Overall comparison results between the conventional M&V method and the proposed randomized M&V method (both upon reaching the stopping criteria for each case, and over a fixed two-year period).

Figure 3.1 shows the overall results of M&V methods comparison and for clarity, we plotted conventional M&V results in grey, randomized M&V results after satisfying all stopping criteria in green, and the randomized M&V results sampled for the entire 24 months in blue. Subplots (a) and (b) calculate the savings estimation error as the absolute deviation from the true savings (i.e. ) and show the results distribution using the conventional M&V method in the first column, the randomized M&V method that stops after satisfying all stopping criteria in the second column, and the randomized M&V method continues 50%/50% sampling throughout 2 years in the third column. In addition, subplot (a) shows the savings estimated from measured weather conditions, and subplot b) shows the savings normalized on the typical meteorological weather of the building location after using TOWT model. As a result, the conventional M&V method exhibits an average deviation of 6% in savings estimation, whereas the proposed randomized method demonstrates significantly smaller deviations. If the analyst stops immediately after satisfying all stopping criteria, the deviation is reduced to approximately 2%. Extending the M&V period to match the length of the conventional method (24 months) further improves accuracy to 1%. Furthermore, by comparing subplots (a) and (b), we observe a minor improvement in estimation accuracy when a model is fitted to the data to account for weather differences. The model fitting is most beneficial for the shorter dataset (randomized and stopping when all criteria are met, typically 24-36 weeks of data), where it improves estimation accuracy by 0.6%. This is because the weather conditions between the first and second year for each of the locations are relatively similar on average over this time period, and thus the effect of adjusting for temperature as an independent variable in the model is relatively small. Subplot (c) compares the overall timeline of the two M&V methods. The results show that almost all buildings achieve accurate M&V results and meet the stopping criteria within 24 weeks (for this intervention), with the remainder meeting all stopping criteria within 36 weeks. The additional 12 weeks is usually driven by a need to span sufficient weather conditions representative of a full year of data. Meanwhile, the red arrow highlights the excess time required by the conventional M&V method (24 months). Thus, the randomized M&V method finds more accurate results in approximately a quarter of the time required for conventional M&V. Even if it was the case that an existing 12-month baseline data was available at the start of the M&V process, randomized M&V would still obtain a more accurate result, in less time, than obtaining the 12-month retrofit dataset required by conventional M&V.

We also plotted the mean error in Figure 3.2 and we noticed that the uncertainty range associated with the conventional method is significantly larger compared to the randomized method that only takes 36 weeks according to subplot (c) in Figure 3.1.

