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OESP$_G$: A Computational Framework for Multidimensional Analysis of Occupant Energy Use Data in Commercial Buildings

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ABSTRACT

Commercial buildings account for much of the energy use both in the United States and globally. The role of occupant behavior within the physical building has been found to be an important factor in the overall energy use profile of commercial buildings. Recent research has noted the potential energy savings that can be achieved when occupant behavior is beneficially modified. However, frameworks for analyzing occupant behavior are limited in their ability to simultaneously consider three key dimensions of occupant-driven energy use in buildings: *spatial, temporal,* and *social*. In this paper, we present the Occupant Energy Signal Processing

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on Graphs ($OESP_G$) framework, which is able to address the three key dimensions of occupant energy use in commercial buildings through an inherently scalable mathematical structure. We demonstrate the mechanics, applicability, and merits of the $OESP_G$ framework by applying it to occupant energy use data through both a simulated example and real test-bed data from a commercial office building. We find that $OESP_G$ is able to identify situations in which occupant energy use through plug loads is *out-of-sync* with what would be expected based on nuanced spatial and organizational identity, and we note the feasibility of using this framework to make recommendations for temporal and spatial occupancy shifts that would have a positive impact on occupant energy use.

INTRODUCTION

Commercial buildings are responsible for nearly 20% of current energy use in the United States, and they are projected to be the fastest growing energy demand sector worldwide (U.S. Energy Information Administration 2016a; b). As a result, researchers are developing new approaches to enhance the energy efficiency of commercial buildings and reduce the associated environmental emissions and negative sustainability impacts of their energy usage. Specifically, new approaches that bridge the gap between physical building systems and the behavior of building occupants have shown significant promise to enhance the energy efficiency of commercial buildings (Azar and Menassa 2012; Hong and Lin 2012; Meier 2006). However, realizing savings from such new approaches will require a comprehensive and nuanced understanding of occupant behavior as energy usage has been shown to vary dramatically due to occupant dynamics (Clevenger and Haymaker 2006).

With regard to individual occupants, differences in their locations within a commercial building (*spatial dimension*) as well as variations in their schedules (*temporal dimension*) can have strong implications for how the building uses energy (Jazizadeh et al. 2014; Kwak et al. 2014; Lim et al. 2012). Social and organizational networks of people (*social dimension*) have also been found to be an important factor in the energy use trends within a commercial building (Anderson et al. 2014; Chen et al. 2012; Khashe et al. 2016). As a result, a successful socio-technical and occupant behavior based approach to energy efficiency for commercial buildings will require reconciling and analyzing the three key dimensions (spatial, temporal, social) by which building systems and occupants consume energy.

The advent of data streams from low-cost building sensors offers an opportunity to improve the granularity by which we understand building energy use trends in the temporal, spatial, and social dimensions. This improved understanding from high-fidelity data streams enables optimization of building design and controls so that buildings can run more efficiently. However, the methods typically used to analyze occupant energy use data are limited due to their ability to capture only one or two of the three aforementioned key dimensions affecting energy use in commercial buildings. In this paper, we introduce the Occupant Energy Signal Processing on Graphs ($OESP_G$) framework, a scalable computational framework for multidimensional analysis of building energy usage data inspired by the emerging field of signal processing on graphs (Sandryhaila and Moura 2013). We demonstrate the mechanics, applicability, and merits of our proposed framework using a simple simulated example and case-study example comprised of real data from a test-bed office building in Denver, CO.

BACKGROUND

Occupant and Data-driven Energy Efficiency in Buildings

Numerous studies have found that occupant behavior plays a major role in both residential (Gill et al. 2010; Guerra Santin et al. 2009; Majcen et al. 2015; Martinaitis et al. 2015) and commercial (Bonte et al. 2014; Hong and Lin 2012; Norford et al. 1994) building energy performance. Specifically, previous work has indicated that in commercial office spaces, total energy consumption can be expressed as a combination of a baseline amount of energy consumption and human-driven energy consumption (Taherian et al. 2010). This human element, though important in a commercial building's energy use, is typically difficult to characterize. As a result, recent studies have developed new simulation methods and approaches to model and study occupant behavior in commercial buildings. Azar and Menassa (Azar and Menassa 2012) proposed an agent-based simulation modeling method to study occupants' energy use characteristics as they change over time. Occupant-based models such as these can also be coupled with whole-building energy simulation tools to develop models that building management systems can leverage to address the complex interactions between occupancy and building performance, and ultimately help find opportunities for improved energy efficiency (Menassa et al. 2013).

While providing valuable insight, simulation driven methods and approaches are limited in their ability to leverage new high-fidelity and spatially-granular energy usage data streams in their analysis. Such energy usage data streams could provide deeper insight on human-driven energy consumption at the spatial level of the individual occupant and at sub-hourly temporal intervals. As a result, recent work has begun to leverage these data streams to improve our understanding of energy usage of the built environment (Agarwal et al. 2010; Kazmi et al. 2014; Menzel et al. 2008; Milenkovic and Amft 2013). However, in such data-driven studies the multi-dimensionality of occupant energy usage optimization is not directly addressed. In the following section, we review the three key dimensions of occupant energy usage and classify existing data-driven methods and frameworks in terms of such dimensions to elucidate the primary gap within the current body of work in data-driven occupant energy use analysis.

Dimensions of Occupant Energy Usage

The way in which occupants use energy in commercial buildings can be characterized by three key dimensions: *spatial, temporal,* and *social*. The spatial dimension characterizes where within a building an occupant consumes energy and requires services from building systems. As a result, the spatial dimension is typically considered by building designers and operators by implementing HVAC zoning to improve thermal comfort and, in some cases, energy performance (Smith et al. 2012). Similarly, the temporal dimension characterizes the time of the day in which occupants are present, using energy, and requiring services from building systems (i.e., occupant schedules). From a high level, this is captured through rudimentary occupant schedules that are often built into energy simulations to try and match predicted energy use with actual building energy use (Clevenger and Haymaker 2006; D'Oca and Hong 2015). The social dimension can be characterized by the organizational network dynamics that describe occupant interactions and aspects of occupant behavior in buildings. The impact of the human element is often overlooked due the challenges in modeling occupant behavior, but recent studies have noted that understanding the social dimension has great importance when it comes to minimizing building energy use (Anderson et al. 2014; Gulbinas and Taylor 2014). For example, the inherent social dynamics that describe occupant behavior within a building have been found to have large implications for the effectiveness of energy-use feedback tools that report real-time energy consumption information to occupants (Gulbinas and Taylor 2014). Given the ability to analyze energy use data on a sub-building level using sensors, recent building energy analysis methods and frameworks that recommend efficiency strategies have begun to address these three dimensions, but in many cases only individually. In the following subsections, we briefly discuss current frameworks and classify them in terms of their primary dimension of concern.

