Reducing reliance on deterministic asset ratings to improve the operational energy performance of buildings

Minu Agarwal1, Parag Rastogi2, George Mavromatidis3
1CEPT University, Ahmedabad, India
2arbnco Ltd., Glasgow, UK
3ETH Zurich, Switzerland

Abstract
Deterministic building rating methods that rely on standard operating conditions to rate an asset encourage designers to focus on the building envelope and systems. However, the energy performance of buildings and their systems varies greatly with weather and usage/occupancy. This variation is often classified as an unavoidable performance gap, and is a by-product of an evaluation process that assesses performance under a limited set of conditions. If rating methods take the expected performance variation into account, they could lead to more pragmatic and effective design decisions. This paper examines an example early-stage planning design decision using deterministic and probabilistic approaches towards compliance. A sample decision is examined to show how the design decisions would differ under the two different compliance regimes. Since buildings are expected to have limited robustness in practice, we discuss the challenge of enforcing probabilistic compliance measures after occupancy and show potential solutions for continuous evaluation and enforcement in practice.

Key Innovations
• Probabilistic building energy use compliance criteria are proposed and demonstrated
• Continuous evaluation and enforcement of these criteria is demonstrated

Practical Implications
Incorporating input variation in defining compliance criteria can improve decision-making towards better operational performance. We show how compliance criteria can be enforced after occupancy easily and fairly through continuous evaluation.

Introduction
Buildings designed today reflect a cost-effective response to present laws, occupant needs, and historical weather information. With increasing regulatory and investor pressure, and awareness of the environmental, human, and economic impact of the built environment, more buildings are being designed and renovated to comply with performance benchmarks for energy, indoor environment, life cycle carbon, etc. Conventionally, these benchmarks have focussed on specifying the rated performance of the installed or designed assets of a building, e.g., windows, insulation, HVAC efficiency. For example, the Energy Performance Certificate (EPC) schemes enacted across Europe to implement the EPBD (European Union, 2010). Recent research has shown, however, that a high asset rating calculated using conventional methods does not necessarily translate into efficient energy use (Cheshire et al., 2013; Jones Lang LaSalle, 2012) or high occupant satisfaction (Altomonte et al., 2017).

Deterministic compliance
The practice of using only typical operating conditions to test building designs reduces the impact of building regulations on actual energy use as it enforces an arbitrary, static, apparently “standard” baseline operating condition against which design choices (and construction quality) are judged. This can create perverse incentives where specifications or designs are written to pass the test, rather than deliver desirable environmental and human outcomes under inevitably variable conditions. In this paper, we consider whether evaluation against a plausible set of operating conditions leads to more robust regulations, enforcement, and, ultimately, operational performance. Such evaluations, paired with risk-based benchmarks, could account for natural variation in performance while offering a potential pathway to better enforcement.

Since a building’s operational performance is affected by the conditions within which it operates, principally the weather and occupancy (how a building is used), uncertainty about future conditions creates uncertainty about the building’s ability to meet desired operational benchmarks. This uncertainty is not quantified or estimated at the design stage if the building is only tested under a (single) set of standard or typical operating conditions. Most building regulations or green certification systems do not require designers to consider the uncertainty in estimating future performance resulting from design decisions. Yet, depending on the relative contribution of loads
driven by environmental conditions and human factors, a building could exceed a fixed energy performance benchmark (or energy budget) multiple times during its operation.

**Probabilistic Compliance and Time-scales**

The standard practice for energy-based targets is to assess energy use with quantities aggregated annually. Probability-based thresholds are challenging to evaluate on a realistic time scale if only annual aggregations are considered. For example, a metric that the annual energy use of a building can only exceed a given threshold 90% of the time would be unenforceable year-on-year; an operator could plausibly argue that exceedance in a particular year is part of their 10% “allowance”. Realistically, a building could change owners and be renovated several times in a 50- to 75-year lifespan, complicating accountability. Hence, the measurement of probability- or risk-based metrics must be carried out at much shorter time scales, e.g., days, such that enough data is always available to evaluate a building in a realistic time-frame.

Compliance at shorter time scales is necessary if buildings are to effectively contribute to decarbonisation. Grid carbon intensity in several countries can vary widely throughout a year or even a day, and the cost of a marginal unit of electricity (i.e., one additional kWh used at a given moment) is not constant. With the increasingly dynamic nature of the energy grid, the necessity for buildings to participate as intelligent agents is increasing. So, while targets over long durations such as annual net-zero energy balance are desirable, exceedance of thresholds over much shorter time scales may have outsize impacts on achieving global aims such as decarbonisation.