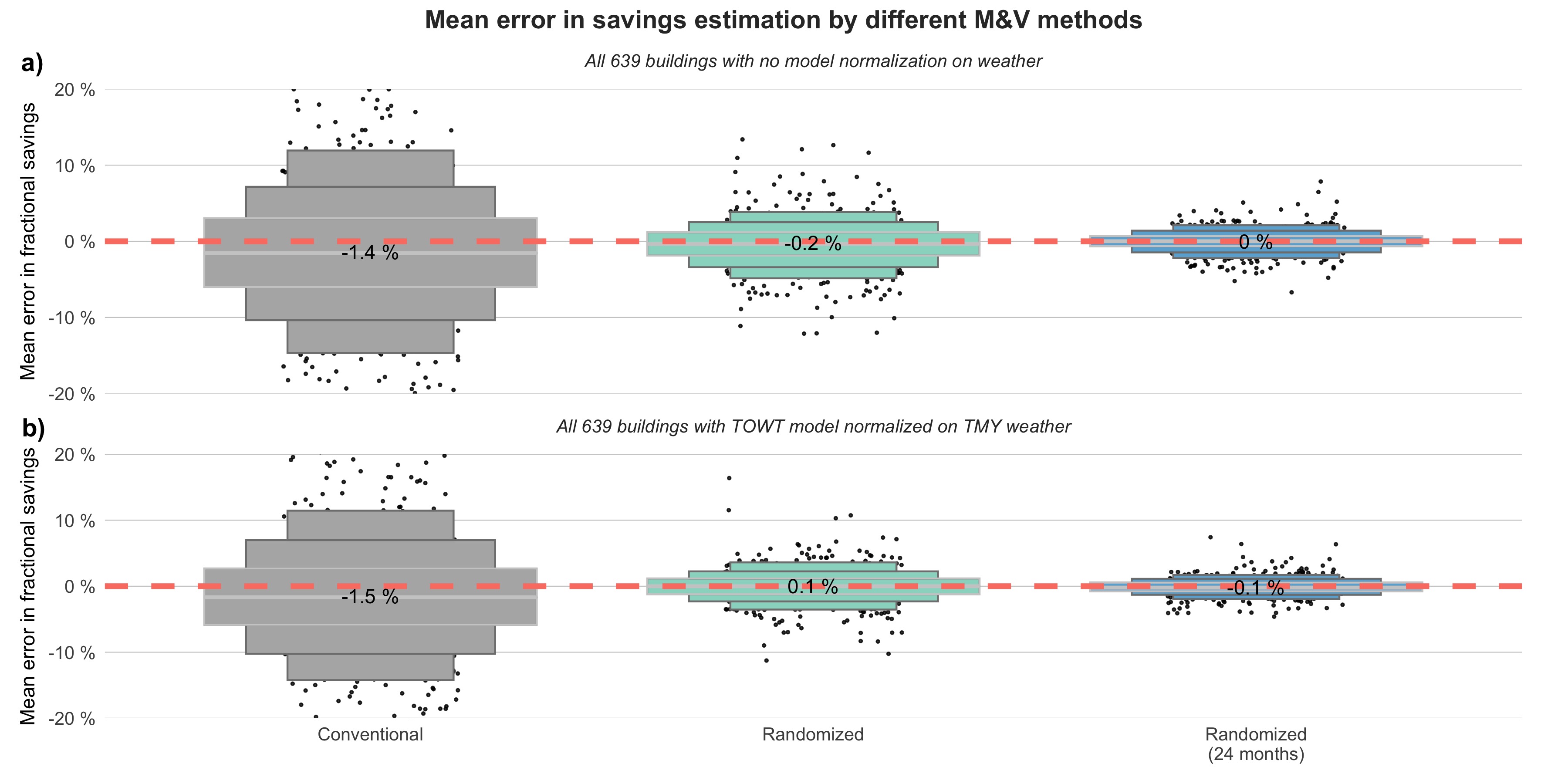


Figure 3.2: Distribution of mean deviation from the ground-truth savings calculated by the two M&V methods

Additionally in the literature, we found another M&V study using over 500+ commercial buildings, but their study scope was to compare the predictive performance of a variety of M&V baseline models from simple weekly mean to more complex machine learning methods using the normalized mean bias error (NMBE) (Granderson et al. 2016). Since we also calculated the normalized savings estimation error, we compared our normalized accuracy for 600+ buildings with the TOWT model and TMY weather with their TOWT model prediction assessment in the following table, highlighting that the model and overall building datasets are performing similarly.

Table 1. Savings accuracy comparison with a similar literature

|  | Reference study results (Granderson et al. 2016) | Our study results |
| --- | --- | --- |
| 25th percentile | -5.85 | -5.84 |
| 50th percentile | -1.25 | -1.68 |
| 75th percentile | 3.86 | 2.67 |

