Enabling Portable and Reproducible Long-term Thermal Comfort Evaluation with Brick Schema and Mortar Testbed

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ABSTRACT

Thermal comfort in buildings is typically assessed through occupant surveys, especially for short-term thermal comfort. For long-term thermal comfort, thermal comfort standards and recent research suggest continuous physical monitoring of temperature is sufficient. However, a lack of formal rules for data representation in building automation systems and the high costs of analytical application development for buildings impede predicting long-term thermal comfort at scale. This paper demonstrates portable and reproducible application development techniques for evaluating long-term thermal comfort with the Brick metadata schema and Mortar data testbed. We take advantage of the relatively large Mortar dataset containing over 25 buildings to improve the generalizability of long-term thermal comfort evaluation. Previous research often performs analysis on limited datasets.

The design of Mortar enables running the same software applications across many heterogeneous buildings, simplifying building analytics application development, and acting as a vehicle for reproducible evaluations in building science. To assess the efficacy of this workflow, we identify six air temperature-based long-term thermal comfort evaluation metrics from the literature and implement them in software. The six indices are temperature mean index, temperature variance index, degree hours index, range outlier index, daily range outlier index, and combined outlier index. During the application development, we find that the calculation of threshold in the daily range outlier index is arbitrary, and the months belonging to cooling and heating seasons with different comfortable temperature ranges are unclear. Also, all long-term thermal comfort indices fail to differentiate between tool hot and too cold. To address this, we develop two new metrics to calculate overheating and overcooling separately. We evaluate our software across all the buildings available in the Mortar testbed. The result shows that 25 buildings with 1953 thermal zones have qualified air temperature sensor data during building occupancy. Based on this building dataset, we analyze Pearson correlation among long-term thermal comfort indices. The range outlier index has a 0.19 Pearson correlation coefficient with the daily range outlier index, compared with the Pearson correlation coefficient of -0.35 at a randomly selected building in Mortar. The opposite result indicates that a small building dataset is not capable of long-term thermal comfort indices development, generating misleading results. With the help of the uniform Brick metadata schema, we also investigate disaggregating the results by buildings, floors, zones, and equipment. We summarize them as a means of identifying problem areas and equipment.

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1 INTRODUCTION

1.1 Long-term thermal comfort

Long-term thermal comfort is the subjective perception of the thermal environment over a long period (three to six months or more, usually in heating and/or cooling seasons) (ASHRAE 2020). There are two main approaches to evaluate long-term thermal comfort. One is surveying occupants' comfort perceptions directly through occupant satisfaction surveys. The survey could be repeated right-now questions as a long-term record of point-in-time thermal sensation (Adekunle et al. 2016; Heidari and Sharples 2002; Berquist et al. 2020), or one-time questions asking for long-term experiences of the thermal environment (Sharifi et al. 2021). The other approach is measuring the thermal environment continuously and predicting those perceptions indirectly through comfort models. Environmental variables like indoor dry-bulb air temperature, mean radiant temperature, airspeed, and relative humidity are required for most comfort models. They can be simulated in building energy modeling (BEM) software during the building design phase. The accuracy of the thermal environment simulation mostly depends on the accuracy of the heating, ventilation, and air-conditioning (HVAC) systems modeling. The installed building automation system (BAS) sensors can serve as a source for the required thermal environmental variables in operating buildings.

1.2 Building metadata schema

Metadata is the information about some aspects of the data, and the metadata schema is a means of representing that information in a structured way. Metadata helps establish a common understanding of the data and the relationships between different pieces of data. Take zone air temperature data as an example. The metadata could be the corresponding air temperature sensor type, the thermal zone the measurement is taken in, the variable air volume (VAV) box that feeds the zone, the floor that locates the zone, the air handling unit that serves that zone, etc. Building designers may apply different metadata standards to a building project depending on the project's lifecycle stage. Industry Foundation Class (IFC) and Green Building XML (gbXML) are two building design and construction standards increasingly used in the industry (Bing et al. 2007). Both are focused on building information modeling for design iteration. However, having structured metadata in the operational phase of the building life cycle is relatively rare in practice today. Usually, the only readily available information from a building automation system is the point name. The naming convention of these point names varies across different vendors, BAS, and sites, and often even within a building itself. This makes extracting information from these systems intricate as all work must be tailored for that specific building, its systems, and its naming convention. It is inefficient and expensive to develop building analytics or control applications that can only be used for one building.