Spatial Dimension: One body of work has looked at improving control of building zones in concert with thermal conditions and preferences of occupants. Such work has been found to improve overall indoor thermal comfort and avoid situations where energy is unnecessarily wasted (Jazizadeh et al. 2013; Schoofs et al. 2011). Azar and Menassa (2015) proposed a data-driven framework to analyze occupancy spatially and propose energy saving actions. Additionally, matching occupant preferences with a *decentralized* control strategy has been found to have significant energy saving potential (Jazizadeh et al. 2014). A spatially driven analysis framework has also been developed for lighting and has yielded energy savings on the order of 50% in case studies (Krioukov et al. 2011).

Temporal Dimension: Recently developed frameworks for improving building energy efficiency consider the scheduling of building activities, and the matching of building schedules with occupancy predictions and/or measurements (Lim et al. 2012; Majumdar et al. 2012, 2016). The synchronization of occupancy predictions with optimized scheduling of meetings has been tested as a strategy for reducing energy consumption in office buildings (Majumdar et al. 2012). Moreover, recent work has also aimed to temporally characterize and predict occupant energy usage in order to identify patterns that could be utilized to formulate energy efficiency strategies for a commercial building (Gulbinas et al. 2015; Khosrowpour et al. 2016).

Social Dimension: Modeling occupant behavior has been shown to improve the understanding of building occupants' changing energy use characteristics over time (Azar and Menassa 2012). Beyond individual occupant behavior, the organizational network dynamics that follow from the social structure of the building have been found to play an important role in improving building energy efficiency (Anderson and Lee 2016; Khashe et al. 2016; Manika et al. 2013; Siero et al. 1996). As interventions are proposed for energy-efficiency purposes in office buildings, the social network structure of the occupants has been shown to be critical in determining and predicting the absolute effectiveness of the intervention strategy (Anderson and Lee 2016). Additionally, the formation of human networks in buildings has also been found to be influenced by the form of the office building, drawing a connection between the human and the spatial dimension of occupant behavior (Sailer and McCulloh 2012). Despite the growing evidence regarding the impact the social dimension can have on occupant energy usage and commercial building operations, no frameworks have been proposed to analyze the social dimension individually or in tandem with other dimensions.

Thus, there is significant opportunity to further understand how human dynamics and spatial and temporal variability of occupant energy consumption within a building can lead to the identification of energy saving opportunities. Previous studies have been limited by their scope in analyzing all three dimensions of occupant-driven energy efficiency, and, as a result, they may not yield the insight into the complex dynamics of building energy use necessary to maximize energy savings associated with new occupant driven approaches to energy efficiency. In this paper, we introduce—and test on real data—the Occupant Energy Signal Processing on Graphs ($OESP_G$) framework, a scalable computational framework that is capable of analyzing all three dimensions of occupant-driven energy efficiency in buildings. The framework aims to provide a method for identifying situations in which energy use in the study building is not in synchronization with what would be expected based on the temporal patterns, spatial layout and organizational network structure of the building's occupants, thereby simultaneously addressing the three key dimensions of occupant energy usage in commercial buildings.

METHODOLOGY

Applying the $OESP_G$ framework to building energy use data consists of four main steps: (1) gather data describing the building's spatial layout, social structure, and time-series energy use, (2) construct a graph representing the spatial and organizational structure of the building, (3) analyze building energy use data by representing the data as signals, and (4) characterize the energy use data. In this section, we introduce the framework, highlight the underlying mathematical and graph theory concepts from the literature, and demonstrate the mechanics of the framework using a simulated example. We utilize energy use data at the plug load because it provides a good proxy for changes in occupant behavior (see the Appendix for further information and empirical data).

Discrete Signal Processing on Graphs

The emerging field of signal processing on graphs (Sandryhaila and Moura 2013; Shuman et al. 2013), develops methods of analysis of signals supported by graphs. In particular, the Discrete Signal Processing on Graphs (DSP_G) framework in (Sandryhaila and Moura 2013, 2014) extends concepts from traditional signal processing to data that can be indexed by vertices on graphs. Signals indexed by graphs arise in many situations where data is collected, including measurements from sensor networks (Akyildiz et al. 2002), community preferences (Leicht and Newman 2008), and many others. A central contribution of the current work is to expand and adapt the underlying concepts from DSP_G for the problem of multi-dimensional analyses of building energy use data. As such, our $OESP_G$ framework adopts the adjacency matrix of the graph structure as its main building block and utilizes a graph Fourier transform to expand a signal into a Fourier basis in the graph spectral domain.

Consistent with previous work (Sandryhaila and Moura 2013), we define the relationships between data elements (i.e., occupants) as a graph $G = (\mathcal{V}, \mathbf{A})$, with N occupant nodes, where $\mathcal{V} = \{v_0, \ldots, v_{N-1}\}$ is a set of occupant nodes and **A** is the weighted adjacency matrix of the graph. Each data element is indexed by an occupant node v_n, and each weighting $\mathbf{A}_{n,m}$ of the edge from v_n to v_m describes the directed weighting from the *n*th node to the *m*th node. The distinct eigenvalues $\lambda_0, \ldots, \lambda_N$ of the adjacency matrix **A** are the *graph frequencies* and form the *spectrum* of the graph. The eigenvector corresponding to any graph frequency is the *frequency component* corresponding to that frequency.

For each node, power draw values are continuously collected. The power values are defined for each occupant in the set:

$$\mathbb{P} = \{\mathbf{P}_0, \ldots, \mathbf{P}_{n-1}\} \;\forall\, n \in N \tag{1}$$

where $\mathbb{P}$ is the set of all power vectors ($\mathbf{P}_\mathrm{n}$) for all N occupants and n is the node index. Each occupant's power values are collected in the vectors defined above, and defined as:

$$\mathbf{P}_n = \{p_n^t, \ldots, p_n^T\} \tag{2}$$

where $\mathbf{P}_\mathrm{n}$ is the vector of all power draw values for occupant n, t is the time index, and T is the total number of periods of data collection. It is important to note that when analysis is being conducted in near-real time parameter T will continue to grow as data is collected and more time periods are added to the power draw vector $\mathbf{P}_\mathrm{n}$.

In order to account for variations in typical power draw values for the different occupant workstations, power values are normalized using a running normalization process:

$$\bar{p}_n^t = \frac{p_n^t}{p_n^{t,max}} \tag{3}$$

where $\bar{p}_n^t$ is the normalized power draw value at time t for occupant n, and $p_n^{t,max}$ is defined as:

$$p_n^{t,max} = max(p_n^{t-c}, \ldots, p_n^t) \tag{4}$$

where c is a parameter indicating the number of periods over which the current value is normalized. For example, if $c = 12$, and the time step is chosen to be one hour, the running normalization normalizes each value over the previous 12 hours of data.