## 3.1 Non-routine events impact

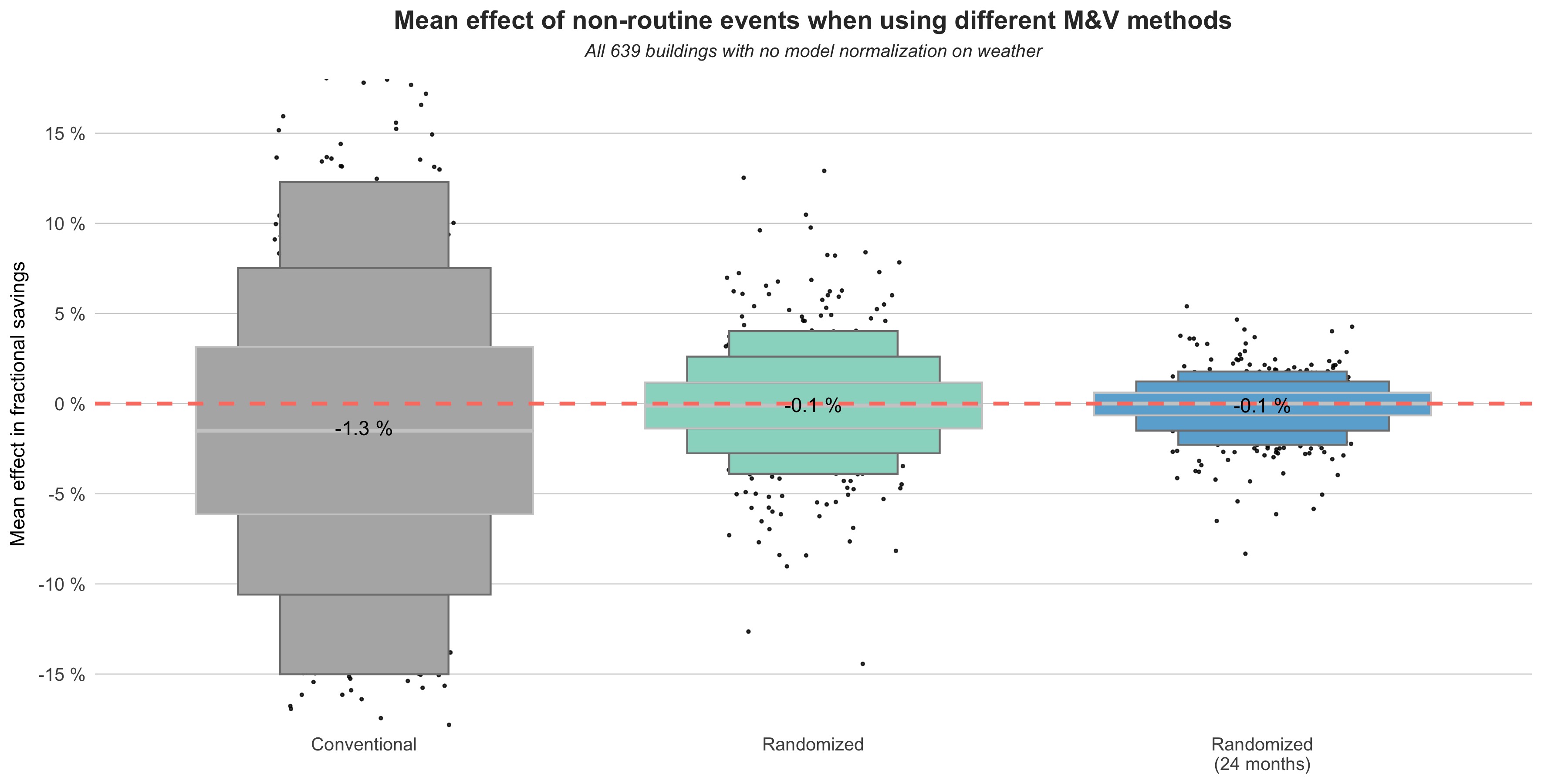


Figure 3.3: Comparison between the two M&V methods in detecting no intervention effect when buildings are subject to static non-rountine events and gradual operational drift.

As mentioned in Section 2.1, the majority of the selected buildings are affected by operational drift, which is the reason why we observe baseline electricity usage changes throughout the two year period. To evaluate the robustness of the two M&V methods to the effect of operational drift and non-routine events, we repeated the M&V run on the original dataset prior to the application of the reset control. In other words, there is no intervention applied here, so the most reliable M&V method will be the one that detects closer to 0 kW savings using the measurements. Therefore, the here are calculated as:

Figure 3.3 shows the randomized M&V method (both at the time of satisfying all stopping criteria and at the end of a two-year period) produced consistent results. We included the absolute deviation () figure in the supplementary material. Similarly to Figure 3.1, stopping when meeting all stopping criteria generally yields slightly larger uncertainty than continuing for 24 months. However, it still yields a more accurate result than the conventional method. Interestingly, similar to (Granderson et al. 2016) where they obtained a median normalized deviation around -1.25%, our analysis on conventional method shows that the typical deviation is -1.3%, meaning that the typical building is decreasing energy use slightly in this dataset in the absence of any known intervention. Thus, if a building analyst were to apply an intervention to this building and use conventional M&V to measure the effect, they would ‘detect’ 1.3% energy savings even when the intervention had no actual impact on energy performance.

# 4 Discussion

## 4.1 TOWT modeling accuracy

To evaluate modeling accuracy, we used the Coefficient of Variation of Root-Mean Squared Error (CV(RMSE)) as the primary error metric. Since CV(RMSE) is a normalized measure, it enables direct comparison across different model-fitting results. According to ASHRAE Guideline 14, whole-building baseline models should achieve a CV(RMSE) below 25% for computing savings or 30% when less than 12 months of measurements are available (ASHRAE 2023). In our study, Figure 4.1 compares the model fitting accuracy of the two M&V methods and it shows around 87.5% of the models fitted in the randomized M&V method are code compliant while 80% for the conventional M&V method. As the quantity of the training set is the same, this highlights the impact of data sampling on model fitting accuracy, and for TOWT, the distribution of outdoor weather conditions sampled in the training dataset is influential. The conventional method trains the model using the entire first-year dataset, if the location is heating or cooling dominant, the data-driven model is trained using colder or warmer outdoor conditions leading to biased model coefficients. Although the random sampling in our study does not specifically block the outdoor temperature factor, the CV(RMSE) distribution shown in the figure indicates a significant improvement in model fitting accuracy.

