# Data-driven occupancy schedules for commercial buildings

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**Abstract**

Standard schedules of occupancy are one of the backbones of building energy simulations. Some schedules that are in use today were published 40 years ago and have not been modified ever since. In this work, we aim at reviewing the representativeness of such standard schedules by comparison to a large data set. We extracted popular times data for commercial buildings, which has the same data structure as occupancy profiles, from the Google maps platform for 13 representative US cities in different climate zones. We use the mean absolute error and the earth mover's distance as measures of difference in profile scale and shape, respectively. Additionally, we define energy impact metrics, such as the peak value and the time of the peak, to quantify differences that potentially have significant impacts on simulation results. We compared data of restaurant and retail buildings to the respective standard schedules. We found significant differences between standards and data, especially in energy impact metrics. Observed mean peak values were 10 - 40% (occupant capacity) different in the city with the overall best agreement to standards. Moreover, our results indicate that the categorization into weekdays, Saturday and Sunday day types should be reconsidered. In a second step, we compared data among the different cities and found relatively smaller differences, which might be rooted in climatic or socioeconomic influences on peoples' behavior. This leads us to believe that location-specific data should be considered to more precisely capture occupant behavior.

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*Keywords:* Occupant Behavior, Occupancy schedule, Occupancy profile, Cell Phone Location Data, Building Energy Simulation, Urban Energy Model

## 1. Introduction

### *1.1. Building energy modeling and occupant presence*

Engineering-based (physical) bottom-up building energy models [1, 2] are commonly used to forecast the performance of new buildings or to assess the impacts of various retrofit measures for existing buildings. One main weakness of such models are the many assumptions made regarding the behavioral aspects of energy consumption, e.g., the hours of occupancy and building systems usage [1]. In fact, energy-related occupant behavior is one of the main factors affecting building energy consumption and a major source of uncertainty in simulations [3, 4]. Standardized schedules, also called profiles or diversity factors, are 24-hour time series of fractions of nominal space occupancy, lighting loads, appliance loads or building systems operation. Standardized schedules are used when the actual behavior is unknown. This can lead to problems regarding the appropriateness of simulation results since many users are not aware of the origins of these schedules and their intended purpose.

### *1.2. The origins of standard schedules for the American context*

The development of standard occupancy schedules was historically closely linked to the emergence of computers and the first building energy simulation programs. While the first of such tools (*HCC* in 1965) was used to calculate peak loads for the summer and winter design days [5], soon after tools were developed to calculate the annual energy demand in hourly time steps. They were *NBSLD*, the predecessor of *BLAST*, and the *Post office program*, the predecessor of *DOE-2* [5, 6]. NBSLD required the input of an occupancy schedule, which was defined as *normalized 24-hour profile.* The developers of these tools were at the same time part of the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Task Group on Energy Requirements (TGER), which in 1969 published the special bulletin "Procedure for Determining Heating and Cooling Loads for Computerized Energy Calculations; Algorithms for Building Heat Transfer Sub-routines" [5, 6, 7]. These publications would become the foundation of DOE-2 and

BLAST, which later were combined into the state-of-the-art energy modeling tool EnergyPlus [7].

In 1975 ASHRAE/IES published the first version of the influential *Standard 90: Energy Standard for Buildings Except Low-Rise Residential Buildings*, which introduced annual energy analysis as a means of comparison of alternative building designs to standard designs. It mandated the calculation procedure to explicitly cover the number of people during occupied and non-occupied periods as part of the internal heat generation. Also, the calculation procedure had to be consistent with the algorithms proposed by ASHRAE [8]. However, typical values for occupancy and other schedules were not part of the standard until its 1989 version.

#### *1.2.1. Standard schedules prior to ASHRAE-90.1-1989*

In 1979 the US Department of Energy (DOE) published *Standard Building Operating Conditions (SBOC)* to assist with rulemaking of energy performance standards for new buildings [9]. The SOBC included set point temperatures, occupant densities, and profiles for lighting, occupancy, HVAC systems, domestic hot water usage, vertical transportation systems, and exhaust fans. The SBOC were intended to be used to estimate the design energy requirements for new buildings. 14 building types were defined, and look-up tables provided occupancy, lighting and system schedules on a zone level, see table 1. For most building use types, except for the hospital, a predominant profile for the whole building was defined.

The SBOC were based on studies by the American Institute of Architects Research Corporation (AIA/RC), studying a sample of randomly selected commercial buildings. In Phase 2 of the research, 168 building designs were studied. Each original design team supplied detailed data describing the energy-related physical and operational characteristics of their designs for the purpose of energy requirement simulation [10]. The published schedules were the averages of the data provided by the designers [9]. Some of those schedules would later find their way into ASHRAE 90.1-1989.

#### *1.2.2. Standard schedules of ASHRAE 90.1*

ASHRAE first introduced standardized occupancy schedules for the *Building Energy Cost Budget (ECB) Method* of ASHRAE 90.1-1989. The ECB describes the Prototype Building Procedure and lists standardized occupancy schedules to be used for the 9 prototype buildings, see Tab. 1.

Table 1: Standard schedules of occupancy for building performance simulation of different building use type categories published from 1979 until present.

| Use Type Category | DOE (1979) | ASHRAE (1989) | ASHRAE (2004) | DOE/NREL (2011) | ASHRAE (2013) | COMNET v3 |
|---|---|---|---|---|---|---|
| Retail | Shopping Center,[Z] Store[Z] | Retail | Retail | Retail, Strip Mall, Supermarket | Schedule C[C] | Retail |
| Restaurant | - | Restaurant | Restaurant | Quick Service Restaurant, Full Service Restaurant | Schedule B[B] | Restaurant |
| Health | Clinic,[Z] Hospital,[Z] Nursing Home[Z] | Health | Health | Hospital[Z] Outpatient Health Care | Schedule E[E] | Health |
| Assembly | Community Center,[Z] Gymnasium,[Z] Theater/Auditorium[Z] | Assembly | Assembly | - | Schedule H[H] | Assembly |
| Office | Office, Large,[Z] Office, Small[Z] | Office | Office | Large Office, Medium Office, Small Office | Schedule A[A] | Office |
| Warehouse | Warehouse | Warehouse | Warehouse | Warehouse | Schedule L[L] | Warehouse |
| Hotel | Hotel/Motel[Z] | Hotel/Motel | Hotel/Motel | Large Hotel,[Z] Small Hotel,[Z] | Schedule F[F] | Hotel/Motel |
| School | School, Elementary[Z] School, Secondary[Z] | School | School | Primary School,[Z] Secondary School,[Z] | Schedule G[G] | School |
| Multi-family | Multifamily High-Rise Residential,[Z] Multifamily Low-Rise Residential[Z] | | | Midrise Apartment[Z] | Schedule D[D] | Residential |
| Manufacturing | - | | Light Manufacturing | | Schedule J[J] | Manufacturing |
| Gymnasium | | | | | Schedule I[I] | Gymnasium[I] |
| Parking | | | | | Schedule K[K] | Parking[K] |
| Laboratory | | | | | | Laboratory |
| Data Center | | | | | | Data Center |

[Z] Building model contains schedules for zone-level usages
[A] for Courthouse, Office, Post Office, Town Hall
[B] for Dining: Cafeteria/Fast Food, Dining: Family, Dining: Bar Lounge/Leisure
[C] for Library, Museum, Retail
[D] for Dormitory, Multi-family
[E] for Fire Station, Health Care Clinic, Hospital, Police Station, Transportation
[F] for Hotel, Motel, Penitentiary
[G] for School, University
[H] for Convention Centre, Exercise Centre, Motion Picture Theatre, Performing Arts Theatre, Religious Building, Sports Arena
[I] for Gymnasium as part of a School
[J] for Automotive Facility, Manufacturing Facility, Workshop
[K] for Parking/Parking Garage
[L] for Warehouse

The ECB Method provides a simulation-based approach to demonstrating code compliance. The simulated annual energy cost of the *proposed building design* cannot exceed the benchmark simulation to be code compliant. For both simulations, identical occupancy schedules have to be used [11].

In 2004 standard schedules re-appeared in the *Standard 90.1 User's Manual*. In the 2004 version of ASHRAE 90.1, the Performance Rating Method (PRM) was introduced. It is a method to quantify a proposed building design's improved performance relative to a baseline. An hourly simulation tool must be used to calculate the annual energy operating costs. The occupancy schedules have to be identical for both simulations and should represent typical conditions. Where actual schedules are not known, the user's manual to the standard gives schedules based on ASHRAE 90.1-1989 as examples of typical input data [12, 11]. According to [13] these schedules published in the original version of 90.1-1989 were modified by Addendum L in 1994 by a public review process. However, by comparing occupancy schedules from 1989 to 2004, it becomes evident that only the schedules for *Office* and the *Sunday* of *Assembly* and *Restaurant* were adjusted. Additionally, in 2004 a new use category *Light Manufacturing* was introduced with occupancy schedules identical to the *Office* use.

In the meantime, the DOE published reference building energy models containing occupancy schedules.

### *1.2.3. Schedules of DOE commercial reference buildings*

In 2011 reference building energy models were developed by the DOE to standardize energy efficiency research. These models were meant to represent reasonably realistic building characteristics and construction practices. Fifteen commercial building types and one multifamily residential building were determined by consensus between DOE, the National Renewable Energy Laboratory (NREL), Pacific Northwest National Laboratory, and Lawrence Berkeley National Laboratory, and represented approximately two-thirds of the commercial building stock [13].

The occupancy schedules for these models were directly taken from the ASHRAE User's Manual for 90.1-2004 for *Retail, Restaurant* and *Office* buildings. The *Health, Hotel, School* and *Warehouse* schedules were taken from Advanced Energy Design Guide (AEDG) Technical support documents [14, 15, 16, 17] developed by ASHRAE in collaboration with other institutions[1]. These occupancy schedules were in turn again based on ASHRAE standards, modified by inputs of the respective project committee members [14, 16, 18]. For the residential building, the source is another technical report about building energy modeling [19]. However, that document does not mention any occupancy schedules.

Different from the building-level schedules of ASHRAE, some schedules were defined on the zone-level: The Hospital, School, and Apartment building models specified schedules on the zone level. Additionally, sub-categories of buildings for Retail, Restaurant, and Health were introduced, see Tab. 1.