In this paper, we discuss and demonstrate how conventional approaches to energy compliance can be upgraded to deliver more effective decarbonisation efforts. We discuss both how codes may be reformulated to use risk-or probability-based metrics, and how these metrics may be enforced over realistic operational time scales. We use a case study to present an example design decision. The decision involves a binary choice between two contrasting design alternatives based on complying with a fixed energy benchmark. Using the current context of design decision making, i.e., single value performance thresholds, the decision could be simple since the design alternative with performance closest to the benchmark would be chosen. However, once we account for uncertainty in performance, several scenarios emerge where the two designs are equivalent. This paper demonstrates the significance of design decisions made by architects on future compliance, and the difficulty of ensuring those decisions have the expected outcomes of reduce the energy demand of buildings in operation.

The discussion in this paper is limited to space conditioning loads as those are influenced by the weather, building envelope related design decisions and occupant behaviour. Electricity use for lighting and plug loads, while important for decarbonisation efforts, is not considered in this case study. In the rest of this section, we discuss the need and background for risk-based performance metrics, and how compliance may be enforced in practice. In the next section, we discuss existing standards and codes and how they may be adapted to explicitly include uncertainty. Then we present an example of a threshold-based metric and how compliance to it may be assessed. We conclude with a discussion of the outlook for such metrics.

**State of the Art**

In most rating systems and energy codes, the final performance rating is awarded based on the performance of a model of the ensemble of building systems under some standard or “typical” test conditions. The selection of standard or typical operating conditions to simulate the performance of building and system designs reflects the necessity of simplifying compliance for wider impact and accessibility. In principle, more efficient systems or building components should lead to more efficient building operations, all else being the same. So, the comparison of two design choices under these typical operating conditions is assumed to be representative of the expected performance of a building over its lifetime.

**Metrics, Standards, and Codes**

Fixed energy performance-based benchmarks for asset rating and permitting before construction are well
established. Such benchmarks typically allow some degree of project specific adjustment by offering different benchmark values by building type and climate zone, e.g., the ASHRAE 90.X and 189.X series. However, concerns relating to the performance gap and increasing impetus towards Net Zero Energy Buildings (NZEB) point toward a future of continuous post-occupancy compliance, and not just nominal compliance in the design phase. In this section we look at the existing codes and standards that enforce compliance during operation.

The 2015 International Green Construction Code sets a compliance path based on maximum permissible operational energy use intensity (EUI) [kWh/(m²-year)] based on building type, occupancy levels and climate zone. The compliance requirements are relaxed under “non-standard” weather and occupancy conditions. The definition of non-standard condition however is left open to the implementing bodies and a case for such conditions must be presented by the building owner. Barring this exception, the EUI-based targets must be met for every year of operation. BFS 2011:6 in Sweden is one of the few energy codes in Europe that also requires compliance based on post-occupancy energy performance. This is in line with the building directives (Energy Performance of Buildings Directive) formulated in 2014 where the upper limit on the EUI is also set by building type and climate zone. The issue of non-compliance to this directive remains under debate. (Schwarz et al., 2020) found that while two consecutive years of non-compliance under this code can result in cancellation of a building-permit, withdrawing permit from operational buildings is a contentious issue and no building in Sweden so far has been issued such a notice. The example of Sweden indicates that such code compliance paths could pose a significant risk to building owners if implemented widely, with implications on the design and planning process that must be followed to protect the building later. Green building certifications such as LEED (v4.1) and NABERS have created systems for recertification of buildings after they are occupied, wherein buildings are judged based on their measured performance. In principle, this creates an incentive for designers, owners, and operators to ensure a building is robust against expected variations in operating conditions.