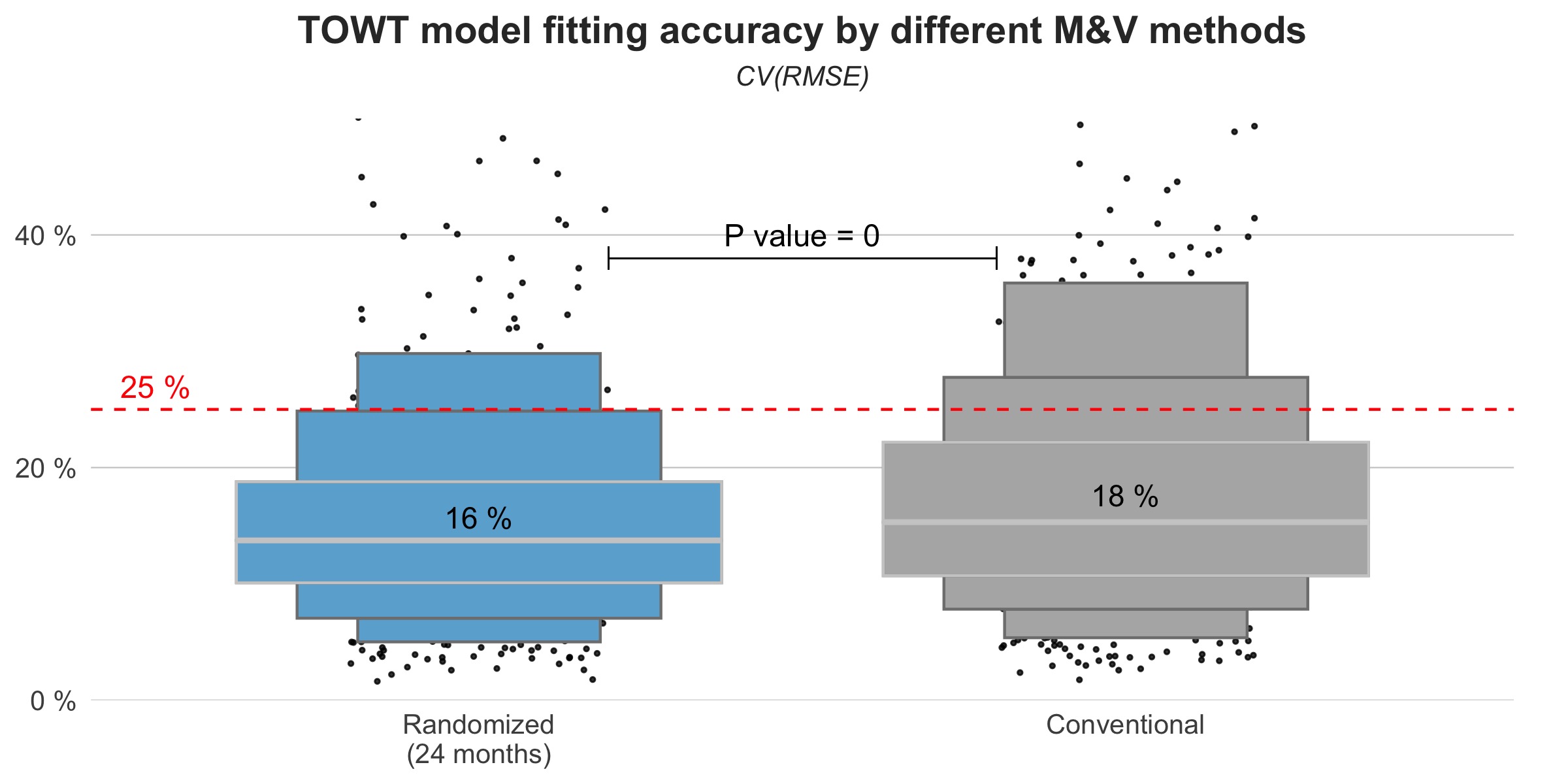


Figure 4.1: TOWT model fitting accuracy distribution for all buildings included (with each data point representing one building)

## 4.2 Sampling interval impact

In some cases, particularly those involving large thermal mass and active thermal energy storage systems or operating continuously, there can be a substantial time-lagged effect associated with interventions. This means that the effect of one control strategy may persist after switching to another. To mitigate such carryover effects, building analysts may choose to drop non-consecutive days in the switchback experiment. For example, consider a heat pump hot water heater where the tank is charged at very different times of the day by the intervention strategy compared to the baseline strategy. When switching strategy, the tank may be much warmer or cooler than typical for that strategy, thus influencing subsequent measurements, particularly the performance measured on the first day (i.e., a non-consecutive day). In such cases, increasing the sampling interval (e.g., sample strategies every 2 or 3 days instead of daily) and discarding measurements from those non-consecutive days can eliminate carryover. However, this approach reduces the total data collected: for instance, sampling every 3 days would drop 1/6 of measurements and sampling every 2 day means would remove 1/4 of measurements. Therefore, by increasing the sampling interval, there is an accuracy penalty due to a reduction in how often samples occur, and when decreasing the sampling interval, there is an accuracy penalty from dropping more non-consecutive days. To quantify such trade-off, 4.2 shows the accuracy of different sampling intervals and the consequence of dropping the non-consecutive days in the dataset at the time when randomized M&V produces a result (after satisfying all stopping criteria).