#### *1.2.4. Contemporary sources of standard occupancy schedules*

For the 2013 edition of the ASHRAE 90.1 standard the calculation procedure of the *Envelope Performance Factor* in section *5.6 Building Envelope Trade-Off Option* was changed from previously empirical equations to hourly simulation with a computer program [20, 21]. The envelope trade-off option allows designers to improve certain building envelope components to make up for other components that do not meet the standard's requirements, thus allowing for higher flexibility in envelope design [11]. The method consists of rules for building energy simulations to compare baseline envelope performance to the proposed envelope performance. For these simulations 14 standard schedules and loads according to *Building Area Type* are provided in an online document on the ASHRAE website [22]. These schedules are largely the same as in 2004. However, some important modifications can be noted: E.g., *Health* was converted from day time operation to 24-h occupancy, and *Restaurant* increased the occupancy in the AM hours, see Fig. 1 (right). Many schedules, however, remained exactly the same since 1979. For instance the *Retail*, of which the historic non-evolution is depicted in Fig. 1 (left).

Nowadays, standard schedules are also available from other sources. COMNET is an initiative to standardize building energy modeling [23], on the COMNET web portal[2] a set of 14 default schedules of building operation is available. Most schedules reference ASHRAE and are identical to the 2013 schedules for the Building Envelope Trade-Off. However, some additional

[1]The AEDG are developed by ASHRAE in collaboration with AIA (American Institute of Architects), IESNA (Illuminating Engineering Society of North America), USGBC (U.S. Green Building Council) and the DOE (Department of Energy).

[2]www.comnet.org

schedules were created by COMNET (*Laboratory* and *Data Center*).

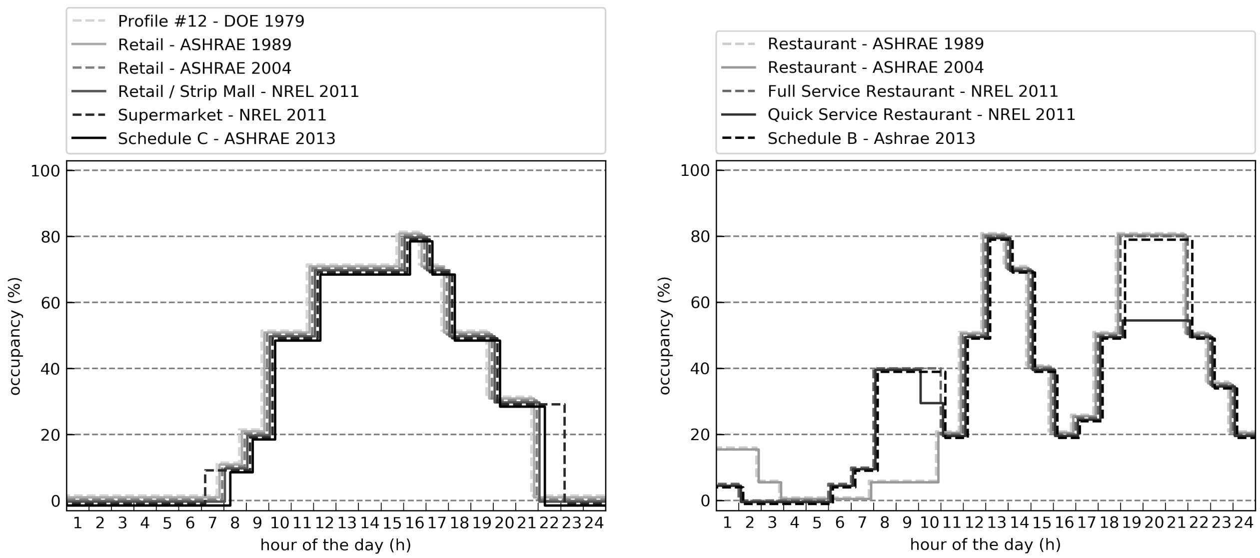


Figure 1: The historic evolution of the retail (left) and restaurant (right) standard occupancy schedule for weekdays from 1979 to present. The retail schedule is quantised in steps of 10%. The restaurant schedule is quantised in steps of 5%. The data is slightly shifted for visualization purposes.

### *1.3. Recent developments in advanced building occupancy modeling and simulation*

Research efforts for improving energy-related occupant behavior modeling and simulations are consolidated in IEA EBC Annex 66: "Definition and simulation of occupant behavior in buildings" [24] and the currently ongoing follow-up Annex 79 "Occupant-centric building design and operation" [25]. Reviews in 2015 and 2016 [26, 27] confirmed that there were not many models and tools available for advanced occupancy simulation. The tools that did exist were developed for office and residential use type buildings exclusively. As part of [26], a software module was developed to include three representative occupancy models. Namely, Chang's model [28] to simulate the occupancy state of a space, Page's model [29] to simulate the number of occupants in a space, and Wang's model [30] to generate the spatial location of each occupant and the space-level occupancy for the whole building. As part of IEA EBC Annex 66 and Annex 79 data-based models and agent-based models for building occupancy have been developed [31, 32, 33, 34, 35, 36, 37]. E.g., In [32] data-mining methods were used to derive office occupancy schedules from appliance power consumption measurements. In [33] data-mining methods were used to derive archetypal working profiles of individual occupants from measured occupancy data of 16 private offices with single or dual occupancy. In [36] machine learning techniques were used for daily occupancy patterns recognition for improving the energy efficiency of an office building. An agent-based model for office buildings has been developed by [37]. It is depending on expert user inputs, such as, e.g., the typical arrival times of each occupant, the number of planned meetings per day, and the probability distribution of meeting durations. The explicit goal of Annex 79 is the development of the next generation of "dynamic, stochastic, agent-based, and data-driven" [25] occupant models. The current common practice is, however, still the use of standard assumptions [25].

### *1.4. The use of standard schedules for building and urban energy systems simulation*

Table 2 summarizes the purpose of standard schedules of occupancy published over the years.

Table 2: Purposes of published standard schedules

| Publisher | Purpose |
|---|---|
| DOE (1979) | Development of Building Energy Performance Standards (BEPS) legislation |
| ASHRAE (1989) | Building Energy Cost Budget (ECB) Method: Code compliance via simulation |
| ASHRAE (2004) | Building Performance Rating Method: Estimation of % energy savings of advanced building designs |
| DOE/NREL (2011) | DOE commercial building research: technology assessment, design optimization, analyze advanced controls, develop energy codes and standards, and to conduct lighting, daylighting, ventilation, and indoor air quality studies |
| ASHRAE (2013) | Envelope trade-off: Envelope code compliance via simulation |

On the building scale standard schedules are widely used for code compliance, systems design and research purposes as intended by their publishers

[13, 38, 25].

However, in our review about occupant behavior in urban building energy models [39] we found that standard schedules of occupant presence are widely used beyond their original purpose. We found tools and studies that used standard schedules, among others, to:

- Generate patterns of anthropogenic heat generation,
- Generate energy demand patterns for district energy infrastructure design, and
- Generate energy demand patterns for district energy systems operation optimization.

Besides being potentially outdated and being used out of the scope of the original purpose, those standard schedules might also be used beyond their original context of North America. For instance, in Singapore ASHRAE schedules are used in research as well as in industry practice. Research example include a baseline energy model for institutional building in Singapore that used OpenStudio default schedules [40], a DOE-2 commercial building model to evaluate effects of green roofs [41], and DOE-2 office building models [42]. In industry practice, ASHRAE schedules are used to obtain Green Mark[3] certification of new buildings.
We believe that it is time to revisit these standards of commercial buildings by exploring new data sources - especially in the context of emerging sensing and data collection opportunities.

### *1.5. New data sources for occupancy*

Nowadays, new data sources of building occupancy are becoming available. Cell phone positioning systems use different signals, such as radio signals of cell towers, GPS signals, and Wi-Fi signals to determine the accurate location of the phone [44]. Indoor positioning algorithms, using additional data of sensors embedded in smartphones, such as accelerometers and magnetometers, can determine the position of a cell phone inside a building [45].

Coupled with information about the exact location and floor plans of buildings, data collectors, such as Google (see Fig. 2, left) or Facebook (see

[3]Green Mark is Singapore's building energy efficiency and sustainability certification scheme, introduced in 2005 [43].

Fig. 2, right) are confident to determine the relative number of people visiting a specific building or space within a building in real time. On their respective online platforms, hourly aggregated and normalized data is published as so-called *popular times* data (Google) or *popular hours* data (Facebook).

The resulting data has the same structure as the standard schedules published by ASHRAE and others for building energy demand simulation. I.e., typical 24-h profiles for each day of the week. In [46] already directly extracted such data for simulation of a supermarket in the UK, due to lacking standard schedule for a 24-h operating retail building [46]. In Japan, researchers used Google *popular times* data to estimate quasi-real-time energy demand in a commercial district in Tokyo. They used a geospatial statistical interpolation, to infer the popularity/energy demand of commercial buildings without available data [47]. In China, researchers collaborated with a large Chinese social media company to collect occupancy data for different building use types from mobile positioning requests. They extracted typical schedules and used them in EnergyPlus building simulations and calibrations [48, 49].

Even though currently data about non-public buildings, such as offices and residential buildings are not published anywhere, we speculate that this data might be collected in the same way as for public buildings and possibly will be available at some point in time.

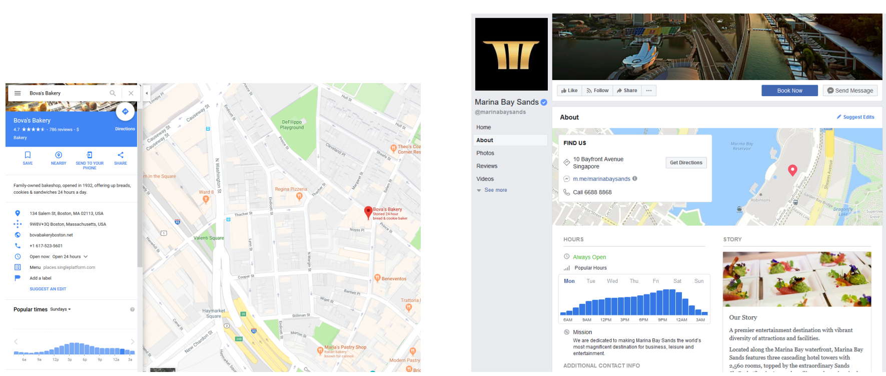

Figure 2: Example of a google maps / google places page of a public place in Boston (left). The *popular times* feature displays normalized hourly visitorship for each day of the week. Example of a facebook page of a public place in Singapore (right). The *popular hours* feature displays normalized hourly visitorship for each day of the week. Screenshots taken on 26/11/2018.