Finally, each snapshot of normalized plug load power draw becomes an individual *graph signal*, defined as a map:

$$\bar{p}_n^t(v_n) \mapsto s_n \tag{5}$$

where s_n represents the graph signal coordinate associated with the occupant node v_n. The graph signal can be represented as a vector:

$$\mathbf{s} = [s_0, \ldots, s_N]^T \in \mathbb{R}^N \tag{6}$$

We utilize a Fourier transform to expand the signal into the graph spectral domain. In this initial work, we assume a graph structure with undirected edges, such that $\mathbf{A}_{n,m} = \mathbf{A}_{m,n}$, causing eigendecomposition of $\mathbf{A}$ to be in the real domain. As such, the eigendecomposition is as follows:

$$\mathbf{A} = \mathbf{V}\Lambda\mathbf{V}^{-1} \tag{7}$$

and the graph Fourier transform of the signal s is:

$$\hat{s} = \mathbf{F}s \tag{8}$$

where $\mathbf{F} = \mathbf{V}^{-1}$ is the graph Fourier transform matrix. The values of $\hat{s}_n$ characterize the *frequency content* of the signal s. To analyze the frequency content of the signals in the context of the graph frequencies, we utilize the concept of *total variation on graphs* from DSP_G (Sandryhaila and Moura 2014), which provides a mathematical basis for ordering frequencies. In classical discrete signal processing, the total variation of a discrete signal is defined as the sum of magnitudes of differences between consecutive signal samples. Total variation applied to arbitrary graphs, such as the graph defining occupant relationships, is determined by the eigenvalues of the adjacency matrix $\mathbf{A}$. The total variation of an eigenvector $\mathbf{v}_n$ of a matrix $\mathbf{A}$ is:

$$TV_G(\mathbf{v}_n) = \left|1 - \frac{\lambda_n}{|\lambda_{max}|}\right| \|\mathbf{v}_n\|_1 \tag{9}$$

where $\|\mathbf{v}_n\|_1$ is the L1-norm of the eigenvector $\mathbf{v}_n$. The TV_G value for each normalized proper eigenvector is between 0 and 2. Theoretical analysis of the TV_G concept can be found in (Sandryhaila and Moura 2014).

By sorting frequencies from low to high by their total variation, the variability associated with the differences in weighting between nodes becomes accessible. *If a signal's frequency content is concentrated in the lower frequencies, the variation in the signal's values follows the weighting pattern of the graph, i.e., two nodes with a relatively high weighting between them would have relatively similar expected signal values.* When signals from sensors across a spatial and social domain are expected to have little variability (as would be the case when occupants who are both near each other and part of the same organization are using relatively similar amounts of energy), the graph spectral plot would be expected to have this characteristic shape. However, with more variability across nodes with large edge weightings, the signal would have more of its energy in the higher frequencies. This change in the graph spectral plot could allow for potential flagging of unexpected occupant energy use in a given building or floor plan.

Fig. 1 depicts the overall flow of the OESP_G framework. First, physical locations of occupant workstations as well as the organization or team to which the occupant belongs to are recorded (1). We note that the framework can be utilized for lower spatial resolutions (e.g., groups of desks), but a key strength of the OESP_G framework is its ability to efficiently process high spatial resolution data. This spatial and social information is used to construct a graph that describes the underlying structure of the building (2). The computationally intensive part of the framework is the eigendecomposition of the graph's adjacency matrix (3), which allows the structure of the building's occupant network to be decomposed into characteristic frequencies and characteristic frequency components that describe variability across the graph structure—with higher frequencies indicating localized areas of higher signal variability across the constructed graph. The eigendecomposition results in the graph Fourier transform matrix (4), and using the concept of total variation on graphs (5), the frequency spectrum can be ordered from high to low (6). The eigendecomposition of the adjacency matrix need only be done once, allowing the framework to easily scale to large buildings—and even districts of buildings—with thousands of occupants. Once the graph describing the spatial and organizational layout of occupants in the building has been defined and decomposed, energy use data collected through plug load sensors can be analyzed in the spectral domain. The plug load sensors collect snapshots of power usage at regular intervals, which become the signals in the $OESP_G$ framework (7). The iterative aspects of the framework involve normalizing the data (8-9) and multiplying the normalized signal (10) with the graph Fourier transform matrix to determine the frequency content of the signal (11). This process allows for the creation of the frequency plot (12), which can be analyzed to understand spatial, temporal, and social dynamics of each energy-use signal. As long as data is being collected (13), new signals can be defined and new frequency plots can be created at each period.

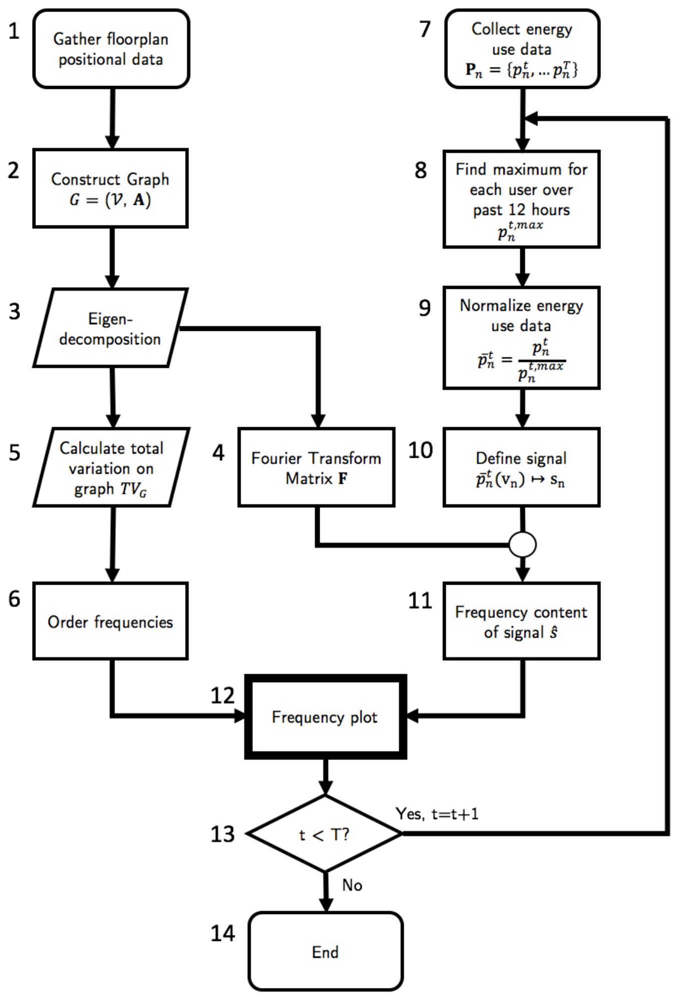


Fig. 1. OESP$_G$ framework flow

SIMULATED EXAMPLE

In this subsection, we present a simple simulated example to elucidate the core concepts of OESP$_G$ and demonstrate its applicability to identifying potential anomalies in energy use across the floorplan of a building.