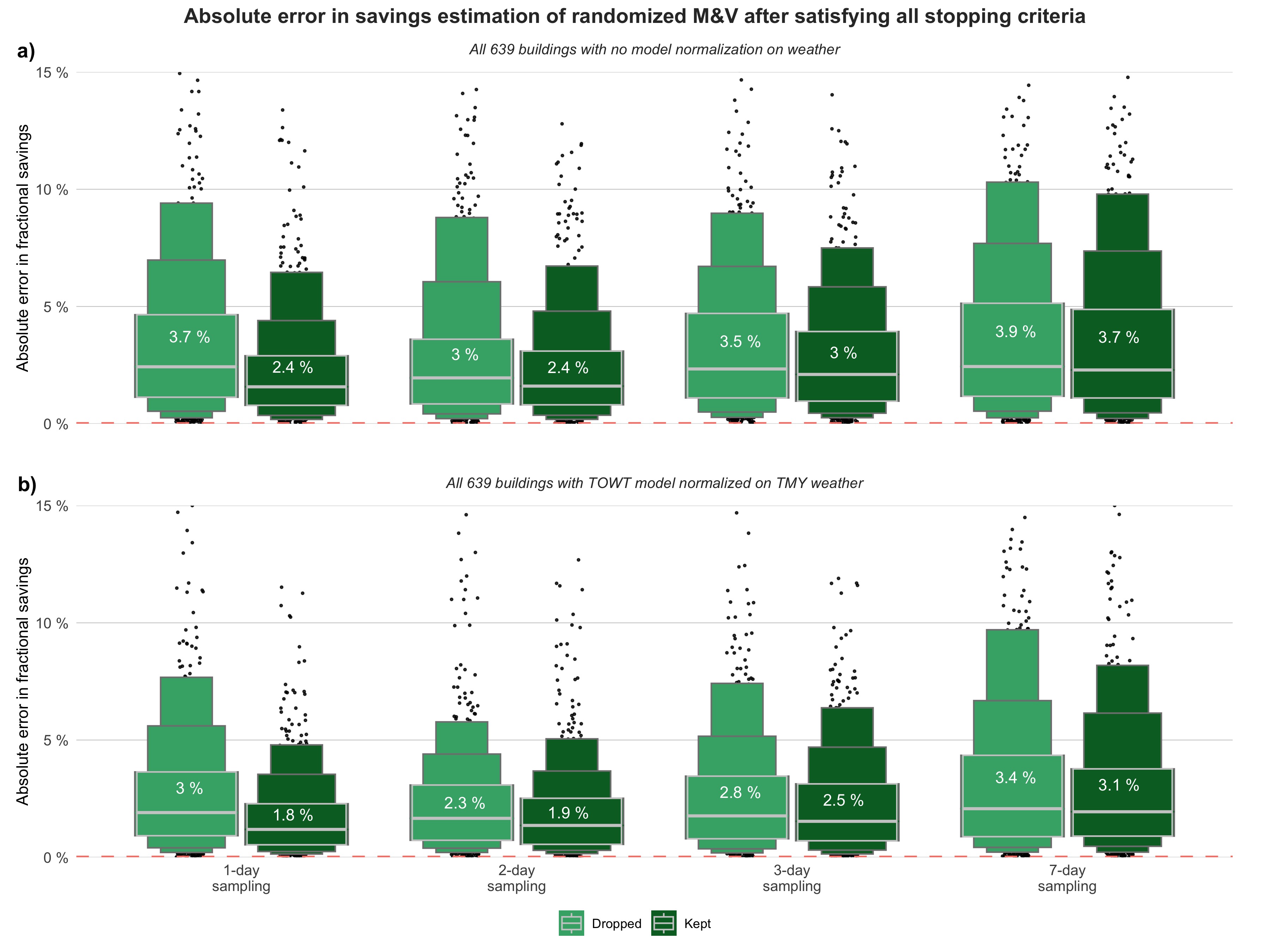


Figure 4.2: Comparison of different sampling interval impact on M&V estimation accuracy (dropped: all non-consecutive days were dropped; kept: all measurements were kept)

To quantify the impact of reduced randomness, all measurements are kept when calculating the distribution shown in the darker-colored set. The results suggest a gradual increase in error from 2.4% to 3.7% when the sampling interval increases from daily to weekly intervals. This is due to the fact that increasing the sample interval means reducing randomization. To quantify the combined impact of data loss due to preventing the carryover effect, we generated the lighter-colored set, which drops all non-consecutive days. As a result, we noticed a significant increase in estimation error when sampling daily, which led to a similar accuracy compared to weekly intervals. Therefore, considering this trade-off, we recommend using a two-day sampling interval if the carryover effect is likely but expected to last less than one day, and then normalizing the estimation via energy modeling. We also included the mean deviation distribution and the accuracy distribution calculated after all stopping criteria were satisfied in the supplementary material and the results show the same indication.