1.3 Interoperability and portability

Interoperability is a characteristic of a product or system that enables information exchange. Most metadata are not interoperable throughout a building lifecycle due to schema's semantics, structure, and syntax (Fierro et al. 2020). For example, building energy modelers usually encounter interoperability issues when transferring building geometry data from building information modeling (BIM) to BEM software. They must redraw the building geometry in the BEM software. Also, most BIM and BEM software cannot represent HVAC systems information in the gbXML model, though they are well defined in the schema. One reason is that the relationships between HVAC equipment and the relationship between HVAC and other assets in the building are unclear (Sun et al. 2020). Portability is the usability of software in a different computing environment. For example, software developed based on Linux is portable on all computers with the Linux operating system. In the context of the building, the computing environment refers to BAS or building database. Though many building analytics and control algorithms implementations are available, they are not portable due to hardcoded metadata, building structure and HVAC systems assumptions, data availability, etc. (Fierro et al. 2018).

2 METHODOLOGIES

Brick schema (Balaji et al. 2018) and Mortar testbed (Fierro et al. 2018) have attracted attention from computer science, civil engineering, and building science. Brick is an open-source and uniform metadata schema for buildings. It can define assets in the built environment, like many other metadata schemas, and construct the relationships between them. Brick builds on semantic web technologies including resource description framework (RDF), web ontology language (OWL), and shapes constraint language (SHACL) which provide an expressive and flexible basis for the consistent and formalized exchange of information and permit the use of Brick metadata in a wide array of software. Mortar is an open testbed for portable building analytics (Fierro et al. 2018). It consists of three components: a database of time-series data for all the buildings in the platform, a database of Brick models which describe the buildings and contextualize the time-series data, and an application programming (API) for developing analytical applications over the data and metadata. Each data source in a building --- sensors, setpoints, and other I/O points exposed by the BAS --- has a corresponding representation in the Brick model capturing salient attributes of the data source and its relation to the rest of the building and its subsystems. This allows applications to discover building data by its purpose, behavior, and context instead of by name. With this abstraction, the same application can discover relevant data in a variety of buildings without any reconfiguration. As of the time writing this paper, Mortar spans 43 buildings and over 1 billion data points. Users can develop and test different applications by accessing the platform's API from local or online Python integrated development environments (IDE). This architecture simplifies the development and evaluation of applications across multiple buildings (Fierro et al. 2018). The uniform building metadata schema and related time-series database enable the portability of applications. In other words, users can run different applications across different buildings without reprogramming or substantial reconfiguration. In this paper, we develop a long-term thermal comfort evaluation app with various packages. The analysis scale can be zone, floor, building, or HVAC equipment, like air handling unit (AHU) and VAV box. The reproducibility is assured by virtue of being built with open-source software on a reproducible and interactive computational environment. The software along with the six metrics developed in this paper are open-source and free to use and are available in an online GitHub (SDB 2021) repository along with other Mortar applications. We use Binder (Sun 2021) for the reproducible and interactive environment configuration.