Data Simulation

The floorplan, social network structure, and energy use data are all simulated in this example. The relative locations of the simulated plug load sensors are shown in Fig. 2. Eight sensors are used, with three clusters of individuals. The two corner clusters each contain three individuals sitting near each other, with each of the two clusters belonging to a different organization. The cluster of circles on the bottom left of the figure is organization 1 (blue circles), and the cluster of squares on the top right is organization 2 (red squares). The third cluster of two individuals, located directly in between the two corner clusters, contains one individual from each organization.

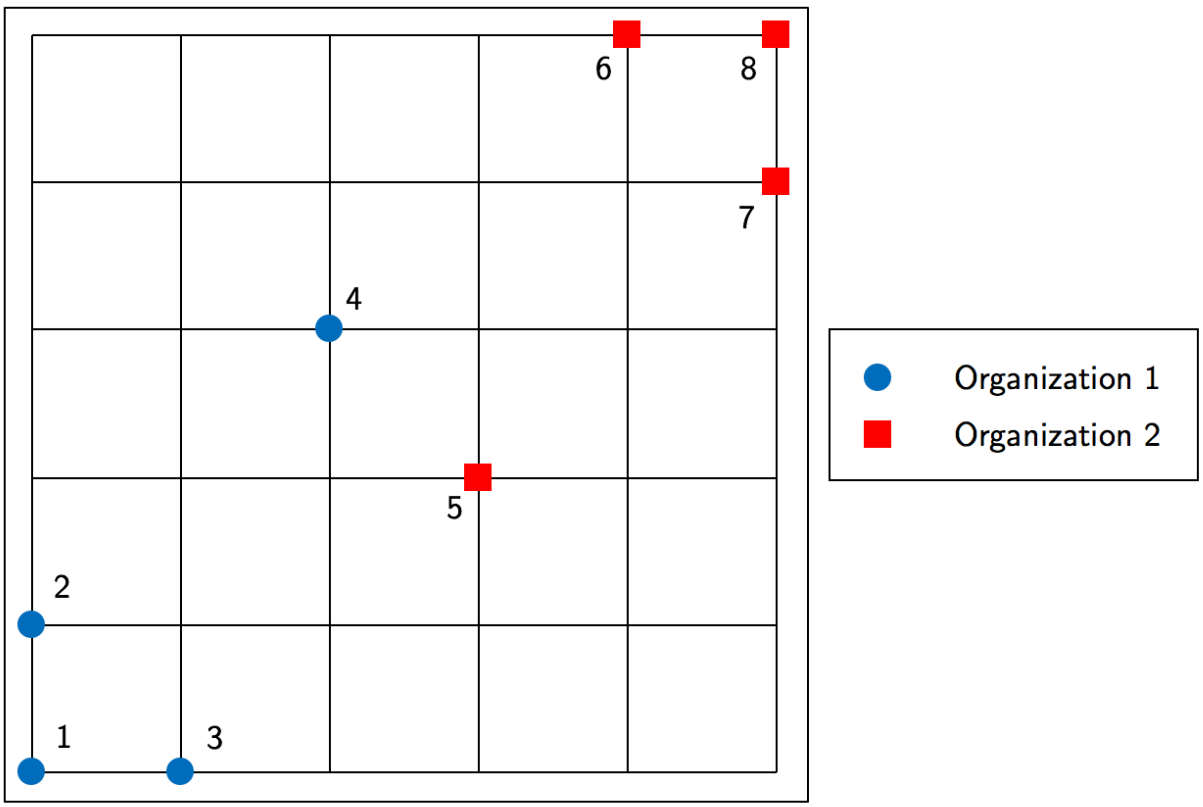


Fig. 2. Simulated floor plan with plug load sensors in three spatial clusters and two organizations (circles and squares)

Energy use data streams for each sensor provide a snapshot of power usage for the sensor at 20 minute intervals. The simulated sensors capture data for simulated occupant workstations that can be in one of three states: working, on break, or not present. Values for these states are derived from a study by Lawrence Berkeley National Lab on representative power draw from commonly used office desk equipment. The purpose of assigning typical real power draw values to occupant states is to simplify the simulated example for illustrative purposes. The "not present" state is assigned to 2W of power draw (roughly corresponding to a laptop and monitor in off mode), the "on break" state is assigned to 10W of power draw (roughly corresponding to a computer display and laptop in sleep mode), and the "present state" is assigned to 50W of power draw (roughly corresponding to a laptop and monitor in awake mode) (Lawrence Berkeley National Laboratory 2016). The standard work schedule is chosen as 9am-5pm, with an hour lunch break at 12pm. Variations on this schedule are used to test how spatial, temporal, and social variations in occupant energy use can be captured using the proposed framework.

Graph Construction

Using the simulated locations of sensors on a floorplan as the basis for a graph, the adjacency matrix can be calculated. The graph is constructed as an undirected weighted graph wherein each node is connected to all other nodes. Edge weightings are calculated through two components: (1) the Gaussian weighting function capturing the physical distances between sensor locations, and (2) a binary function capturing the organizational identity of the sensor and its associated occupant. For two nodes n and m, the graph weighting is found as