Net-Zero Energy Buildings (NZEB) have also become a popular target in many countries. For example, the EU is currently deliberating the requirement for all new buildings to be NZEB by 2021 and existing buildings by 2050. The state of California, USA, requires all new residential buildings to be net-zero energy on an annual basis from 2020. However, the current requirements of this code (Edminster, 2018) are in line with asset rating methods and there are no measurement and verification requirements after occupancy. The current method for sizing of the solar photovoltaic array to meet the electric load is based on acquiring consumption data derived from another similar code-compliant project. Future NZEB certifications will likely require a post-occupancy performance reporting program (Berkland et al., 2016), especially as the ability of buildings to participate in Demand-Side Reduction (DSR) and Management (DSM) programs becomes more important. While some of these newer energy codes come into full effect after occupancy, designers and building owners need to plan for compliance from the outset. Guides such as CIBSE TM54 (Cheshire et al., 2013) try to pre-empt the performance gap issue in the design phases of projects due to the limited scope of energy use calculations. The main focus of this guide was to avoid reporting energy performance estimate as a single value; and rather a range derived from the best and worst case scenarios. However, it is often difficult to know what is the best and worst case a priori and compliance that must be achieved under unknown future conditions. Thus, design decision making before construction comes to include uncertainty by default. The classic reaction in building design is over-sizing and factors of safety. For example, the current recommendations for sizing HVAC systems from ASHRAE result in systems designed to meet peak loads whose probability of occurrence in historical data is approximately 1% (Owen, 2019). This means that unless there is a drastic shift in climate or usage, the HVAC system will fail to provide adequate cooling or heating for only a small fraction of most years. While factors of safety make sense when designing system capacity, the same approach cannot be taken to minimising operational energy use. The system cannot increase efficiency on demand, or the provision of heating changed for the end of a year because the energy budget has run out.

Methods

Alternative compliance frameworks have been proposed based on testing resilience as a desirable quality in itself (Clarke, 2018, 2019). This process relies on deliberately introducing edge cases and combinations of conditions under which a building is expected to fail into simulation. Such an approach can standardise the quantification of the robustness of design decisions using a realistic set of testing conditions. This allows designers to demonstrate that their designs meet some given compliance threshold, a familiar process in building design and approval. However, in this framework, the threshold would be based on statistical quantities calculated over simulation with multiple realistic conditions.

The statistical criteria for acceptance proposed in this paper are based on the common experimental approach of comparing two choices of designs, machines, or treatment methods through repeated measurements over a range of plausible test conditions.
This could be done, for example, by calculating a p-value for a given null hypothesis, e.g., that two designs for a new building or retrofit deliver equal performance. If the significance level is chosen as 5%, for example, a p-value lower than that suggests that the null hypothesis may be rejected, i.e., the two designs do not deliver equal performance. In practice, p-values and hypothesis testing are difficult to interpret and implement, and simplicity is desirable when designing a benchmark or test for compliance to improve adoption and consistency of application. Instead, we propose a method where the probability of exceedance over a set of weather conditions and occupancy and usage profiles is calculated for existing thresholds. These conditions can be generated using some pseudo-random generator, whose parameters would be governed by a standard or standards body. These probabilities can then be used to evaluate the building’s performance while accounting for the natural variations in this performance due to conditions beyond the control of a designer. A conventional compliance criterion could be written as:

$$\sum_{t=1}^{T} (y_{\text{typ},t} \geq y_{\text{th}}) = Y_{\text{typ}} \leq y_{\text{th}},$$

(1)

where $y_{\text{typ},t}$ is the energy use (or any other performance metric of interest) calculated from a model with typical weather and occupancy conditions and aggregated over a period $T$, usually 1 year, to get $Y_{\text{typ}}$, and $y_{\text{th}}$ is the energy use threshold. Usually the energy use would be ‘normalised’ by the area of the building (Energy Use Intensity, EUI, in kWh/m$^2$) to not artificially inflate the EUI of larger buildings.

The compliance criteria would take the general form:

$$P\left(Y_t \geq y_{\text{th}}\right) \leq \varepsilon_{\text{th}},$$

(2)

where $Y_t = \sum_{t=1}^{T} (y_t)$ and $P\left(Y_t \geq y_{\text{th}}\right)$ is the probability of the energy use (or another metric) exceeding a given threshold $y_{\text{th}}$, and $\varepsilon_{\text{th}}$ is some tolerance, e.g., 0.9 or 90%. An example of this kind of compliance metric would be the daily energy use intensity (EUI) for heating a building cannot exceed 70 Wh/m$^2$/day for more than 90% of the days in its lifetime, calculated every year. Shortening the period, $T$, over which the energy a compliance criterion is evaluated makes the calculation of an aggregated quantity such as percentage over/under a threshold more meaningful. In the results section below, we show how such a compliance criterion may be used to make a design decision. We use an example threshold of 70 Wh/m$^2$/day (approx. 25 kWh/m$^2$/year) for heating.