### *1.6. Research questions*

Given that, on the one hand, standard occupancy schedules are based on estimations from many decades ago, and, on the other hand, new data sources that track peoples' location are becoming increasingly available, we pose the following research questions: (1) Are standard schedules of ASHRAE (still) representative of real-world observations? And (2) should these schedules be used in multiple climatic and socioeconomic contexts?

For this publication, we focus on retail and restaurant as commercial building use-types with relatively high availability of data and at the same time high HVAC and electricity consumption.

We are using *popular times* data published for *places*, i.e., commercial buildings or zones of commercial buildings, available on the Google maps platform [50].

Regarding the data collection, we are focusing on *Downtown* areas of large cities. They typically contain a high density of commercial buildings, and they presumably experience relatively similar characteristics of working, shopping and leisure activities around the world.

In the following sections, we introduce the metrics selected to compare occupancy schedules as well as the method of data collection and data processing.

## 2. Methods

### *2.1. Data extraction and processing*

This section describes the data extraction from the Google maps platform and data processing prior to the analysis and comparison.

A two-step data scraping process was implemented to extract as much data as possible while at the same time limiting the number of queries to the Google places application programming interface (API). The parameters are based on experience and trial and error experiments. The *nearby search* query requires a geolocation, a search radius, and a type. The place types that are supported by the search query are listed in [51]. During various experiments with different search radii and supported place types as well as wildcard searches we realized that it is possible to extract up to 100% of all places of the restaurant category by searching for "restaurant", "bar", "cafe" and "night_club". For the retail use category, the same can be achieved by searching for: "store", "shopping_mall", "museum", "library" and "art_gallery" (see also Tab 4). For each of the 9 types, a search with 500 m radius was executed in the specified area. In locations where the number of results might have exceeded the maximum number of results that the API can return, a second search with a radius of 200 m was executed. We are confident that this process resulted in the vast majority of places available in every search area. The API *nearby search* and the web scraping extraction of the popular times data is automated with an open source algorithm [52].

The data extracted of each place includes the place id, the name, the address, the list of types, the location coordinates and, if available, the popular times 24h time series for each day of the week.

NREL defined 16 representative cities of the US climate zones for the commercial reference building models in [13]. The 13 largest ones are Miami, Houston, Phoenix, Atlanta, Los Angeles, Las Vegas, San Francisco, Baltimore, Albuquerque, Seattle, Chicago, Denver, and Minneapolis. The three remaining cities in cold climates (Helena, Duluth, and Fairbanks) were not considered due to their small size. We collected data from the Downtown areas of the 13 large cities. We selected an area of 4 km x 4 km around a central location extracted from a geographical feature representing the business district/financial district/downtown area on Google maps. Table 3 lists the edges of search areas of each city, as well as the name of the Google maps data point, that the area is based on.

#### *2.1.1. Aggregation of data sets*

We used a simple categorization logic based on the frequency of types belonging to a certain category (see Tab. 4) to assign places to the respective ASHRAE categories. In case of equal frequencies, the order of types in the list was used as a secondary decision variable of the assignment.

For consistency with the standard schedules, weekday values are grouped together for analysis, while Saturdays and Sundays are considered separately.

Data of days where places are closed or no occupancy is reported due to lack of data (e.g., "Not enough data yet for Tuesdays") are excluded from the analysis.

#### *2.1.2. Mean vs. Median*

When comparing a data set of schedules, it is not entirely clear whether the *representative* behavior of a standard schedule is supposed to represent the mean of observations or rather the median. It seems that originally estimated profiles were averaged to create schedules [9]. However, when

Table 3: Area selection for the extraction of popular times data of places from Google maps. All data were extracted on 12 March 2019. The cities are ordered according to climate zone. The climate zones are depicted in [13]. They range from 1 (very hot), 2 (hot), 3 (warm), 4 (mixed), 5 (cool), to 6 (cold), with subdivisions into A (moist), B (dry) and C (marine) zones. Zones 7 (very cold) and 8 (subarctic) are not considered here.

| abbre-viation | climate zone | google place name for center coordinates | southwest edge of search area (lat,lng) | northeast edge of search area (lat,lng) |
|---|---|---|---|---|
| MIA | 1A | Downtown Miami, Miami, FL, USA | (25.753196845299694,-80.21180781414786) | (25.789302978551977,-80.17193175274947) |
| HOU | 2A | Central Business District, Houston, TX, USA | (29.734721581744154,-95.38584147212512) | (29.7708069376959,-95.34448692156576) |
| PHX | 2B | Downtown Phoenix, Phoenix, AZ, USA | (33.43368327947898,-112.09597121702917) | (33.46974773608694,-112.05294847908701) |
| ATL | 3A | Downtown, Atlanta, GA, USA | (33.737677745380665,-84.40995416990314) | (33.77374042699837,-84.36678019162068) |
| LA | 3B-CA | Financial District, Los Angeles, CA, USA | (34.03249578872265,-118.27870463612754) | (34.06855674149175,-118.23538179301042) |
| LV | 3B-other | Downtown, Las Vegas, NV, USA | (36.14903303808023,-115.15777826853218) | (36.18508138081113,-115.11332055263757) |
| SF | 3C | Financial District, San Francisco, CA, USA | (37.77655276451901,-122.42264641504573) | (37.81259120376751,-122.37723155471627) |
| BAL | 4A | Downtown, Baltimore, MD, USA | (39.273990064695866,-76.63989850267983) | (39.31001926338947,-76.59353201649512) |
| ABQ | 4B | Downtown, Albuquerque, NM, USA | (35.073641593764485,-106.67758580779306) | (35.109696385250906,-106.63371953857586) |
| SEA | 4C | Downtown, Seattle, WA, USA | (47.58703266879561,-122.36095993903159) | (47.623009507421145,-122.30776362329615) |
| CHI | 5A | Chicago Loop, Chicago, IL, USA | (41.86062603316649,-87.6491421998699) | (41.89663905537564,-87.60095407272682) |
| DEN | 5B | Central Business District, Denver, CO, USA | (39.72677793461622,-105.0177095785645) | (39.762804318876405,-104.97104106946128) |
| MIN | 6A | Downtown West, Minneapolis, MN, USA | (44.95621052401934,-93.29867483554544) | (44.99220399028241,-93.247966304615) |

Table 4: Categorization of google places to ASHRAE use categories.

| ASHRAE category | google types | | |
|---|---|---|---|
| RETAIL | art_gallery[s], | electronics_store, | museum[s], |
| Used for: | bakery, | florist, | pet_store, |
| Library | bicycle_store, | furniture_store, | pharmacy, |
| Museum | book_store, | hardware_store, | shoe_store, |
| Retail | car_dealer, | home_goods_store, | shopping_mall, |
| | clothing_store, | jewelry_store, | store[s], |
| | convenience_store, | library[s], | supermarket[s] |
| | department_store, | liquor_store, | |
| RESTAURANT | bar[s], | | |
| Used for: | cafe[s], | | |
| Dining: Cafeteria/Fast Food | restaurant[s], | | |
| Dining: Family | night_club[s], | | |
| Dining: Bar Lounge/Leisure | meal_takeaway | | |

[s] Types used in search for data collection.

ASHRAE tasked researchers in the 1093-RP project to compile diversity factors and schedules of lighting and receptacle loads in office buildings for energy and cooling load calculations, they advocated in favor of the median of measurements. In their work, the median was used to create DOE-2, BLAST, and EnergyPlus input files. The median was chosen over the mean because its value is not affected by outliers [53].

In this work, we are using the mean and the median for comparison of collected data to standard schedules. We run all analyses for the mean as well as for the median. However, we only present selected results in detail.

### *2.2. Metrics for quantitative comparison of schedules*

When comparing any two 24-hour schedules, we are particularly interested in two general features: The overall scale of occupancy and the overall shape of the profile during the day. Therefore we select the mean absolute error (MAE) as a metric to quantify the difference in scale and the earth mover's distance (EMD) as a metric to quantify the difference in shape of schedules. Both metrics are introduced below.

#### *2.2.1. Mean Absolute Error*

We choose the mean absolute error (MAE) as the metric to quantify the general agreement of scale of any two given schedules. Intuitively the MAE can be understood as the average overestimation or underestimation of occupancy in any given hour in units of absolute % points, i.e., in % of full capacity. In our application, the minimum possible MAE is 0%, representing no difference between two schedules. The maximum possible MAE is 100%, representing a 100% difference for every hour of the day, i.e., the difference between a fully occupied building and a non-occupied building. We calculate the MAE between two 24-hour schedule time series $a = [a_1, a_2, \ldots, a_{24}]$ and $b = [b_1, b_2, \ldots b_{24}]$ as follows:

$$MAE(a, b) = \frac{\sum_{h=1}^{24} |a_h - b_h|}{24} \tag{1}$$

*2.2.2. Earth Mover's Distance*

We use the concept of the Earth Mover's Distance (EMD), developed for comparing color histograms for image retrieval in computer science [54], to quantify the similarity of shapes of schedules. The same concept applied in mathematics to probability distributions is known as the 1st Wasserstein distance or Mallows distance [55]. The EMD is formulated as a transportation problem and solved with linear optimization. See e.g., [54] for the formal definition of the EMD and e.g., [55, 56] for the formal definition of the Wasserstein distance. For our simple case, we can make us of the definition in Eq. 2 that gives the 1st Wasserstein distance between the distributions $u$ and $v$ as difference between the two respective cumulative distribution functions $U$ and $V$.

$$l_1(u, v) = \int_{-\infty}^{+\infty} |U - V| \tag{2}$$

To intuitively understand the EMD, one schedule is pictured as a mass of earth spread in space, while the other is pictured as a collection of holes in that same space. The EMD measures the least amount of work needed to fill the holes with earth, where one unit of work is quantified by transporting one unit of earth by one unit of distance. This definition is only valid if the two schedules have the same integral [54], i.e., the two schedules have to be normalized. For the normalized schedules $\hat{a}$ and $\hat{b}$ we can calculate the EMD from the difference between the two cumulative sum time series $\hat{C}a$ and $\hat{C}b$, see Eq. 3.

$$EMD(\hat{a},\hat{b}) = \sum |\hat{C}a - \hat{C}b| \text{ where } \hat{C}a_k = \sum_{i=1}^{k} \hat{a}_i, \text{ for } k = 1, 2, \ldots, 24 \quad (3)$$

Because the value of EMD depends on the selection of start and end time of schedules and the convention of 0h - 24h is somewhat arbitrary, we use circular shifts, where elements that shift beyond the last position are re-introduced at the first position, e.g., $[a_1, a_2, a_3, \ldots, a_{24}] \rightarrow [a_{24}, a_1, a_2, \ldots, a_{23}]$, to find the minimum EMD between two schedules, see Eq. 4.

$$\begin{aligned} EMD(a, b) &= \min_{1 \leq s \leq 24} EMD(\hat{a}_s, \hat{b}_s), \\ \text{with } a_s, b_s &= \text{ cirular shift of } a, b \text{ by } s \text{ elements} \end{aligned} \quad (4)$$

In our application, the minimum possible EMD is 0, representing the exact same normalized shape of two schedules. The maximum possible EMD is 12, representing a single hour of occupancy of each schedule shifted by ± 12 hours, e.g., the difference between a schedule with a single hour of occupancy at 4 pm vs. a single hour of occupancy at 4 am. For the exception of a zero schedule, the EMD cannot be calculated as the shape does not contain any mass.