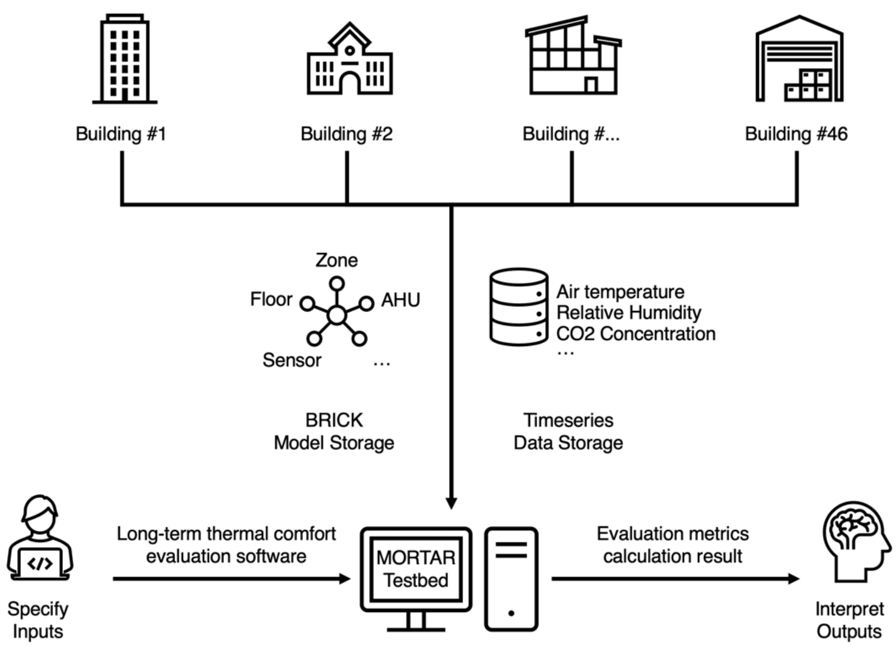

Figure 1 The long-term thermal comfort evaluation software development with the Brick metadata schema and Mortar data testbed, which enable portable, scalable, and reproducible analytics of building science.

3 INDICES CALCULATION

Thermal comfort standards ISO 7730, EN16798, and ASHRAE 55 and research (Carlucci et al, 2021) have suggested several evaluation metrics for predicting long-term thermal comfort based on the physical measurement of the thermal environment. For example, percentage of time outside a Predictive Mean Vote (PMV) range and average Predicted Percentage of Dissatisfaction (PPD) are two methods persist in the standards though they have low accuracy (Cheung et al. 2019). This paper focuses on air-temperature-based metrics, with several considerations. First, humidity and air velocity sensors are uncommon in most operating buildings, compared with zone air temperature sensors. Second, mean radiant temperature can be appropriately estimated by air temperature under typical office buildings (Dawe et al. 2020). Third, among existing metrics and new metrics, operative-temperature-based indices have the best performance (Li et al. 2020). The operative temperature is the average of the mean radiant temperature and ambient air temperature. Therefore, it is reasonable to evaluate the long-term thermal comfort by air-temperature-based metrics.

We only count air temperature sensor data during an occupied time, which we assume from 8:00 am to 5:00 pm, denoted as $t \in A$, because the occupancy data or CO2 concentration data are limited to only a few zones in Mortar. Li assumes the occupied time from 7:00 am to 7:00 pm (Li 2019), which reflects the normal office time in Australia. The default occupied days are weekdays, from Monday to Friday, denoted as $d \in B$. The comfortable temperature range we chose is from 71.6˚F (22.0˚C) to 80.6˚F (27.0˚C) in cooling season and from 66.2˚F (19.0˚C) to 77.0˚F (25.0˚C) in heating season (ISO 7730, 2005). The lower bound of the comfortable range is denoted as T_l and the upper bound of the comfortable range is denoted as T_u. We use T_o to denote the zone operative temperature during the interval time t. The zone operative temperature is assumed to be the same as the zone air temperature in this paper. T_h is the houly mean value of zone operative temperature. δ_T is daily temperature range and T_{th} is a threshold defined by users. Li calculate the threshold as 3.6˚F (2.0˚C) based on the 80th percentile of all observed daily temperature ranges in the SAMBA database (Li 2019). We use the same threshold as 3.6˚F (2.0˚C). We consider the cooling season as from May to October and heating season as from November to April. Li defines the cooling season is from November to April, and the heating season is from May to October (Li 2019). The buildings in her paper are in Sydney, where the seasons are opposite to us in the northern hemisphere. Regardless of the unclearness of the index calculation, we allow users to input customized variable values in the software. Similar metrics can be found in Li's paper (Li et al. 2020).