**Case Study**

We examine a typical decision – choosing between two competing design alternatives – that a design team may need to take early in the project development process. We assess how such a choice could be made based on the probability of the available design alternatives meeting code requirements based on performance after occupancy. The actual design decision described here is not important to the findings of the paper; it only serves as an example of how the probability-based metrics proposed in this paper may be applied in practice.

The case study in this paper consists of a residential neighbourhood on a site of 15,000 m$^2$ in Geneva, Switzerland, with a stipulated floor-area-ratio or built density of 1.0. Two neighbourhood-scale design schemes, each comprising several apartment units, with different building layouts and exterior exposed surface areas, were simulated in EnergyPlus v8.8. One proposal (Option A, Figure 1) consists of 3 buildings that are 20m deep and another (Option B, Figure 1) with 6 buildings that are 7m deep.

Fixed weather inputs include typical weather files and files containing measured weather data from 1981-2016. Random weather time series scenarios (100 instances covering 35 years) were generated using a stochastic weather generator that modifies the distribution of historical data by combining it with the outputs of global/regional climate models (Rastogi, 2016). In the case of fixed occupant related inputs, information on occupant densities, activities, and comfort preferences for the flats were based on the guidance provided in the Swiss norm SIA 2024 (SIA, 2015). In the case of random occupant behaviour, first, 100 instances of household configuration (size, family structure) and behaviour (occupancy, thermostat controls, ventilation, lighting, and electrical appliance usage) were sampled. These samples of household configuration were applied to individual units within an apartment complex. Finally, 100 related time-series for each household configuration were generated based on the method presented by (Flett and Kelly, 2016). An average profile was then used for the fixed occupant inputs case.

The random weather and random occupant profiles were combined using a Monte Carlo (MC) simulation and the resulting building models simulated to get hourly load profiles. The sampling of household types was based on demographic data from the example geographical location (Switzerland). The breakdown of five most common household types in Switzerland is shown in Figure 2 (a). Figure 2 (b) shows the random assignment of household types to design Option B in one of the 100 MC simulations. Other model inputs are described in Table 1.

**Results**

Through this case study, we show that a prudent choice between two contrasting design alternatives (residential neighbourhood designs) can improve the probability of compliance with energy regulations.
when evaluated with awareness of weather and occupant uncertainty. The results of the simulations are presented in two sets of plots (Figure 3 and Figure 4). These plots are meant to demonstrate the application of robust decision-making to a decision, rather than present one option as being better than the other for some specific design brief. Each plot compares simulations with fixed and random inputs to show the effect including uncertainty has on decision-making. The plots also show an evolution and comparison of compliance from fixed annual metrics to probabilistic daily metrics. Both plots use (Empirical) Probability Distribution Functions (ePDF) to show the distribution of outputs from several simulations using different, variable inputs (as described in Table 1).

The output is plotted on the x-axis (e.g., Daily EUI in Wh/m²/day) in bins (e.g., 0-1, 1-2, ⋯) and the y-axis represents the proportion of values in each bin. The y-axis numbers scale with the magnitudes of the values on the x-axis so the area under the curve is equal to 1. For example, the y-axis labels in Figure 3 are 10 times those in Figure 4 since the x-axis labels are $1/10^{th}$ the magnitude. The PDFs plotted here are estimated from data, except for subplot (d) in both figures, which are plots of scaled normal distributions.

Figure 3.a shows that if these two design choices were to be compared using a typical design rating method (EUI calculated with typical or fixed inputs) the choice would be simple: both design options comply with the code-stipulated upper limit on annual heating demand, but Option B uses more energy for heating. The two options here were simulated with the same code-compliant building envelope, code-recommended inputs regarding occupants and equipment, and the most prevalent heating system type (heat pumps with heat recovery). The EUI figures are not strikingly different when using one typical weather file, TMY 2, but the gap between them widens considerably when using TMY 1. This difference in results between TMY file 1 and 2 is concerning, and points to the potential sensitivity of results to weather inputs. That is, if the files were used singly, without knowledge of the other file, simulating with one would place the two options very close while the other would show them well apart. In a realistic design process, energy use is not the only condition, so the results from TMY 2 would make energy only a minor consideration between the two options, but TMY 1 would make Option B the clear winner.