#### 2.2.3. Weighted average

For the selection of overall best fit of data from different locations to standard schedules, we use a weighted average with weights according to the frequency of day types, i.e., 5 for comparing weekday data and 1 for comparing Saturday and Sunday data, respectively. See Eq. 5:

$$\bar{m} = \frac{5 * m_{wk} + 1 * m_{sat} + 1 * m_{sun}}{7} \quad (5)$$

### 2.3. Metrics for energy impact comparison of schedules

Because schedules of occupancy are intended for energy simulations, their direct comparison might not adequately represent the potential differences or errors in simulation results. Therefore we define the following metrics to compare two schedules with respect to their potential impact on simulated building energy demand.

*2.3.1. Number of occupied hours*

The number of occupied hours directly impacts the energy consumption of building systems that are binary presence controlled. E.g., lights that are either on or off, or ventilation systems that are either on or off. The occupied hours are a summation of boolean values, represented in this paper with Iverson bracket notation $[P] = 1$ if $P$ is true; $[P] = 0$ otherwise, that are 1 when there is occupancy, see Eq. 6.

$$OH(a) = \sum_{h=1}^{24} [a_h > 0] \tag{6}$$

As a result of a comparison we report the absolute difference in occupied time $\Delta OH(a, b) = |OH(a) - OH(b)|$.

*2.3.2. Number of full-load hours*

The number of full-load hours directly impacts the energy consumption of building systems that are presence-controlled. E.g., ventilation systems that are controlled via the CO2 concentration. The number of full-load hours also directly impacts the internal gains (sensible and latent) due to occupancy. Set-point controlled HVAC systems react to those internal gains. We calculate the full load hours of a schedule $a$ with Eq. 7.

$$FL(a) = \frac{\sum_{h=1}^{24} a_h}{100\%} \tag{7}$$

*2.3.3. The peak value of occupancy*

The peak value of occupancy is related to the expected peak of energy use for occupancy controlled building systems (e.g., ventilation) or set-point controlled building systems (e.g., latent and sensible cooling demand). The peak is the maximum values observed in the 24h time series, see Eq. (8).

$$P(a) = \max_{1 \leq h \leq 24} a_h \tag{8}$$

*2.3.4. The timing of the afternoon peak*

Typically in cooling dominated climates or seasons, the demand peak of cooling energy is happening in the afternoon, following the diurnal outdoor temperature curve. For forecasting of the daily peak of cooling energy demand, it is of interest to consider the time of the peak value of occupancy in the PM hours. We calculate the maximum possible shift in peak timing in the afternoon hours by comparing the time of peak values (sometimes is more than one peak hour) and calculating the maximum absolute distance between them. E.g., the standard occupancy for ASHRAE assembly on weekdays has a peak value of 80% from 11 AM through 5 PM. If the observed data peak happens at 7 PM the maximum peak shift is calculated as 7 PM - 1 PM = 6 hours. We extract all times of peaks with Eq. (9) and report the maximum difference $\max \Delta TP(a, b)$ between two schedules $a$ and $b$.

$$TP(a) = \{h\}[a_h = \max_{12 \leq h \leq 24} a_h] \quad for \quad 12 \leq h \leq 24 \tag{9}$$

*2.3.5. The maximum ramp-up and ramp-down gradients*

The maximum ramp gradients are defined here as the largest positive and negative change in hourly occupancy. Large ramps in occupancy can be indirectly related to stress in power grids via the sudden increase or decrease in energy demand of occupancy controlled building systems, e.g., an occupancy controlled ventilation system suddenly has to provide much more fresh air to the building. We calculate the maximum ramps with Eq. (10) and (11) and report the differences $\Delta RU(a, b)$ and $\Delta RD(a, b)$ between two schedules $a$ and $b$.

$$RU_{max}(a) = \max_{1 \leq h \leq 24} a_{h+1} - a_h, \quad with \quad a_{25} = a_1 \tag{10}$$

$$RD_{max}(a) = \min_{1 \leq h \leq 24} a_{h+1} - a_h, \quad with \quad a_{25} = a_1 \tag{11}$$

*2.4. Statistical hypothesis tests*

With statistical hour-by-hour hypothesis testing, we want to determine whether the extracted samples of hourly occupancy values might be part of a population with the mean or the median being the standard schedule value. Or in other words: Is it possible that the standard schedule value of a certain hour of the day is the mean or median of real-world observations?

Standard schedule values are often quantized (rounded) to steps of 5% or 10%, e.g., the "true" standard schedule value of 50% might actually be any value between $45.0 < x \leq 55$. Rather than statistically testing the sample observations against all possible continuous values that might result in the quantized value, we perform one-tailed tests for the upper and the lower limits of possible 'true' mean or median values.

Similarly, we can straightforward test if data samples collected from different locations might stem from the same underlying distribution. For this, we select the Kolmogorov-Smirnov test.

The next paragraphs describe the methods selected for statistical hypothesis testing.

*2.4.1. One sample T-testing for sample means*

For the hypothesis that the standard schedule is the mean of real world observations we test our sample mean $\bar{x}$ for every hour of the day against the lower $\mu_{lower}$ and upper $\mu_{upper}$ limits of the quantized standard schedule value with two one-tailed one sample T-tests. For the case of the lower limit we formulate the null and alternative hypotheses as follows:

$$H_0 : \mu_{lower} = \bar{x}$$
$$H_1 : \mu_{lower} < \bar{x}$$

For the case of the upper limit we formulate the null and alternative hypotheses as follows:

$$H_0 : \mu_{upper} = \bar{x}$$
$$H_1 : \mu_{upper} > \bar{x}$$

We calculate the $p{-}value$ and reject the null hypothesis for the alternative hypothesis if $p - value < \alpha/b$ for a selected significance level $\alpha = 0.05$ and Bonferroni correction for testing multiple hypotheses $b = 2$.

In general, we accept the standard schedule value $\mu$ to be representative of the mean if both null hypotheses are rejected in favor of $H_1$. I.e., the mean value of the observed data is likely to be in the range of $\mu_{lower} > \bar{x} > \mu_{upper}$.

In the special case of testing an all-zero sample against a standard value of zero, we accept the standard schedule value $\mu = 0$ to be representative of the mean without any calculation. As a result, we report the number of cases/hours in the range of 0 - 24, where both $H_0$ are rejected for $H_1$, i.e., where the standard schedule is likely to represent the mean of observed data.

*2.4.2. Sign-test for sample median*

For the hypothesis that the standard schedule values correspond to the median of real-world observations we are performing a sign test for the lower and upper limits of the quantized value. The median $\tilde{x}$ is defined as the value separating the higher half from the lower half of a data sample. A sign test for the median is a binomial test for the probability $P$ of a sample being smaller (or larger) than the median under the null hypothesis being $P = 0.5$. For the case of the lower limit we formulate the null and alternative hypotheses as follows:

$$
\begin{aligned}
&H_0 : P(X > m_{lower}) \leq 0.5 \\
&H_0 : \tilde{x} < m_{lower} \\
&H_1 : P(X > m_{lower}) > 0.5 \\
&H_1 : \tilde{x} \geq m_{lower}
\end{aligned}
$$

where $m_{lower}$ is the lower limit of the range of possible population medians. For the case of the upper limit $m_{upper}$ we formulate the null and alternative hypotheses as follows:

$$
\begin{aligned}
&H_0 : P(X > m_{upper}) \geq 0.5 \\
&H_0 : \tilde{x} > m_{upper} \\
&H_1 : P(X > m_{upper}) < 0.5 \\
&H_1 : \tilde{x} \leq m_{upper}
\end{aligned}
$$

The $p - value$ is calculated with the binomial function. We count the occurrences $k$ of $X > m$ and calculate the probability of finding this number of results in our sample of size $n$ under the true probability of $p_0 = 0.5$.

For a selected significance level $\alpha = 0.05$ and Bonferroni correction $b = 2$ the null hypothesis is rejected for the alternative hypothesis if $p - value < \alpha/b$.

In general, we accept the standard schedule value $m$ to be representative of the median if both null hypotheses are rejected.

For the special case of testing $m = 0$ only a single left-tailed test is performed. Since it is impossible to find values of $X < 0$ in our sample, we test for the null hypothesis of finding 50% of values $X > 0$:

$$
\begin{aligned}
&H_0 : P(X > m) \geq 0.5 && \text{for } m = 0 \\
&H_0 : \tilde{x} > m && \text{for } m = 0 \\
&H_1 : P(X > m) < 0.5 && \text{for } m = 0 \\
&H_1 : \tilde{x} \leq m && \text{for } m = 0
\end{aligned}
$$

As a result, we report the number of cases/hours where the tests are rejected, i.e., the number of hours where the standard schedule is likely to represent the median of observed data.