a) Temperature Mean Index

$$I_M = \sum_{t \in A, d \in B} T_o \Big/ \sum_{t \in A, d \in B} t$$

b) Temperature Variance Index

$$I_V = \frac{\sum_{t \in A, d \in B} (T_h - I_M)^2}{n - 1}$$

c) Degree Hours Index

$$I_{DH} = \sum_{t \in A, d \in B, T_o < T_l} (T_l - T_o)t \quad + \sum_{t \in A, d \in B, T_o > T_u} (T_o - T_u)t$$

d) Range Outlier Index

$$I_{RO} = \left(\sum_{t \in A, d \in B, T_o < T_l} t \quad + \sum_{t \in A, d \in B, T_o > T_u} t \right) \Big/ \sum_{t \in A, d \in B} t$$

e) Daily Range Outlier Index

$$I_{DRO} = \sum_{d \in B, \delta_T > T_{th}} d \Big/ \sum_{d \in B} d$$

f) Combined Outlier Index

$$I_{CO} = (I_{RO} + I_{DRO}) / 2$$

4 ANALYSIS RESULTS

4.1 Long-term thermal comfort indices correlation

It is unknown whether the six comfort indices are correlated. We first tested our software at a randomly selected building with 12 zones and calculated the six long-term thermal comfort indices per zone, as shown in Figure 2. Then we executed the software across all 25 buildings with 1953 zones in Mortar, as shown in Figure 3. Each value in the graphs is the Pearson correlation coefficient between every two indices. The Pearson coefficient between the range outlier index and the daily range outliers index is -0.35 at a randomly selected building but becomes 0.19 when across all data in Mortar. The opposite result indicates that a small building dataset is not capable of long-term thermal comfort indices development, generating misleading results. The inversely proportional relationship happens when the zone air temperature tends to be constantly higher or lower than the comfortable range. The Pearson coefficients between the combined outlier index and range outlier index is 1.00, indicating a perfect linear relationship, because the formula of the combined outlier index contains the range outlier index.

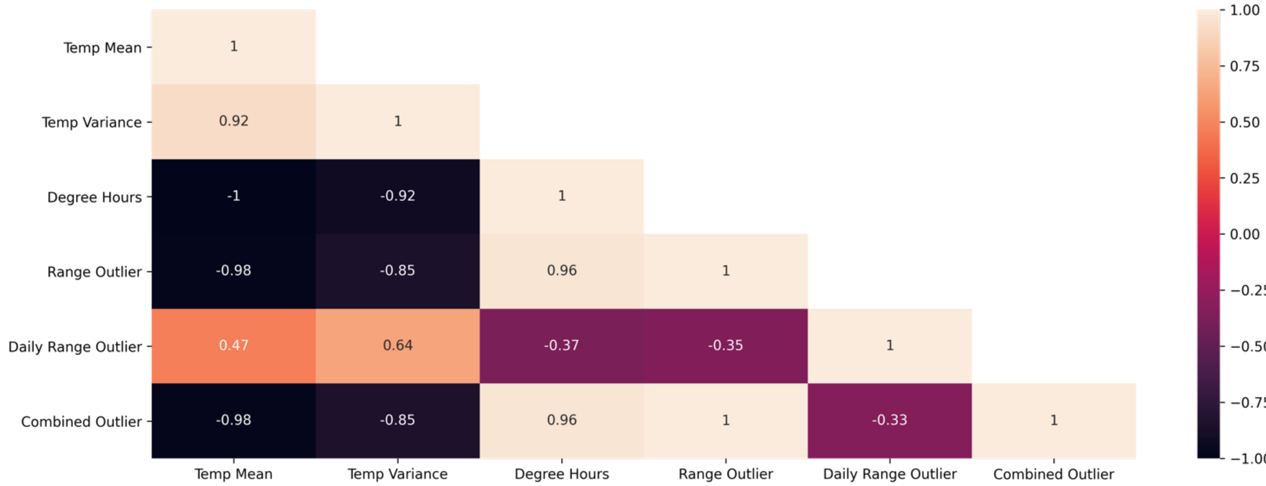

Figure 2 Pearson correlation heatmap based on six long-term thermal comfort indices' calculation results at a randomly selected building with 12 zones in Mortar.