The plots in Figure 3.a and 3.d show a significant overlap between Options A and B. The PDF were drawn using normal distributions scaled and shifted with the results of simulations using historic/measured weather data. The distributions of performance in 3.e and 3.d also show significant overlap – indicating that the lower end of performance from Option B is like the higher end of Option A. For several simulated years, the design options resulted in similar annual energy use figures, making any differences between them less significant. A designer, when making their decision, would have access to historical data to plot 3.d and could use a synthetic generator to plot 3.b. This could help inform them that, while

![Figure 2: (a) Household types in Switzerland (b) Assignment of household types on the design alternative ‘B’. Coloured dots indicate household type from section (a) in one of the Monte Carlo simulations.](image-url)
Figure 3: ePDF of annual total EUI [kWh/m$^2$] for the two design options. The vertical grey line in plots a-d is an example threshold. [a, d] EUI from typical files (circle and triangle markers) versus measured weather data from 1981-2016 (a, box plot) and PDF of normal distributions scaled with data from the historical weather simulations [d]. [b] EUI with random (stochastic) weather files and fixed behaviour (occupancy). [c] EUI from random weather and random behaviour. [e, f] Pairwise EUI differences between Options A and B. The ePDF are drawn from random simulations and the markers represent the difference using typical inputs.

Option B has better performance than Option A in most cases (as confirmed by 3.e), the differences are not large. The peak of differences does not cross zero, and is consistently negative, indicating that Option A mostly gives lower EUI regardless of the weather experienced. Additionally, in most weather scenarios, both designs are code-compliant (energy use is under the threshold).

The previous results all assumed a fixed occupant profile. This is not realistic for a multi-tenant building where occupant diversity is uncontrolled and several apartments will change tenancy every few years. The differences between the options are less cut when Random behaviour and occupancy are considered. The random occupant profiles represent what set points, schedules, and maintenance some unknown future occupants may prefer. Figure 3.c and 3.f show that simulating with realistic occupant profiles changes the outputs significantly: both options now do not meet the annual threshold and the overlap has increased considerably. The difference between the two options (3.f) crosses zero, indicating that for some occupant profiles, Option A would do better.

Since the fixed and random occupant profiles are from different sources, the total impact of the random profiles increased the heating usage on average. The shift has approximately the same impact on both design options (shapes and spreads of outcomes change in a similar fashion) and makes both options non-compliant. The randomness of occupant behaviour results in a marked difference from expected simulated energy use, and make the differences between Options A and B irrelevant.

Figure 4 shows that thresholds over shorter evaluation periods (e.g., days) can provide more enforceable compliance criteria and more nuanced decision-making. For this exercise, the heating season was set to 242 days and, in the ePDF plots (4.a, 4.b, 4.c), days with total heating use of 0 Wh/m$^2$ were excluded since the proportion of these days where no heating was required in the building was high and skewed the y-axis. To balance this omission, the absolute number of non-compliant days is printed on each graph.

The ePDF and figures show that there are a considerable number of non-compliant days, about 20-30% of the year with fixed occupant profiles, and these figures do not vary much between the two options. For example, the range of mean non-compliant days for option A is 71-101 for option A and 88-114 for option B. The outcomes for both options contrast with the annual comparisons in Figure 3, where the options were comfortably under the threshold with fixed occupant inputs. A parallel to the change in annual performance between using fixed and random inputs seen in Figure 3.c is in 4.c, where the number of non-compliant days almost doubles from the fixed occupant profiles. The change in compliance with randomised weather is insignificant compared to historical data, showing that the random synthetic weather files represent the measured weather data well. The inclusion of diverse occupant behaviour does change the compliance percentage significantly.

Figure 4.c, 4.d, and 4.e show the number of compliant days for the two options, compared to the outputs from typical weather files (markers). Once again, the results from typical files are both close and appreciably different from simulations with a realistic variety of weather and occupant profiles. The implication
of this series of plots is that while the number of compliant days from typical weather and occupant inputs were as high as 80%, realistic random inputs can drop that down to 10-30%. This is a significant result because it turns a building that complies with an annual threshold according to conventional code-mandated evaluations into one that can, day-to-day, significantly exceed its energy budgets.

**Discussion**

Building occupants and operators seek assurances about expected energy expenses. This is particularly challenging when it is not possible to meter each individual user and costs must be divided evenly. An energy-cost-conscious user may feel vulnerable to uncertainty due to weather and energy use behaviour of other occupants in the building. This is especially relevant for social and low-cost housing, where occupants may be at higher risk of fuel poverty. While the criteria proposed in this paper cannot improve the apportionment of costs in a building without the requisite sub-metering, including uncertainty in design decisions can potentially lead to more robust designs where surprises are minimised.