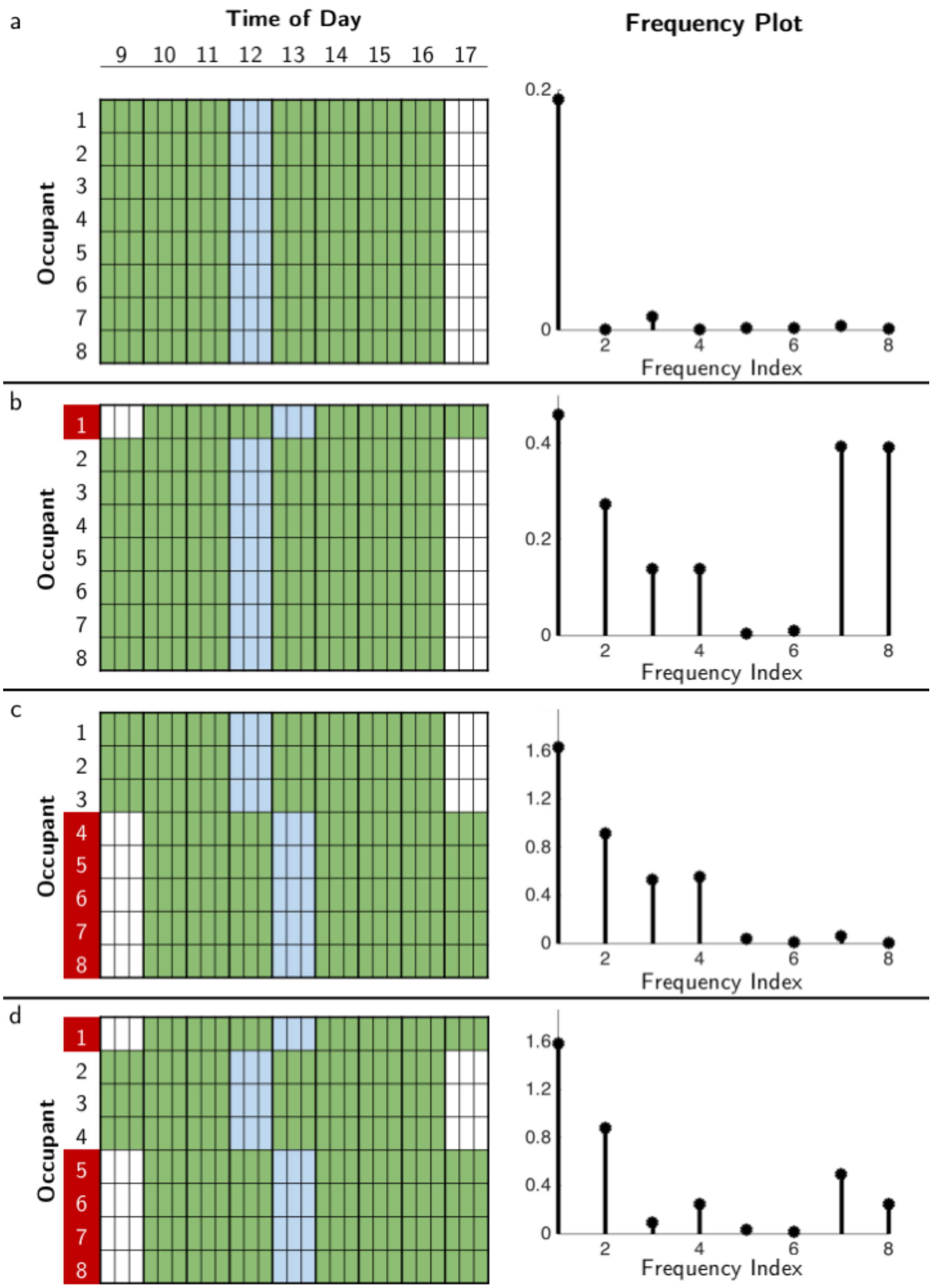
$$\mathbf{A}_{n.m} = \mathbf{A}_{m.n} = e^{-\frac{d_{n,m}^2}{2\sigma^2}} + \alpha f_s(n,m) \tag{10}$$

where $d_{n,m}$ is the Euclidean distance between the nodes, the Gaussian standard deviation σ is a user defined parameter that controls the width of the distribution (for the purpose of this example, we assume the standard $\sigma = 1$), and the function $f_s(n,m)$ describes the social network relationship between the two nodes, with $f_s(n,m)$ taking a value of 1 if the two occupants are in the same organization, and 0 if the two occupants are not in the same organization. In this example, therefore, the social structure is modeled directly after each occupant's organizational identity, but we note that other relationships, including those at the sub-organization level, can be utilized to build the social component of the edge weightings. Additionally, the social dimensions could include other relationships beyond institutional identity, such as networks of friends or social groups. However, for this analysis, the social dimension is limited to organizational identities. The weighting α weights the importance of the social dimension of the graph structure, with a higher value indicating that the social dynamics are expected to be of higher importance. For our example, we assign α to be equal to 1 indicating that social dynamics are of the same importance as spatial dynamics.

The spatial component of the graph construction gives a larger weighting to edges connecting nodes that represent sensors physically near each other, and smaller weighting to edges connecting nodes that represent sensors far away from each other. The intuition behind this notion of edge weighting comes from the expectation that individuals sitting near each other are more likely to have similar energy use and occupancy patterns compared with individuals sitting far apart from each other. Additionally, the social component of the graph construction gives larger weighting to edges connecting nodes that are part of the same organization, following the intuition that people of the same network would be expected to have relatively similar energy use and occupancy patterns.

Analysis

Given the eigendecomposition of the adjacency matrix, as found in eq. (7), each energy use signal can be expanded into the graph spectral domain, following the OESP_{Gs} framework process described above. Fig. 3 shows the graph spectral plot for each of four possible schedules in the simulated building. In the schedules shown in the figure, dark green is associated with the *working* state, light blue with the *on break* state, and white with the *not present* state. The graph spectral plots to the right of the schedules show the frequency content for the 12pm signal. This signal is chosen because the simulated schedule shifts have impacts on which occupants are on break and which are at their desk at 12pm. Fig. 3a is the baseline scenario in which each occupant in the simulated building has the same schedule: start work at 9am, take a break from 12pm to 1pm, and leave at 5pm. Fig. 3b-d represents scenarios in which shifts by one or more individuals are made according to the associated schedule. The spectral analysis for each scenario indicates that the change in schedule has impacts on signal frequency content. A sensitivity analysis on the parameters introduced in eq. (10) shows that varying either σ or α has little effect on the frequency plots. In the sensitivity analysis, we allowed σ and α to change by multiplying or dividing by 2, and in all cases, we observed the same overall trends as shown in Fig. 3, in which $\sigma = 1$ and $\alpha = 1$. After the running the sensitivity analysis on scenario (d), the maximum change for the lowest frequency was 0.7% and the maximum change for two highly expressed high frequencies (indexed 7 and 8) was 12%.



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341 *Fig. 3. Schedules and graph spectral plots for simulated example*

Simulated Example: Results and Discussion

When all eight simulated plug load sensors follow the same schedule, the graph spectral plot indicates that the analyzed signal's frequency content is concentrated in the lowest frequencies, as shown in Fig. 3a. When one individual shifts his or her schedule, as tested in Fig. 3b, the graph spectral plot shows an increase in signal energy in the higher frequencies. This increase in high frequency energy is caused by the now-incongruous energy use patterns between the shifted individual (occupant 1) and the two non-shifted individuals in the same cluster who are closely related to occupant 1 both spatially and socially (occupants 2 and 3).

Fig. 3c and Fig. 3d show two examples in which all of organization 2 shifts along with one member from organization 1. Occupants 5-8, who comprise all of organization 2, all shift their schedule by one hour in both scenarios. When occupant 4 shifts with them, the graph frequency plot shows increased power in the middle frequencies. When occupant 1 shifts with them, the graph frequency plot shows increased power in the higher frequencies. This result makes sense given that occupant 4, while engaging in behavior different from the rest of his or her organization, is both more spatially related to organization 2 and less spatially related to organization 1 than is occupant 1. When occupant 1 shifts, the result is similar to that from the situation depicted in Fig. 3b. If we are interested in detecting situations that could lead to recommendations for more efficient building management, this analysis can provide insight into subtleties associated with complex occupant behavior. The situations in (c) and (d) seem very similar, yet it becomes clear from this analysis that the spatial incongruity in (d) would make it impossible to implement energy-saving strategies such as reduced HVAC service to a zone encapsulating the cluster of occupants 1, 2, and 3.