#### *2.4.3. Kolmogorov-Smirnov test for two samples*

We use the two-sample Kolmogorov-Smirnov (KS) test to determine whether two data samples from two different locations might be part of a common, overall population. The two-sample KS test is a general, nonparametric method to test whether two samples are drawn from the same distribution. The null hypothesis $H_0$ and alternative hypothesis $H_1$ of the test are:

$$
\begin{aligned}
&H_0 : \text{the two samples come from the same distribution} \\
&H_1 : \text{the two samples come from different distributions}
\end{aligned}
$$

We calculate the test statistic of two samples from two locations at the same hour of the day. We reject the null hypothesis at a level of $\alpha = 0.05$. In the exceptional case of all zero values in the samples, we do not reject $H_0$, without performing any test. As a result, we report the number of hours per day where $H_0$ was not rejected in favor of $H_1$, i.e., the number of hours $0 \ldots 24$ where the distribution of popularity in the two locations is similar.

## 3. Results and Discussion

### *3.1. Data collection*

Fig. 3 (left) shows the number of retail and restaurant places extracted in each city after categorization. Fig. 3 (right) shows the share of retail and restaurant places in each city with popular times data. The smallest sample

(91 retail places) was collected in Albuquerque, the largest (1250 restaurant places) in San Francisco. On average 54% of restaurant and 13% of retail places in downtown areas contain popular times information on Google maps.


Figure 3: Number of retail and restaurant places with and without popular times data extracted in a 4km by 4km area in the vicinity of downtown neighbourhoods in different cities in the U.S. (left) and relative share of places with available popular times data relative to the total number of places (right).

### *3.2. Part A: Comparing data to standard schedules*

This section contains the results of the basic and energy impact comparison of mean and median data to the respective standard schedules of ASHRAE in the most up-to-date version (2013). We compared quantized means and medians of all cities and all day types to the corresponding ASHRAE schedule. Because we can not present all comparison results in this paper, we select one of the best fitting data sets for discussion in this section. For this selection, we use the weighted averages of two quantitative comparison metrics EMD and MAE, calculated with Eq. (5).

#### *3.2.1. Restaurant*

The ASHRAE schedule for Restaurant (2013) is defined in steps of 5%. Therefore we quantize the mean and median schedule extracted from the popular times data also in steps of 5% to ensure a fair comparison when calculating EMD, MAE and the various energy impact metrics. When looking at the overall weighted EMD and MAE of the mean and median for different locations, the quantized mean is a better fit for both metrics in all locations (see Fig. 4). We are using a ranking system to select the location to be discussed in detail. The overall best fit is observed for the data of Los Angeles (1st rank in EMD and 3rd rank in MAE), followed by Phoenix and Seattle. For these reasons, we present the comparison results of the mean data for Los Angeles vs. the ASHRAE 2013 Restaurant standard schedule in this section.

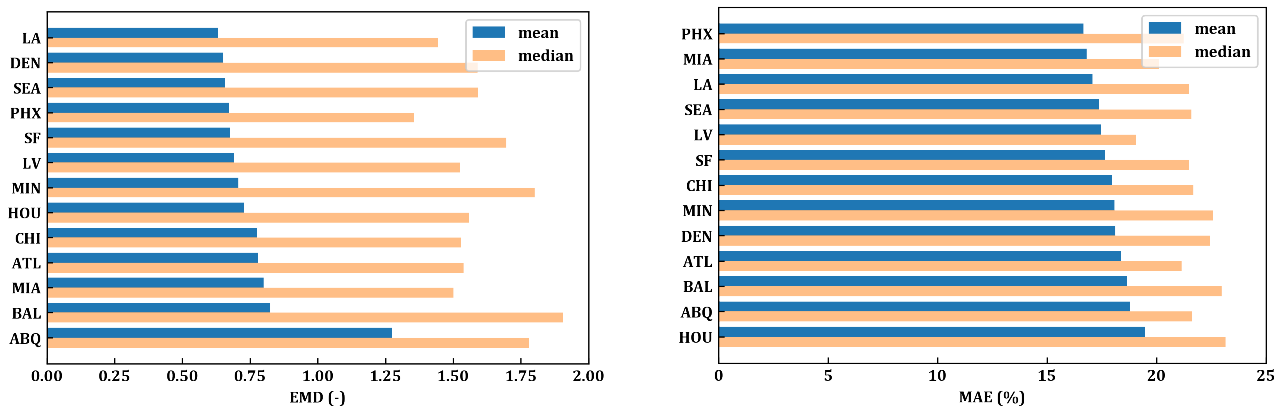


Figure 4: Weighted averages of EMD (left) and MAE (right) between quantized mean and median restaurant popular times and ASHRAE standard schedules for different cities. The cities are ordered in descending order according to their fit of the data mean.

Fig. 5 presents the results of the EMD and MAE calculation as well as of the statistical hypothesis testing of the quantized sample data means vs. the respective ASHRAE standard schedule in the form of a heatmap. Additionally to the comparison between the corresponding day types weekday (WK), Saturday (SAT) and Sunday (SUN) we present the comparison to the non-corresponding day types as well. The EMD is in the range of 0.5 - 1.1. The best fit of shape between sample data and standard schedule is observed for WK, the worst for SUN. The MAE is in the range of 13-19% for corresponding day types. The best fit is observed for SUN, the worst for WK. However, when comparing to other day types, the differences are often smaller. Regarding the hypotheses testing results, the best agreement is found to be between WK data and SUN standard. Overall there is no consistency in the results.

Fig. 6 presents the results of the energy impact comparison between the Los Angeles restaurant data sample and the standard schedules. We note that differences in occupied hours are small or zero for all day types. The

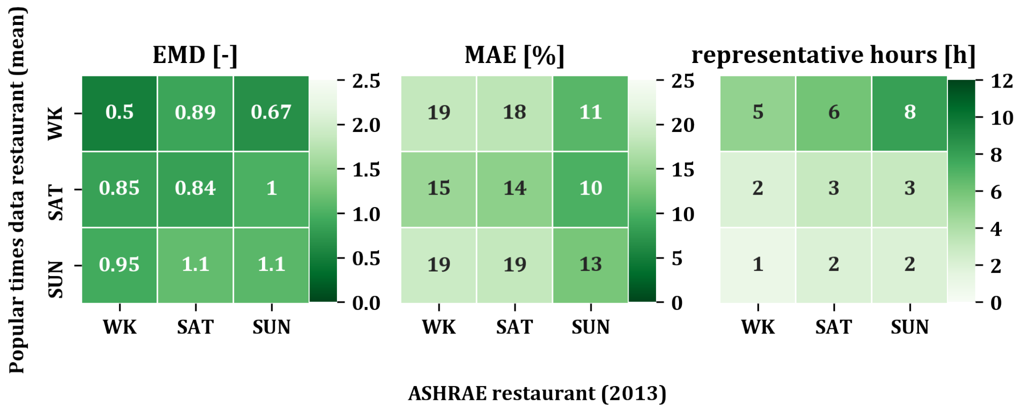


Figure 5: Heatmaps of EMD (left) and MAE (middle) between quantized mean popular times data of Los Angeles and ASHRAE standard schedules for different day types and results of hypothesis testing (right) of the data samples. The EMD is in the range of 0...12, MAE is in the range of 0...100%. Representative hours according to hypotheses testing range from 0...24 h. In all heatmaps darker shading means better agreement.

differences in full load hours are between 1.2 and 4.3 hours, with WK data vs. WK standard having the alargest difference of all comparisons. Peak values of standard schedules are misstated by 25 - 40 % of full capacity. The time of the afternoon peak is misstated by up to 7-8 hours for WK and SUN. Only on SAT, the standard schedule is representing the afternoon peak time with some accuracy. The maximum ramp up and ramp down events for each day type are misrepresented by up to 35 % of full capacity. Similar to the quantitative metrics, the energy impact metrics often display a better agreement to standard schedules of non-corresponding day types.

*3.2.2. Retail*

The ASHRAE schedule for Retail (2013) is defined in steps of 10%. Therefore we quantize the mean and median schedule extracted from the retail data also in steps of 10% to ensure a fair comparison when calculating EMD, MAE and the various energy impact metrics. When counting the cases (cities) where the mean or the median of data result in a better fit, the Retail use category is not as decisive as Restaurant. See Fig. 7. However, there is a slight preference of the mean (5 vs. 8 for EMD and 9 vs. 4 for MAE). We rank the locations according to their overall fit of mean data for the selection of the detailed discussion in this section. Minneapolis has the best

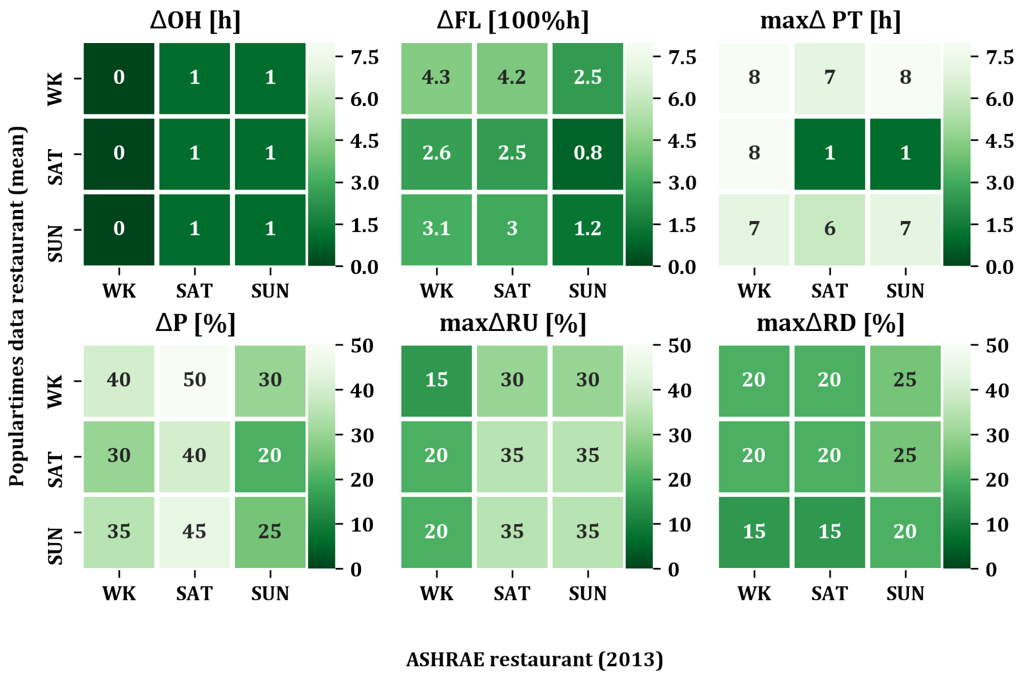


Figure 6: Heatmaps of energy impact metrics between the quantized mean popular times data of Los Angeles and ASHRAE standard schedules for different day types. The top row displays the difference in occupied hours $\Delta OH$ (top left), the difference in full load hours $\Delta FL$ (top center) and the maximum shift in peak time $max\Delta PT$ (top right). The bottom row displays the difference in peak value $\Delta P$ (bottom left), the maximum difference in ramp up $max\Delta RU$ (bottom center), and the maximum difference in ramp down $max\Delta RD$ (bottom right). In all heatmaps darker shading means better agreement.

agreement (1st in MAE and 2nd in EMD), followed by Houston and Albuquerque. Therefore we present the results of the comparison of the mean data for Minneapolis vs. the ASHRAE 2013 Retail standard schedule in this section.