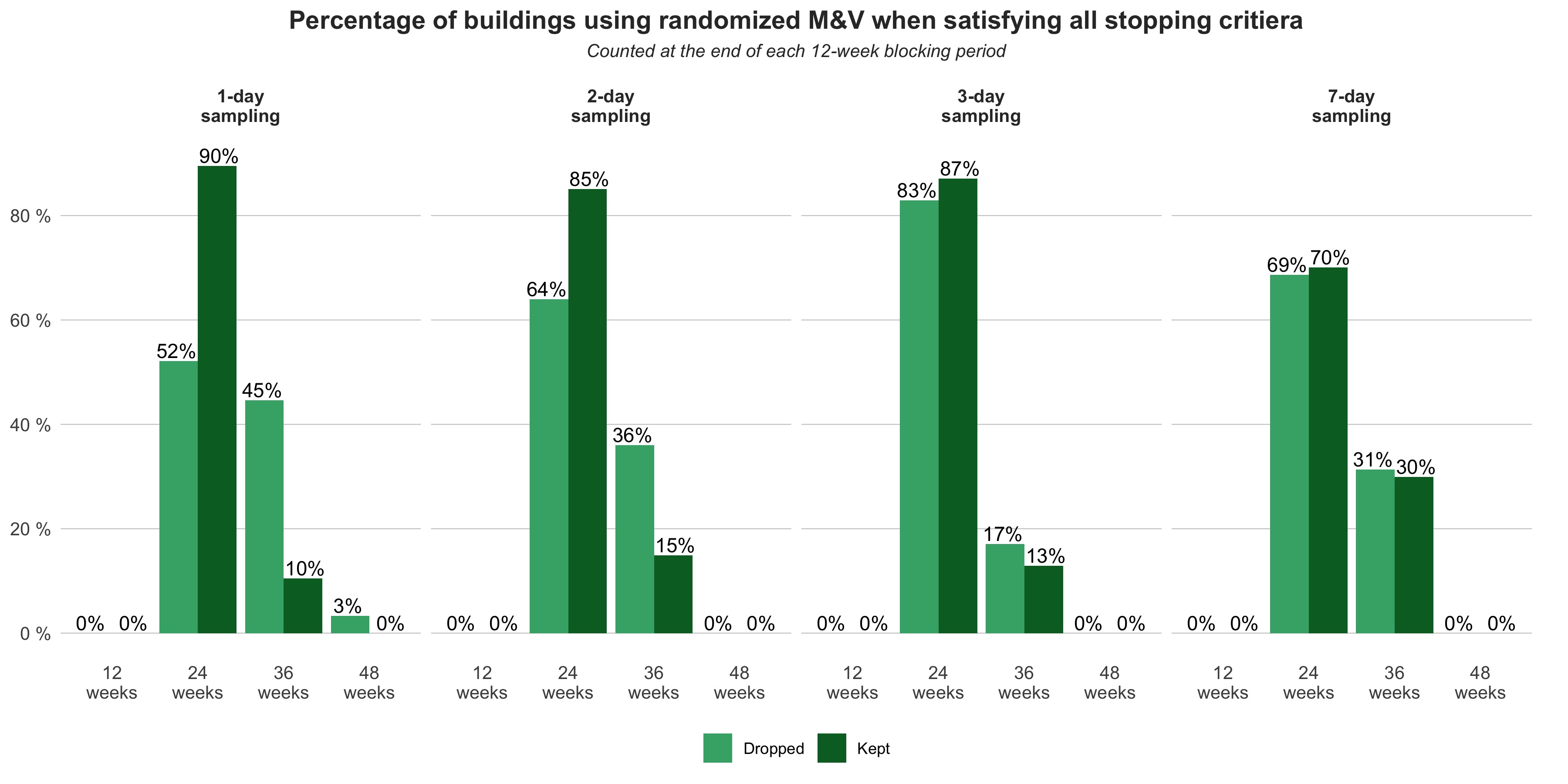


Figure 4.3: Comparison of time required to satisfy all stopping criteria when considering dropping non-consecutive days (or not)

Sampling at different intervals and excluding non-consecutive days also impact other stopping criteria, such as the time needed to satisfy statistical uncertainty and weather conditions thresholds. In Figure 4.3, we compared the percentage of buildings satisfying all stopping criteria under different sampling intervals, with or without dropping non-consecutive days. The results indicate that randomized M&V concludes more quickly when all data are retained, particularly at shorter intervals. For instance, when sampling at a one-day interval, 90% of buildings meet all criteria within 24 weeks if no data are dropped, but this number decreases significantly to 52% when non-consecutive days (account for 1/3 of the data) are excluded. As the sampling interval increases, this difference gradually diminishes: when sampling at a weekly interval, removing non-consecutive days has no impact on the timeline of meeting stopping criteria.