A single detection of this incongruity could lead to recommendations for schedule shifts that more closely align spatially-related individuals of the same organization or across organizations, allowing for potential energy savings. Repeated detections could also lead to recommendations for spatial adjustment of occupants, which could also lead to potential energy savings. This simulated example illustrates the ability of the $OESP_G$ framework to identify incongruities along the three dimensions of occupant energy use that it analyzes, by detecting large values for the higher frequencies in the frequency plot. The example highlights the power of the framework in terms of detecting situations in which recommendations for energy efficiency strategies could make a real impact on a building's performance.

CASE STUDY: OFFICE BUILDING IN DENVER, CO

In this section, we apply the $OESP_G$ framework to analyze real data and formulate strategic recommendations for energy efficient operations of a case study office building in Denver, CO.

Data Collection and Normalization

Data was collected using off-the-shelf plug load monitors (i.e. Monster Cable 300MC PowerControl unit) installed at individual desks throughout two floors of an existing and occupied 6-story office (40,000 ft2) test-bed building in Denver, CO. In this building, employees were typically present between 9:00 a.m. and 5:00 p.m. from Monday to Friday. Workstations most often included computers, monitors, space heaters, and electronics chargers, and these appliances were connected to the plug load monitor through a power strip. The Monster Cable 300MC plug load monitors connected to standard North American 120 V outlets and communicated information to the included Monster Cable edge-router (GTW 100) that uploaded data to a database via an Ethernet based internet connection. Real time power draw (W) was collected at 20-minute intervals. More information regarding the Monster Cable 300MC plug load monitoring equipment specifications and test-bed building set-up can be found in Gulbinas and Taylor (2014) and on manufacturer's retail website ("Amazon.com" 2016). Within the two floors of the building, data was collected for a total of 27 individuals' workstations in 5 separate organizations. The physical location of each sensor as well as the organizational association of each individual was recorded to indicate the spatial and social attributes associated with each workstation; these attributes are shown in Fig. 4. The color of the sensor on the test-bed building floorplan refers to the organizational identity of the occupant associated with the sensor, with each color representing one organization.

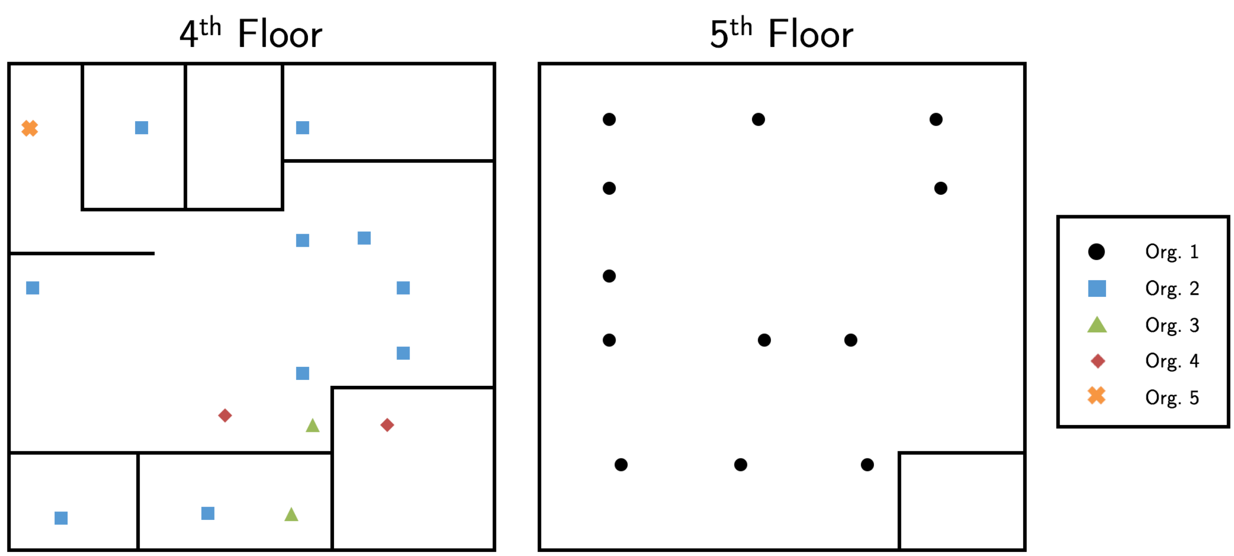

Fig. 4. Workstation locations superimposed on building floorplans

We captured power use at 20 minute intervals for each workstation in the study. Typical values for power use ranged from 50W to 200W for the workstation, depending on the appliances plugged into the power strip. To account for this range in absolute values of power draw, we normalized each workstation's power use over the previous 12 hours of data collection, as described in the Methodology section. This method allowed for comparisons among individuals' relative energy use behavior over the course of a single work day.

Case Study: Results and Discussion

By applying the $OESP_G$ framework to this data, we were able to analyze the variability in energy use behavior in terms of spatial layout and social network structure across the floor plans of the building. Both physical distances and organizational affiliations were used to construct the adjacency matrix, following eq. (6) above. Spikes in frequency content for high frequencies are of interest because they indicate instances of high variability, i.e., points in time in which individuals are not drawing power as one would expect. These expectations are embedded in the graph construction. We would expect occupants with similar spatial characteristics (i.e., those sitting close to one another) to have similar energy use patterns, and similarly, we would expect occupants with similar social characteristics (i.e., those that are part of the same organization) to have similar energy use patterns. In general, occupants with similar characteristics have higher edge weightings between them. When similar occupants have distinctly different energy use patterns, their energy use behavior can be considered *out-of-sync* with expectations.

Using this framework, we can apply a threshold to the higher frequencies. When the frequency contents of the higher frequencies cross the threshold, occupant energy use behavior is deemed *out-of-sync*. For the purposes of this case study, we utilize simple heuristics from previous work (Sandryhaila and Moura 2014) to indicate the high frequencies of interest to be the half at the top of the spectrum (14-27 in this application) and the frequency content threshold to be 1 on the y-axis. Using this simple threshold, certain *out-of-sync* signals can be detected and analyzed. Both Fig. 5a and 5b show the frequency plot of each signal over the course of a full workday in gray, as well as one signal that is detected as *out-of-sync*. In Fig. 5a, the detected signal, in red, occurs at 2:40pm, and in Fig. 5b, the detected signal, in blue, occurs at 3:00pm.