Fig. 8 presents the results of the EMD and MAE calculation as well as of the statistical hypothesis testing of the quantized sample data means vs. the respective ASHRAE standard schedule in the form of a heatmap. Additionally to the comparison between the corresponding day types weekday (WK), Saturday (SAT) and Sunday (SUN) we present the comparison to the non-corresponding day types as well. The results show that for the WK the shape of the standard schedule matches relatively well to the sample

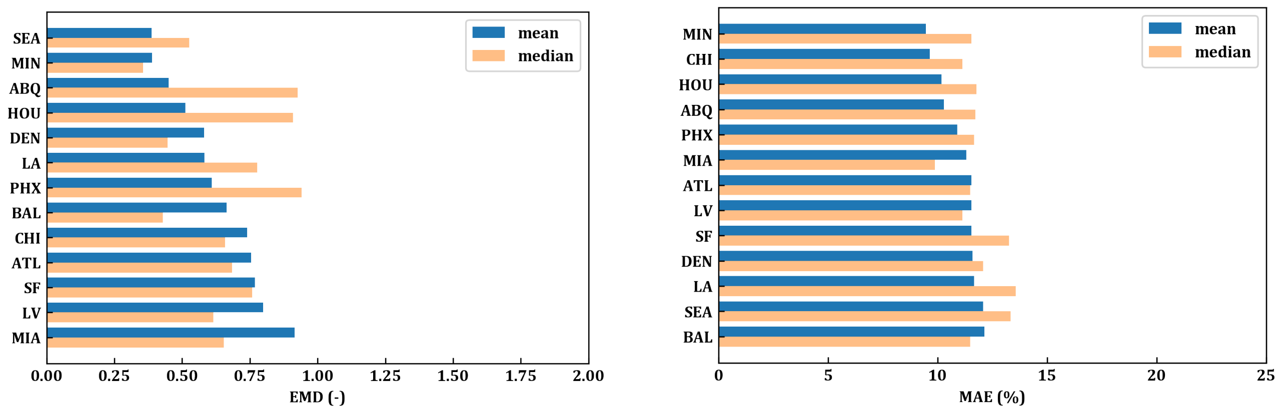


Figure 7: Weighted averages of EMD (left) and MAE (right) between quantized mean and median retail popular times and ASHRAE standard schedules for different cities. The cities are ordered in descending order according to their fit of the data mean.

observations. The MAE is in the range of 8-10% for corresponding day types. However, when comparing to other day types, the differences are sometimes smaller. For instance, when considering EMD and MAE the WK standard schedule is a better fit for the SAT data. Regarding the hypotheses testing results, the best agreement is found to be between WK data and SAT standard. Overall there is no consistency in the results.

Fig. 9 presents the results of the energy impact comparison between the Minneapolis retail data sample and the standard schedules. We note that differences in occupied hours are relatively small for WK and SAT conditions, however for SUN the standard schedule is off by 4 hours. The differences in full load hours are between 1.4 and 2.1. Peak values of standard schedules are misstated by 10 - 30 % of full capacity. The time of the afternoon peak is misstated by up to 3 hours for all day types. The maximum ramp up and ramp down events for each day type are misrepresented by up to 20 % of full capacity. Similar to the quantitative metrics, the energy impact metrics often display a better agreement to standard schedules of non-corresponding day types.

### *3.3. Part B: Comparing data in different contexts*

This part contains the comparison results of Retail and Restaurant *popular times* profiles between different US cities. Fig. 10 shows the results of the pairwise hourly Kolmogorov-Smirnov hypotheses testing between the

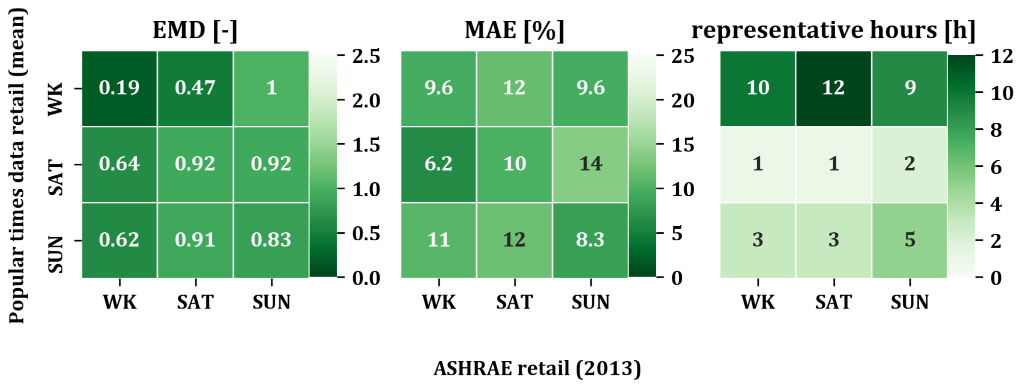


Figure 8: Heatmaps of EMD (left) and MAE (middle) between quantized mean popular times data of Minneapolis and ASHRAE standard schedules for different day types and results of hypothesis testing (right) of the data samples. The EMD is in the range of 0...12, MAE is in the range of 0...100%. Representative hours according to hypotheses testing range from 0...24 h. In all heatmaps darker shading means better agreement.

different locations. There are no distinct patterns recognizable linking neighboring climate zones. We present a more detailed analysis and discussion in the following sections.

For consistency with Part A, we present only the comparisons of quantized data means. In order to uncover the real differences between locations, we quantize the mean to 1% values. We are considering only weekday (WK) data in this part. Besides presenting the quantitative comparison of EMD and MAE, we focus on the most interesting energy impact results, which are the peak values and the timing of the afternoon peak for both commercial building use types.

*3.3.1. Restaurant*

Fig. 11 shows heatmaps of EMD (left) and MAE (right) between mean popular times of restaurants on WK for the selected cities in the U.S. Regarding the shape of the profiles we observe the smallest differences between Denver and Minneapolis, Denver and Seattle, Minneapolis and Seattle, and Minneapolis and San Francisco. The most substantial differences are observed between Albuquerque and Las Vegas, and Albuquerque and Baltimore. The MAE is in the relatively small range of 0 - 7% of full capacity. The smallest differences are observed between Atlanta and Los Angeles, Chicago and Seattle, Denver and Minneapolis, Denver and San Francisco,

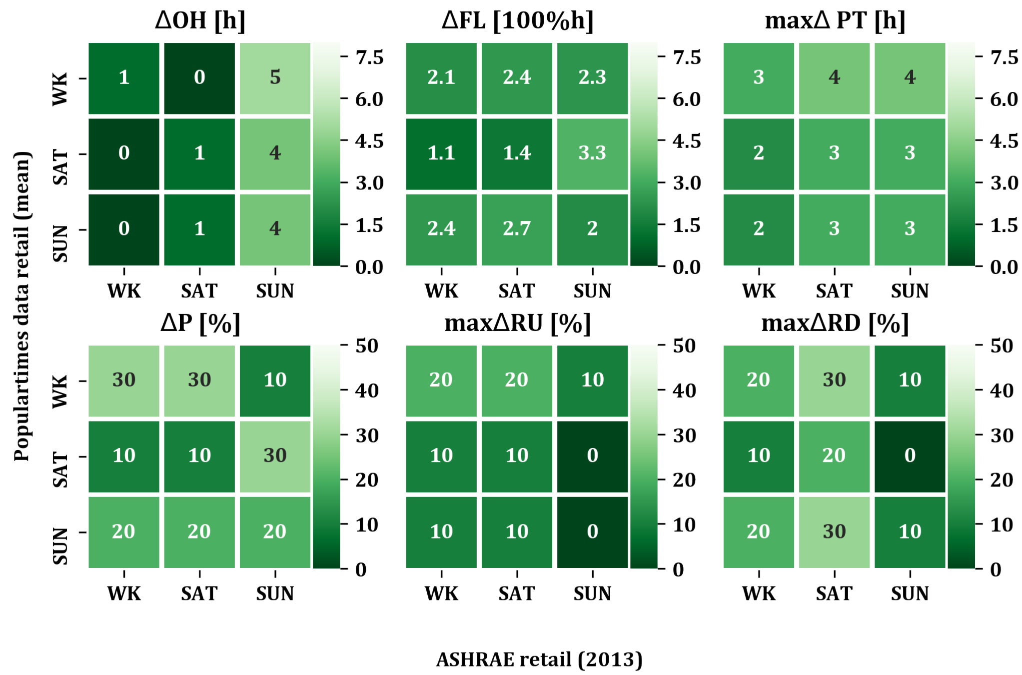


Figure 9: Heatmaps of energy impact metrics between the quantized mean popular times data of Minneapolis and ASHRAE standard schedules for different day types. The top row displays the difference in occupied hours $\Delta OH$ (top left), the difference in full load hours $\Delta FL$ (top center) and the maximum shift in peak time $max\Delta PT$ (top right). The bottom row displays the difference in peak value $\Delta P$ (bottom left), the maximum difference in ramp up $max\Delta RU$ (bottom center), and the maximum difference in ramp down $max\Delta RD$ (bottom right).

Denver and Seattle, Minneapolis and Seattle, and San Francisco and Seattle. The largest differences in scale are observed between Albuquerque and Las Vegas, Albuquerque and Miami, and Albuquerque and Baltimore.

One potential explanation for similarity could be the climate, cities in cold climates (Denver (climate zone 5B), Minneapolis (6A), Seattle (4C), Chicago (5A)) form pairs with small differences. Good agreement of MAE can also be found for one pair in warm climate of Atlanta (3A) and Los Angeles (3B-CA). On the other hand, the good agreement of EMD between Minneapolis and San Francisco or MAE between Denver/Seattle vs. San Francisco cannot be explained with the climate.