## 4.3 Sampling ratio impact

Another advantage of using randomized M&V is the flexibility of changing the sampling ratio after the target savings are detected. For instance, the building owner can continue sampling at a 50%/50% ratio between the baseline and the intervention to further reduce the uncertainty associated with the savings. Alternatively, they could switch to 100% intervention to maximize cost savings, though this approach risks the baseline becoming outdated over time, which is another trade-off to consider. A middle-ground approach may be to continue sampling at a 20%/80% ratio or 10%/90% between the baseline and the intervention. To compare those possible choices to a building owner, figure 4.4 shows the results of changing the original 50%/50% sampling ratio after satisfying all stopping criteria and continuing a new ratio till the end of the two-year period. Those results were calculated without dropping non-consecutive days and include the initial 50%/50% sampled data. On the far left, we also provided the case when the building owner continues with no change in sampling ratio. The results show that as the sampled baseline days and intervention days become unbalanced, the savings estimation error grows from 1% to 5%. This is reasonable since sampling at 10%/90% is similar to the conventional M&V method. And on the far right, we show again the accuracy of the conventional M&V method, which is still worse then sampling at 10%/90%. Also, We include the mean deviation version in the supplementary material.

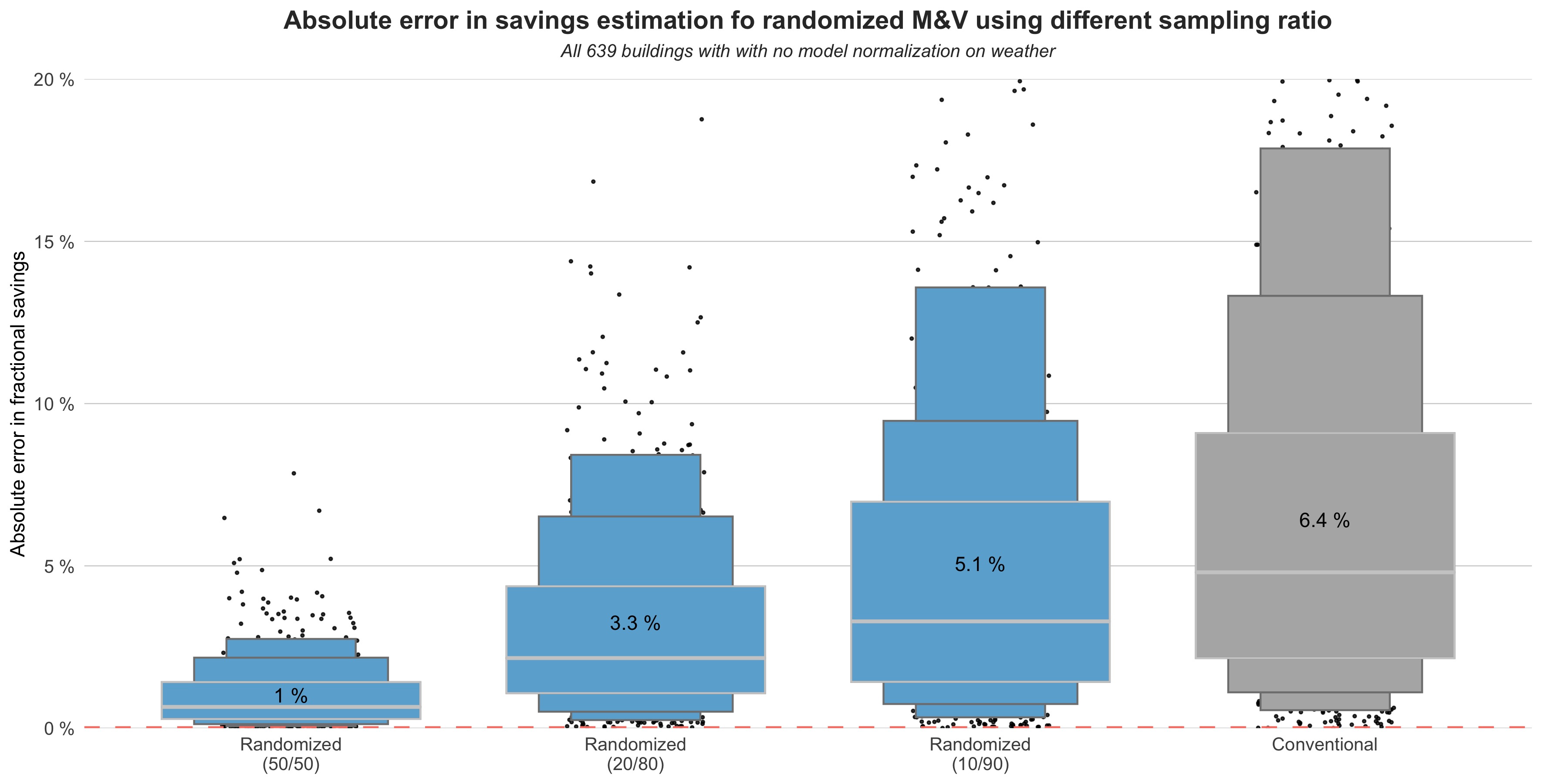


Figure 4.4: Comparison of different sampling ratio impact on M&V estimation accuracy over the entire 24 months

## 4.4 Limitations

Aside from the general limitation that this method only applies to the subset of interventions in buildings that are easily switchable, we identify two key limitations in this study:

1. The simulated intervention remains somewhat generic and simplistic considering the diverse building types and climate zones in the BDG2 dataset. As the primary focus is to accurately detect the intervention (or any intervention) effect so for simplicity, we applied the parameters listed in Table 1 uniformly across all buildings. Yet, in some cases, raising the water temperature by 1°C might yield more or less than the specified 8% electricity savings due to target buildings’ demand flexibility. For example, one field validation of HVAC optimization shows additional savings might be limited if other best practice controls are already implemented (Granderson et al. 2018).
2. For the main analysis, we assumed no carryover effect and a daily sampling interval would suffice for most commercial buildings, but certainly exceptions exist. However, in the discussion, we addressed such concern by comparing different sampling strategies and the impact of dropping measurements from non-consecutive days.