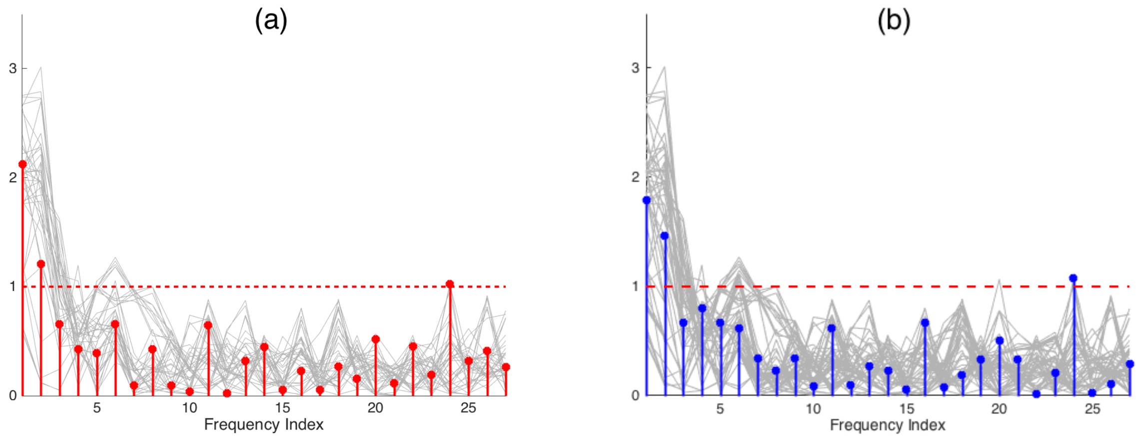

Fig. 5. Frequency plots for one representative workday, with detected signals: (a) 2:40 p.m.; (b) 3:00 p.m.

In this particular example, two signals are detected, one right after the other. The first occurs at 2:40pm on the analyzed workday, and the second occurs at 3:00pm on the analyzed workday. Since the signals are captured at 20 minute intervals, this detection could indicate that 40 minutes of the workday are in the *out-of-sync* condition. The high frequency that caused these detections is the 24th, as can be seen in Fig. 5a and 5b. To understand the cause of the *out-of-sync* condition as detected in this analysis, the eigenvector associated with the 24th eigenvalue—as ordered by the total variation—can be plotted and its components can be analyzed (Fig. 6). Analyzing this eigenvector provides insight into which nodes are responsible for the signal detection (Deri and Moura 2015). The figure shows that nodes 5, 6, 7, and 8—nodes that are both close to one another and part of the same organization—are most highly expressed in this 24th frequency. With a relatively high amount of power in this high frequency, it would be expected that the highly expressed nodes in the corresponding eigenvector would exhibit incongruous power draw behavior. In this example, the power values at nodes 5-8 describe a situation in which power values for nodes 5 and 8 rapidly become small compared to recent patterns, while power values for nodes 6 and 7 are near the maximum amount of power drawn recently. Specifically, at both detected signals, occupants 6 and 7 are both drawing more than 80% of their individual maximums (as iteratively measured over the previous 12 hours), while occupants 5 and 8 are both drawing 0% of their individual maximums (as iteratively measured over the previous 12 hours). This data is summarized in more detail in Table 1.

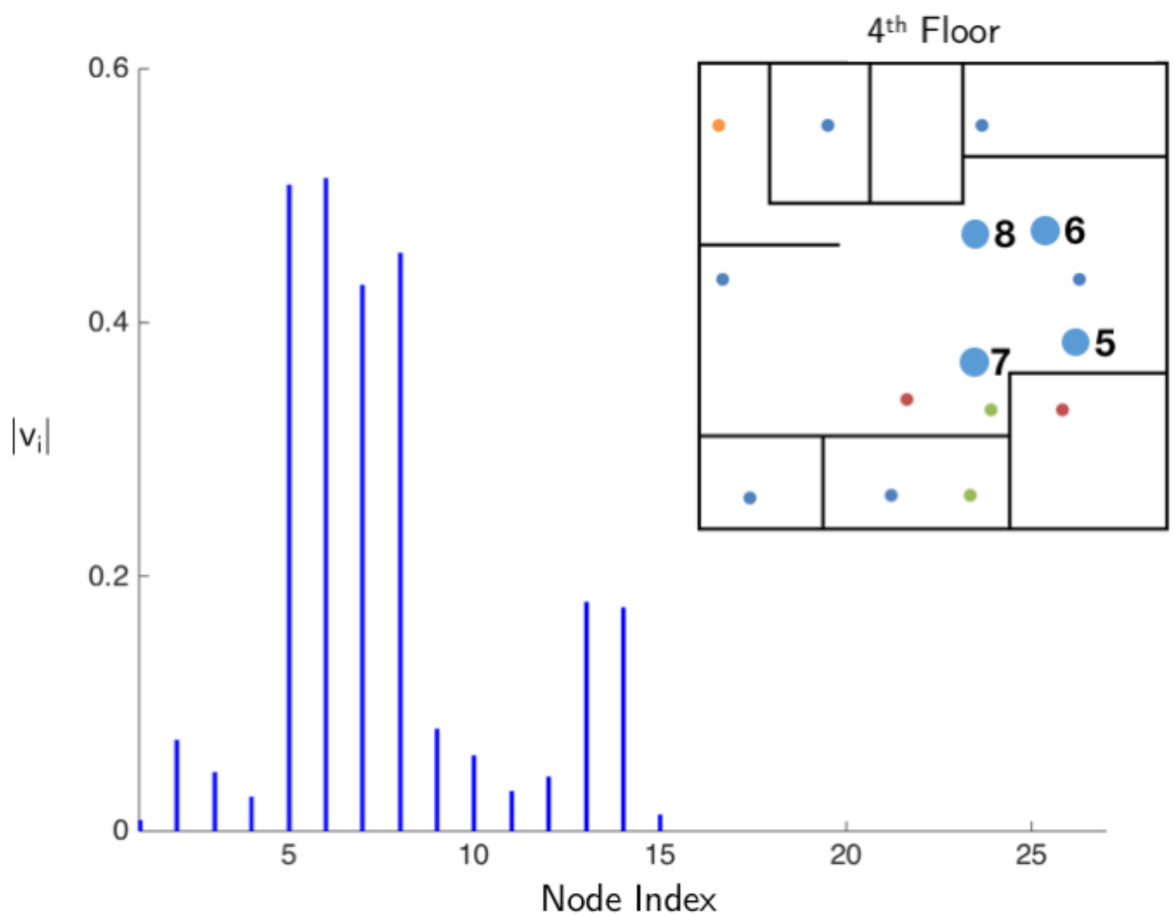

Fig. 6. Components ($|v_i|$) of the eigenvector of the 24th frequency of the plot in Fig. 5 (detected as out of sync)

Table 1: Summary of power draw values for out-of-sync *signals*

Occupant Node	Normalized power draw, 2:40pm (fraction of maximum)	Normalized power draw, 3:00pm (fraction of maximum)	Mean normalized power draw over full day (fraction of maximum)
5	0	0	0.22
6	0.87	1.00	0.39
7	0.87	0.87	0.40
8	0	0	0.25

Energy efficiency recommendation strategy

Using power values as a proxy for occupant behavior, we can draw the conclusion that the two groups of two individuals are following different schedules, resulting in a situation in which building energy use for things like lighting and thermal comfort might not be as efficient as possible. If a recommendation can be made such that all four occupants follow the same schedule for the day, the signals that were once detected are no longer detected (Fig. 7). The figure shows much lower energy exhibited by the 24th frequency for the same signals that caused the energy in the 24th frequency to exceed the learned threshold we had set. By making a schedule-shifting recommendation for the occupants so that all occupants within a zone of the building follow the same schedule over the course of a day, we are able to show that the high frequencies in our framework are sensitive to recommendations that more closely align individuals who are expected to engage in similar behaviors.