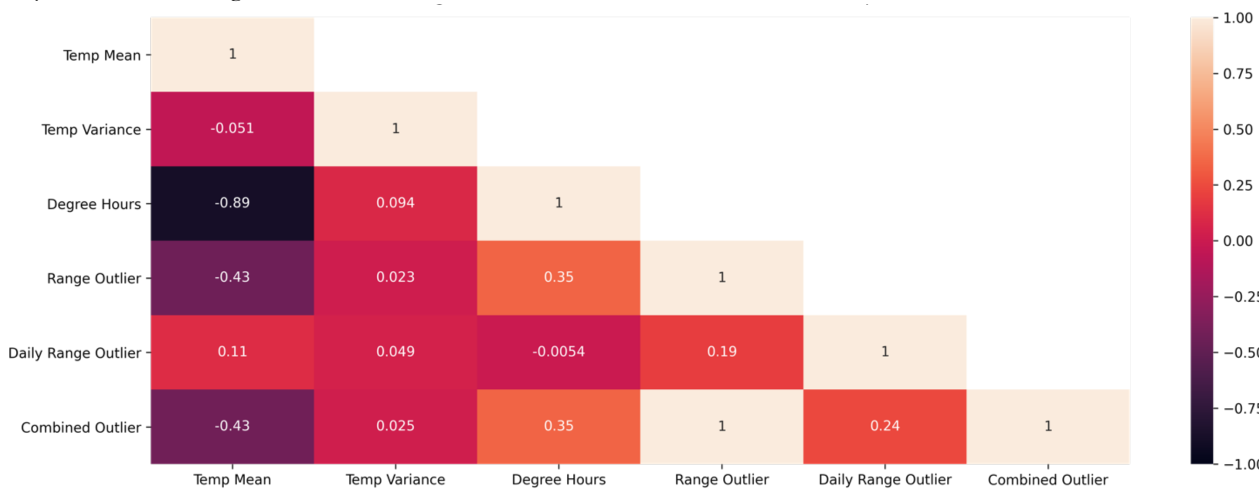

Figure 3 Pearson correlation heatmap based on six long-term thermal comfort indices' calculation results across 25 buildings with 1953 zones in Mortar.

4.2 Investigating the range outlier index values

We chose the range outlier index I_{RO} as the primary metric in this part of the analysis, as it is the most accurate index from existing thermal comfort standard (Li et al. 2020). This metric calculates the exceedance from the absolute comfortable temperature range. Therefore, it measures the magnitude of discomfort, though the analysis is called long-term thermal comfort evaluation. An index value of 0.50 means that half of the occupied time at the zones is outside the comfortable range. Take a randomly selected building from Mortar as an example. We calculated the range outlier index on all zone air temperature sensors at this building and filtered out the highest ten values. Figure 4 is the Brick model of metadata related to those ten zone air temperature sensors. The parallelogram box denotes instances of Brick equipment classes, e.g., AHU and VAV boxes. The ellipse represents instances of Brick point classes, which is the zone air temperature sensor in the graph. The Brick location instances are rectangular boxes, such as rooms, floors, HVAC zones, etc. The relationship defined between different entities enables scaling the index values calculated at sensors into AHU or floor levels. One of the insights we can gain is that AHU02 serves more uncomfortable rooms than AHU01, and Floor2 contains more uncomfortable rooms than Floor1, indicating opportunities to improve operation.