The mismatch between modelled and actual performance is sometimes characterised as the performance gap (Menezes et al., 2012). This gap is important since differences in predicted and actual energy use can, over a large sample of buildings, have significant impact on decarbonisation efforts and user acceptance of energy policies. The mismatch can also reduce user acceptance of energy-efficiency measures, especially if it results in higher-than-expected energy bills or worse-than-expected comfort or health outcomes (Cheshire et al., 2013). In characterizing this performance gap, however, the effect of the environmental and human factors (boundary conditions) that were unpredictable at the time of design and construction is confounded with the impact of design decisions. The natural variation in these factors (boundary conditions to the performance of a building) creates a variation in building performance. This may be confused with the gap in performance due to poor design choices, improper operation and maintenance, or poor construction.

The risk-based metrics proposed in this paper are based solely on the probability of exceeding a limit. These could be further refined for a combined evaluation of exceedance and the extent of violation, allowing for better planning based on the impact of an exceedance. To make design decisions under risk-based compliance thresholds, commensurate decision-making methods are needed. For example, using an Expected Value Metric (EVM) (Wald, 1950) such as Maximin, a pessimistic or risk-averse decision maker would base their decisions on the most adverse boundary conditions and choose the design alternative that delivers the least worst performance. Regret-based metrics (Savage, 1951) account for the full set of possible outcomes (compared to EVM) under uncertainty and the design alternative with the least maximum regret is considered the fittest under the minimax regret decision rule.

**Conclusion**

This paper proposes refining existing energy compliance codes and standards with probabilistic or risk-based criteria. While probabilistic outcomes can be difficult to communicate in practice, the compliance criteria described in this work are realistic and enforceable. An expectation of deterministic results has been built into existing building evaluation and design methods. However, linking these new metrics to intuitive quantities such as daily energy spend and rewards/penalties could improve compliance, and make the metrics accessible and understandable.

Code requirements that include post-occupancy compliance monitoring could be formulated as a climate zone- and building type-based threshold that cannot be exceed more than some predetermined fraction of time since occupancy. A further adjustment to the threshold could be done by accounting for local weather during each time interval of compliance check. While this does not help with overall grid decarbonisation objectives – a unit of energy consumed in ‘unusual’ weather or ‘usual’ weather was still consumed – it acknowledges the basic dependence of energy use on external conditions, and the limited ability of buildings to mitigate this sensitivity.

Newer iterations of popular green building certifications require measured performance data to maintain certification, e.g., LEED v4.1, RESET Air. Benchmarks may evolve to acknowledge that energy performance is variable over the lifetime of a building. That is, while a building that may be compliant under a fixed set of conditions when it was designed or constructed, but that the environmental conditions under which it operates may enhance or hinder its energy performance. This increases the justification for designers to make design decisions while accounting for uncertainty in performance.

Net-zero energy performance design goals often include an upper limit on renewable energy generation/supply. Achieving net-zero without drastic imbalances in demand and supply across time requires resilience and flexibility on both the demand and supply sides. When working with such a constraint, understanding the type of occupants and their energy usage patterns is imperative in designing systems robust to dynamic, variable, occupant-driven demand. Similarly, quantifying the potential variability in weather-driven demand and renewable generation in a changing climate contributes to improved project robustness.
Figure 4: ePDF of daily EUI [Wh/m²] for the two design options, compared to a compliance threshold [top row, a-c]. The figures in the boxes are the mean ± standard deviation of the number of days in a year with heating energy use greater than the threshold, over all simulated years. Plots in the bottom row show the distribution of percentage of days in a year when heating demand is below the threshold. Results from typical files overlap and are plotted as singe point markers. [a, d] PDF of historical (1981-2016) performance against the threshold (a) and of normal distributions with the mean and standard deviation estimated from the historical weather simulations (d). [b, e] EUI with random (stochastic) weather files and fixed behaviour / usage patterns. [c, f] EUI from random weather and random behaviour.

Acknowledgements

For part of this work, Parag was hosted at Strathclyde University and RIKEN-AIP, and his work was funded by the Swiss National Science Foundation’s Postdoc.Mobility grant P2ELP2_168519.

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