Possible explanations for dissimilarity could be connected to socioeco-

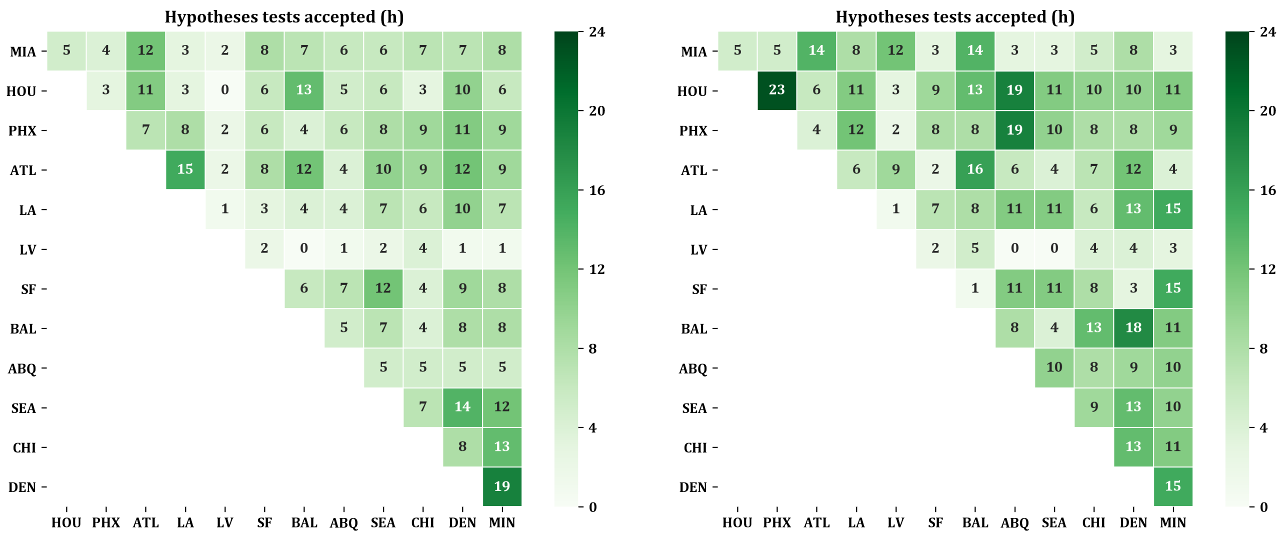


Figure 10: Heatmap of pairwise Kolmogorov-Smirnov hypotheses testing results for popular times data of restaurants (right) and retail places (left) on WK for different cities. The cities are ordered according to their climate zone.

nomic factors as well as climate. For instance, the overall largest differences in EMD and MAE are observed between Albuquerque (4B) and Las Vegas (3B-other). These cities are different in climate (cold semi-arid vs. subtropical hot desert climate) as well as in the structure of their economy (high-tech, research vs. tourism, gaming, and conventions).

Fig. 12 shows the pairwise comparison of selected energy impact metrics. Peak values (left) and the difference in PM peak timing (right) between different locations are displayed. Most of the locations experience a very similar peak with differences in the range of 0-7% full capacity. Larger differences of 7-10% are uncommon and only observed for Albuquerque vs. other locations, and Phoenix vs. other locations. Interestingly, Albuquerque and Phoenix are in very good agreement. However, the observed differences in PM peak timing are very significant. Two distinct groups can be identified: (1) ABQ, ATL, CHI, HOU, LA, PHX and (2) BAL, DEN, LV, MIN, SF, SEA. And then there is Miami, which is different from every other city. When looking at Fig. 13 we can explain these groups. We observed that the restaurant occupancy typically experiences two peaks, one at lunchtime and another one at dinner time. Group (1) has the higher of the two peaks at lunchtime/midday, while in group (2) the higher peak is observed at dinner-

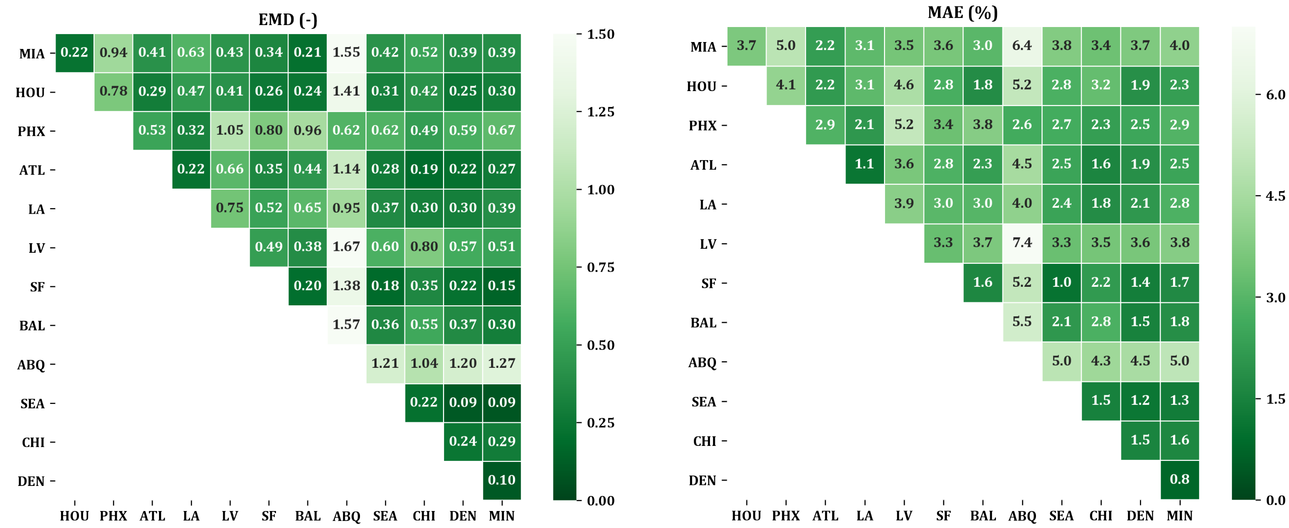


Figure 11: Heatmap of pairwise EMD (left) and MAE (right) between quantized mean popular times of restaurants on WK for different cities. The cities are ordered according to their climate zone.

time/evening. Miami happens to have two peaks of exactly the same value. It seems this behavior is rather unrelated to climatic differences. That is why we speculate the reason could be found in socioeconomic factors.

*3.3.2. Retail*

For the retail category we note that the scale and shape of profiles are very similar, see Fig. 14. The EMD takes values between 0.1 - 1.1, the MAE between 1 - 6% of full capacity. The largest difference in shape and scale is observed between Albuquerque and San Francisco. The smallest difference in shape and scale is observed between Baltimore and Denver.

Peak values for retail are also very similar, see Fig. 15. Differences in peak are between 0-9% of full capacity. Larger differences are observed between Houston and San Francisco, and Houston and Seattle. The time of the peak is approximately the same in all cities (maximum 1 h difference), except for Chicago and San Francisco, which show a behavior different from the rest. While most of the cities experience a peak at 1 PM or 2 PM, those two remain at an almost constant occupancy until 5 PM or 6 PM where they experience a second peak, see also Fig. 16.

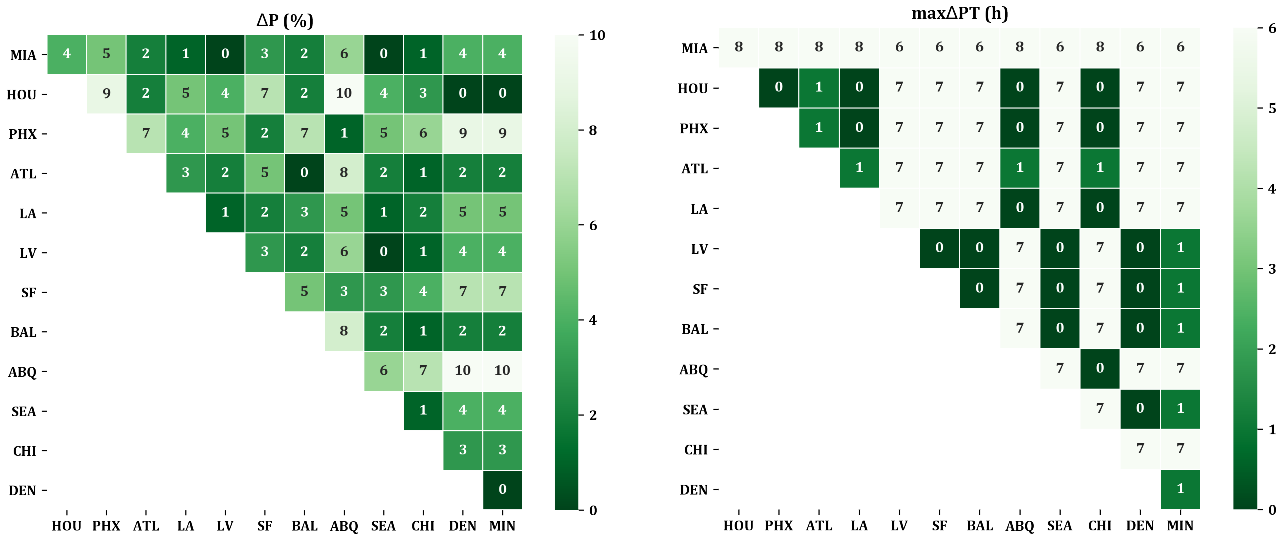


Figure 12: Heatmap of pairwise peak value (left) and timing of PM peak (right) between quantized mean popular times of restaurants on WK for different cities. The cities are ordered according to their climate zone.

## 4. Limitations

The main limitations of the work presented in this paper are related to the non-transparency of the data source. We found no publicly available information on the data collection, data processing, and data publishing processes. Multiple issues could lead to skewed or biased results and should be addressed if raw data, or similar data from other sources, becomes available in the future. With regards to data collection, they are: (1) a bias towards places with larger capacity due to the higher probability of data collection, (2) a bias towards places visited by a particular population demographic due to a higher probability of cell phone ownership or higher penetration of location data collecting applications. With regards to data processing and publication the current limitations are: (3) potential seasonal effects that might be or might not be reflected in the published data, (4) the estimation of the of 100% *popularity* or *occupancy*, i.e., the places' capacity, based solely on the historical record of data collection might be an over or underestimation.