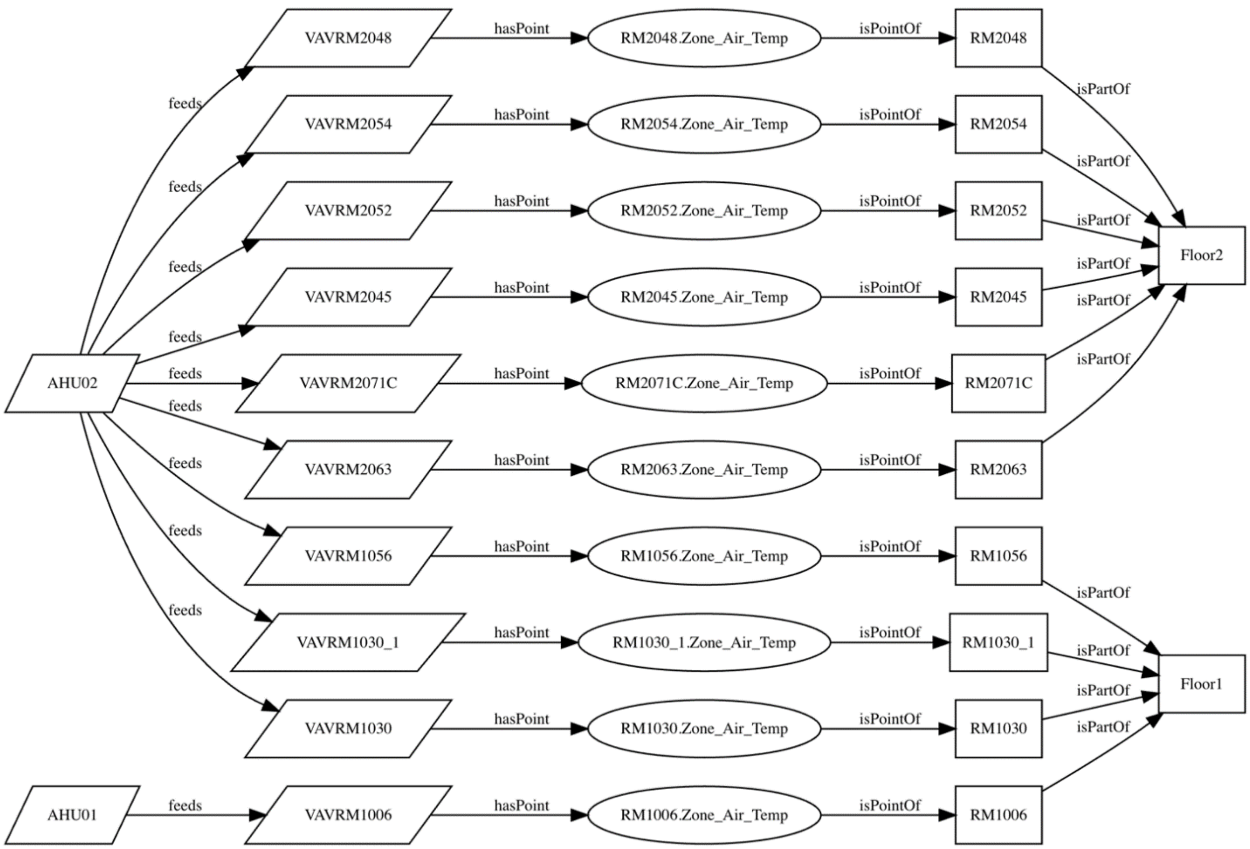

Figure 4 Brick metadata model of ten air temperature sensors with the highest range outlier index values at a randomly selected building in Mortar, indicating problematic equipment (AHU02) and area (Floor2).

4.3 Overcooling and overheating evaluation metrics

The range outlier index I_{RO} does not differentiate whether the temperature is higher or lower than the range. Therefore, we developed two new metrics to calculate the percentage of overheating outliers I_{OH} and the percentage of overcooling outliers I_{OC}. On the one hand, too hot in the summer and too cold in the winter might harm vulnerable occupant's health. On the other hand, overcooling in the summer and overheating in the winter waste building energy.

Overheating means that zone air temperature is higher than the upper bound of the comfortable range, represented by $T_o > T_u$. Likewise, overcooling is $T_o < T_l$. The comfortable temperature range we chose is from 71.6 F to 80.6 F in summer and from 66.2 F to 77.0 F in winter (ISO 7730, 2005). Indeed, the sum of these two indices equals the range outlier index.

a) Percentage of Overheating Outlier

$$I_{OH} = \sum_{t \in A, d \in B, T_o > T_u} t \bigg/ \sum_{t \in A, d \in B} t$$

b) Percentage of Overcooling Outlier

$$I_{OC} = \sum_{t \in A, d \in B, T_o < T_l} t \bigg/ \sum_{t \in A, d \in B} t$$

We selected another building in Mortar and executed the long-term thermal comfort evaluation software to calculate the range outlier index, overheating index, and overcooling index at each zone air temperature sensor. In addition to the metadata analysis in Figure 4, we further aggregated these sensors' index values at AHU and Floor levels, shown in Table 1 and Table 2. The floor value is the average of all air temperature sensors located on that floor, and the AHU value is the average of all air temperature sensors that the AHU feeds.