# 5 Conclusion

This research demonstrated the application of a randomized whole-building measurement and verification (M&V) method, comparing its performance to the conventional approach described in the IPMVP and in ASHRAE Guideline 14, using a large, open-source commercial building dataset. The porposed M&V method leverages the randomized experimental design concept from other scientific fields, along with statistical sequential inference techniques, to determine when target savings are detected. We used a virtual control retrofit case—resetting the chilled water setpoint based on outdoor weather conditions—and applied it to over 600 filtered commercial buildings. By comparing the savings estimations of the conventional method with the novel randomized method, we found that the randomized approach provides faster and more robust savings estimations.

Specifically, we showed that throughout 11 different locations assessed in this study, the randomized M&V can provide a saving estimation by 36 weeks (with the majority finished by 24 weeks) once all stopping criteria are satisfied. In contrast, the conventional method requires a full range of baseline and intervention measurements under normal operating conditions, typically taking 6-9 months for each phase. Most importantly, we verified that with a reduced M&V timeline, the randomized method can estimate savings more accurately by showing that the absolute error is only 1 - 2 % for a typical building. Whereas for the much longer two-year conventional method, the estimation error was approximately 6% in a typical building. We also evaluated the impact of non-routine events especially more gradual and subtle operational drift on the proposed M&V method and the results show that baseline changes in the post-retrofit period can deviate savings estimated using the conventional method. As a comparison, we found those events have a very negligible impact on the savings estimated using the randomized method, demonstrating robustness to this issue. Lastly, we consider scenarios where there is a known carryover effect from switching between strategies in the building and assess the impact of dropping samples where the strategy is non-consecutive and varying the sampling interval. Through that process, we showed that for the typical building, if a carryover is likely to be present, then using a 3-day sampling interval and dropping non-consecutive samples yields the optimal design.

We also discussed the impact of model fitting accuracy when using the two methods and we found a significant improvement in our method due to random sampling. We also provide a detailed assessment of using different sampling ratios, those results provide useful considerations to building analysts when generating randomized schedules for a variety of use cases.

# 6 CRediT authorship contribution statement

**Aoyu Zou**: Conceptualization, Data curation, Formal analysis, Methodology, Investigation, Software, Writing - original draft, Writing - review & editing. **Paul Raftery**: Conceptualization, Funding acquisition, Formal analysis, Methodology, Investigation, Project administration, Supervision, Writing - review & editing. **Stefano Schiavon**: Conceptualization, Methodology, Investigation, Supervision, Writing - review & editing. **Carlos Duarte**: Methodology, Investigation, Supervision, Writing - review & editing. **Gail Brager**: Supervision, Writing - review & editing.

# 7 Reproducibility

A reproducible example with analysis code is available (MIT license) at <https://github.com/CenterForTheBuiltEnvironment/genome_mnv>.

# 8 Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

# 9 Acknowledgements

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