With regards to our presented methodology, we are aware that simply extracting the mean and median of the data aggregated into use type and

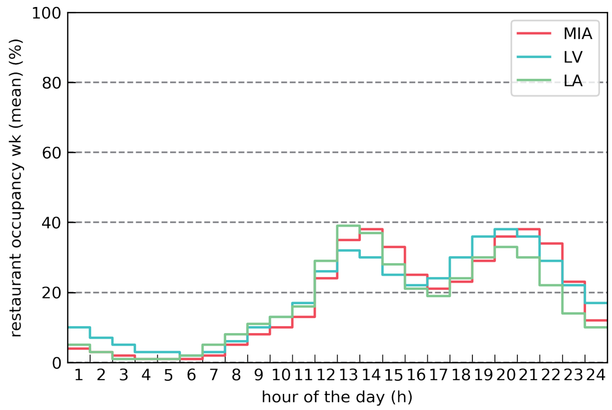


Figure 13: Mean popular times data of restaurants on weekdays for Miami (MIA), Las Vegas (LV) and Los Angeles (LA).

day type categories, does not account for the potential diversity of patterns within these categories. We could form categories based on the observed *popular times* data by using classification and/or clustering techniques rather than on the *type* attribute of the place and the type of day categories proposed by ASHRAE.

We present the results of the quantized mean of data, because of our selection of the most favorable and fair comparison to the standard schedules. However, conceptually the median should represent a better choice as it can be understood as the actual behavior of the place in the center of the sample. The issue with selecting the mean is not only that outliers disproportionally influence the values, but also that it is very unlikely in terms of occupancy to observe hours with zero mean occupancy. This can be somewhat avoided by the quantization to 5% or 10% steps as in the comparison to the standard schedules. However, the *representative schedules* we analyze in the location comparison almost always have an unrealistic occupancy duration of 23-24 hours per day with occupancy of <5% during the night.

## 5. Summary and Conclusion

Standard schedules of occupancy are a by-product of the development of simulation-based building performance evaluation. Some schedules that are being used until today can be traced back as far as 1979 when they were

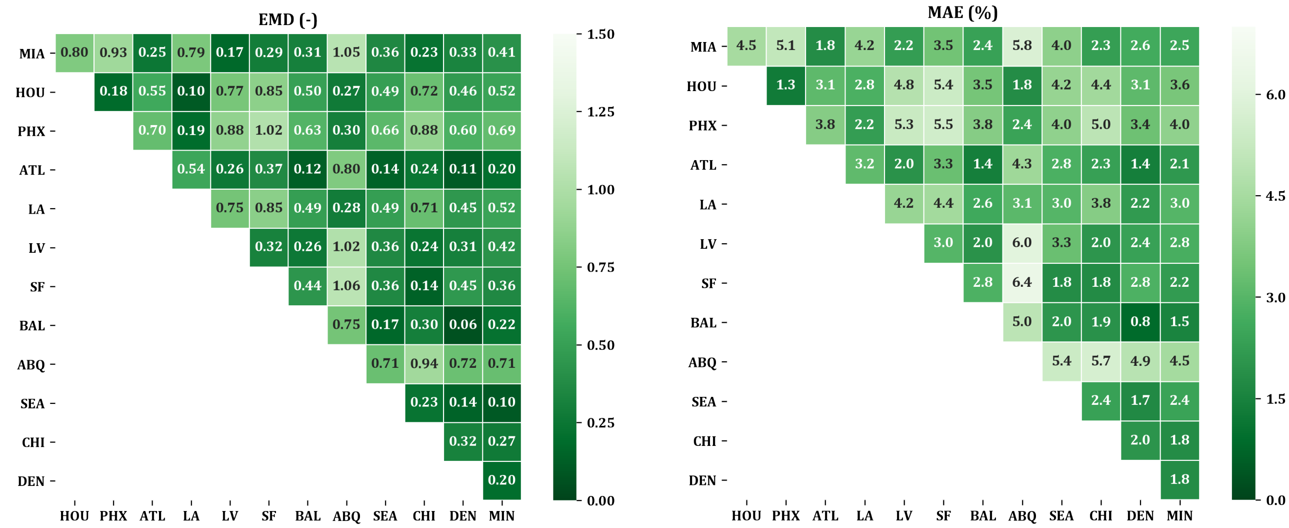


Figure 14: Heatmap of pairwise EMD (left) and MAE (right) between quantized mean popular times of retail on WK for different cities. The cities are ordered alphabetically.

created using expert's educated guesses of that time. Since then, schedules of occupancy have partly been updated but never based on extensive data gathering. With this work, we showed that *place popularity profiles*, which are essentially the same as *building occupancy schedules*, can be gathered from Google maps and compared to standard schedules of occupancy using quantitative, energy impact and statistical metrics. We gathered data for commercial building uses for 13 representative cities in different US climate zones and compared the *Retail* and *Restaurant* use category to the respective ASHRAE standard schedules for weekdays, Saturday and Sunday. We only presented the analysis for the locations with the smallest differences in terms of profile shape (measured with EMD) and profile scale (measured with MAE) and extracted features in favor of the standard schedule (quantized mean) to ensure a fair comparison. Nonetheless, we found significant differences in absolute scale, with MAE around 10-20% of full capacity, as well as in profile shape, with EMD around 0.2-1.1. Regarding energy impact metrics we found that peak values can be off by as much as 40% of full capacity. Furthermore, when cross-checking observed data of a certain type of day with standard schedules of other day categories, often a better agreement was found. Based on these results, we advise to use standard schedules with great care and only for the purpose they are intended to, which is mainly

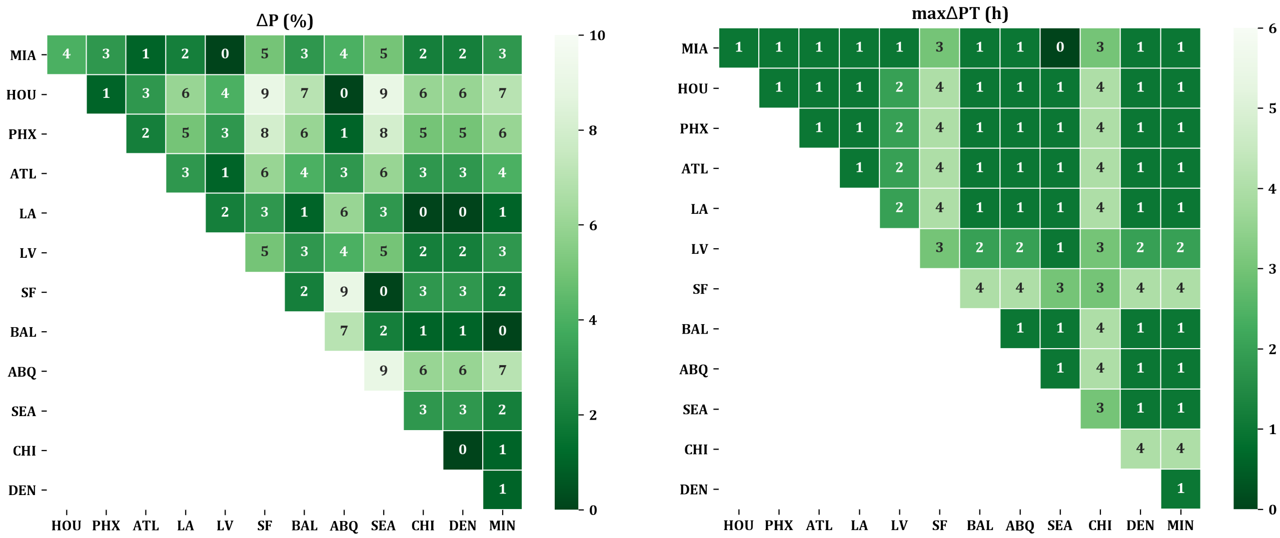


Figure 15: Heatmap of pairwise peak value (left) and timing of PM peak (right) between quantized mean popular times of retail on WK for different cities. The cities are ordered alphabetically.

building design trade-off analysis. Especially for larger simulations on the neighborhood-scale or district-scale, where a realistic *average behavior* is desired, e.g., for the planning and design of district energy systems, we advise against using the currently available standard schedules of occupancy.

In the second part of the analysis, we focused on differences between locations and their possible correlation to climatic and socioeconomic factors. Overall, we observed that differences in shape and scale of schedules between data of different locations are much smaller than between data and standard schedules. However, we found some evidence that suggests that climatic and socioeconomic factors might influence visitor behavior, especially to restaurant buildings. This might make it necessary to use location-specific, customized occupancy schedules for building simulation.

## 6. Outlook

Besides looking into the diversity of profiles and the extraction of typical patterns of occupancy based on observation data, we think it is necessary to explore the potential implications of our findings onto energy simulations.

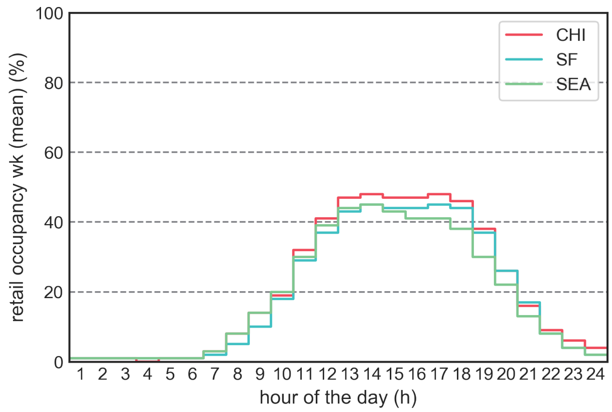


Figure 16: Mean popular times data of retail places on weekdays for Chicago (CHI), San Francisco (SF) and Seattle (SEA).

The focus of further work will be the application of data-based occupancy schedules for commercial buildings in a real case study. In order to research the impacts of using data-based schedules compared to the benchmark of standard occupancy schedules on the district scale, extensive simulations with an urban energy modeling tool are planned. We propose to test different models of occupancy in conjunction with different levels of impact analysis, e.g., occupancy patterns on the district scale, energy demand on the district scale, and energy systems design on the district scale.

We argue that only if ultimately the energy systems design is fundamentally affected, it is necessary to model occupancy in detail for urban energy modeling. However, this is yet to be shown.

## 7. Acknowledgements


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