Table 1. Long-term Thermal Comfort Index Calculation across Floors at a randomly selected building in Mortar

Floor	Range Outlier Index	Overcooling Outlier Index	Overheating Outlier Index
floor0	0.05	0.03	0.02
floor1	0.22	0.21	0.01
floor2	0.14	0.13	0.00
floor3	0.16	0.12	0.04
floor4	0.13	0.13	0.00
floor5	0.08	0.08	0.00
floor6	0.14	0.13	0.01

Table 2. Long-term Thermal Comfort Index Calculation across Air Handling Units at a randomly selected building in Mortar

AHU	Range Outlier Index	Overcooling Outlier Index	Overheating Outlier Index
AHU00	0.04	0.03	0.01
AHU01	0.24	0.24	0.01
AHU02	0.14	0.13	0.00
AHU03	0.16	0.12	0.04
AHU04	0.13	0.13	0.00
AHU05	0.08	0.08	0.00
AHU06	0.14	0.13	0.01

5 CONCLUSIONS

Evaluating long-term thermal comfort through occupant surveys usually costs too much time, money, and resources. An efficient and reasonable evaluation method is through continuous temperate monitoring. We summarize six air-temperature-based evaluation metrics from existing standards and research papers. They are temperature mean index, temperature variance index, degree hours index, range outlier index, daily range outlier index, and combined outlier index. We program these indices into software and find that the calculation of threshold in the daily range outlier index is arbitrary, and the months belonging to cooling and heating seasons with different comfortable temperature ranges are unclear. Therefore, we allow users to input customized variable values in the software. Also, all long-term thermal comfort indices don't differentiate between overheating and overcooling. We develop two new metrics to calculate them separately in the software.

We utilize the Brick metadata schema and Mortar testbed to advance the long-term thermal comfort evaluation method with portability and reproducibility. The portability enables the analysis across heterogeneous buildings using the same software. The reproducibility allows researchers and building owners to replicate the application development on their computers and reproduce the analytical results. We conduct the Pearson correlation analysis of the six indices across 25 buildings with 1953 zones in Mortar. We find that the range outlier index has a 0.19 Pearson correlation coefficient with the daily range outlier index, compared with the Pearson correlation coefficient of -0.35 at a randomly selected building. Though we cannot validate the coefficient's accuracy when writing this paper, the opposite result indicates that a small building dataset is not capable of long-term thermal comfort indices development, generating misleading results. We also investigate disaggregating the indices' values by sites, floors, zones, and equipment and summarize them as a means of identifying problem areas and equipment. The relational Brick metadata schema demonstrates the ability of fault detection and diagnostics.

We have learned lessons from the application development on Mortar. First, the software is easier to develop against a single building before generalizing the implementation to a larger dataset. Second, generalizing an application to several buildings will require rewriting the Brick model queries to account for differences in the structure of those buildings. There could be multiple paths to achieve the desired point in the Brick model, using different relationships. Third, choose a common period for when downloading the time-series data for the analysis across heterogeneous buildings.

6 LIMITATIONS AND FUTURE WORK

The 25 buildings we found with available zone air temperature sensors have the same climates, similar building types, and similar occupants. We will add more building data to the Mortar platform. We will also generalize the software to be available for buildings without Brick models. Another limitation of this paper is that the zone air temperature data we queried from Mortar is from the thermostat, which is fixed on a wall and may not represent spatial variation (Kim et al. 2019). We have matched most of the 25 buildings in Mortar with two thermal comfort survey databases, one from the Center for the Built Environment and another from the University of California at Davis. The ground truth data will help validate the accuracy of long-term thermal comfort indices, improve the threshold calculation in the daily range outlier index, and provide guidelines for occupied time, occupied days, and heating and cooling months.

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