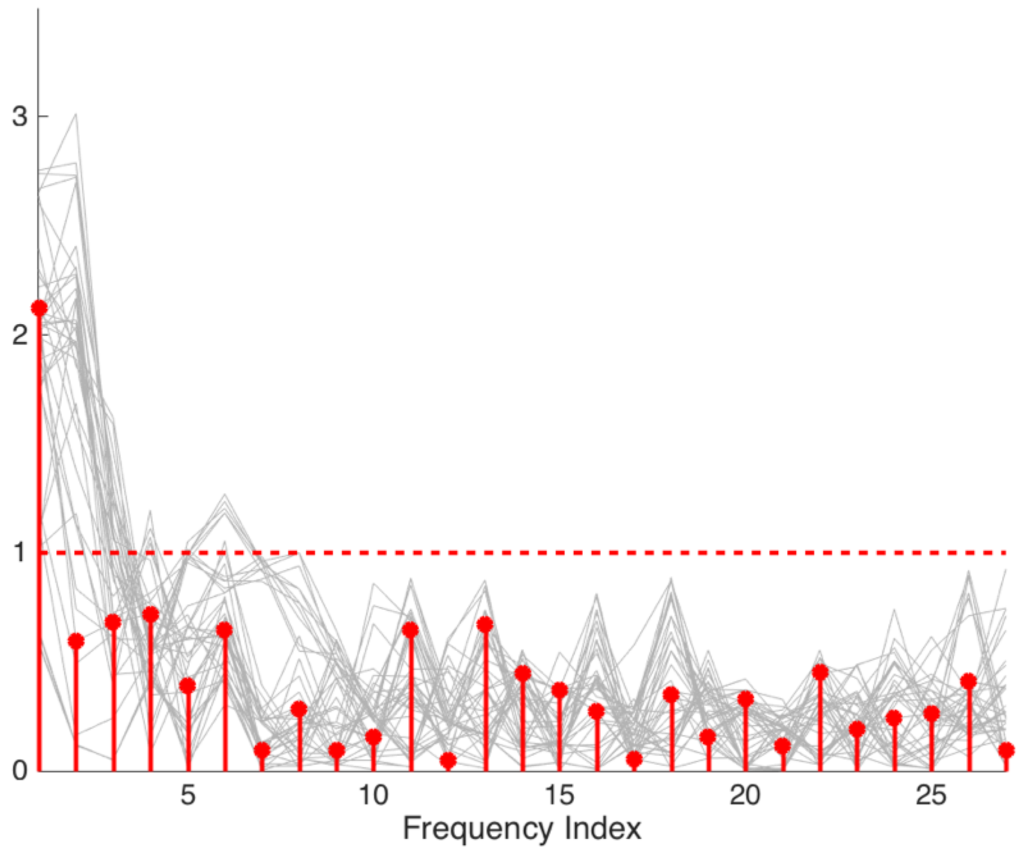

Fig. 7. Frequency plot for one workday after schedule recommendations

In this particular example, the power of the framework is in recognizing points in a workday in which nuanced behavioral dynamics of closely related individuals (by space and social network) are less aligned than would be expected. When situations like these are detected, there exist opportunities to align schedules and take advantage of granular building system controls. Distributed and highly controllable building systems will operate most effectively when complex occupant behavioral dynamics are best understood. This framework introduces a methodology for understanding how occupants use a building and how that behavior differs from our expectations, in terms of spatial and organizational correlations. Using this understanding to improve distributed and precise building controls could lead to large potential energy savings.

One important advantage of the $OESP_G$ framework is its scalability. Very large buildings with many groups of individuals, many floors, and many occupants can be analyzed quickly after the initial work of defining adjacencies and determining frequencies through the Fourier analysis. Signals with relatively high energies in the high frequencies—and the nodes responsible for this result—can be identified in real time for quick recommendations.

LIMITATIONS AND FUTURE WORK

The main limitations for this initial study of the novel $OESP_G$ framework include parameter fitting and recommendation strategies. When assigning the edge weightings that comprise the adjacency matrix, we used typical values to simplify the analysis. Future work should consider a methodology for finding the best weighting scheme for both the Gaussian distance weighting and the organizational weighting. We also note the potential limitation of combining the spatial and organizational components of the building's organizational structure into one weighting. While separating these factors would mean sacrificing the ability of the framework to analyze all three dimensions simultaneously, a focused spatial or social analysis might provide additional insight. Additionally, there is potential for future work to investigate the threshold that is applied to the higher frequencies in order to determine the *out-of-sync* condition. While our method is consistent with heuristics from previous work in DSP_G, further understanding of appropriate thresholding for the domain specific area of occupant analysis could further improve the efficacy of occupant analysis frameworks like $OESP_G$.

One other area of future work could involve improving the signal input vector by constructing a composite signal based on numerous other data sources in addition to plug load monitors. Other data collection devices, such as occupancy sensors, could add information beyond what is available from collecting only energy consumption data. While these data streams could provide additional information valuable in the analysis of occupant dynamics, they may introduce additional uncertainties and challenges in regards to scalability, reliability and fusion of disparate data streams. Therefore, we leave the development of such a composite signal for future work.

There is also potential for future work that considers how best to make recommendations for occupant schedule and spatial shifts in order to both reduce high frequency energy and to ultimately improve building energy performance. This work could include algorithms for building systems, building management practices, and occupant feedback tools. Robust recommendation strategies would create a link between the identification of potentially problematic occupant behavior (what our framework accomplishes) and better building energy performance. Future studies might also consider a scope beyond that of energy use in a single building envelope. As more districts and cities begin collecting live energy use for buildings, the inherent scalability of the $OESP_G$ framework allows for a much larger scale of analysis. An additional flexibility of the framework is that its signal need not be limited to power or energy. Future work might look at other sustainability indicators, such as pedestrian or automobile traffic flows.

One exciting potential area of research that builds off this framework is the inverse problem considered in this paper. That is, given the spatial layout of occupants and a dataset describing their energy use behavior, could the inherent social structure of the building be inferred by minimizing the energy in the high frequencies of the signals' frequency plots over time? Such an analysis would provide valuable insight into how social networks form within a building given organizational identity, spatial configuration, and energy use. This insight would be valuable for the design of new buildings that aim to maximize occupant interaction and minimize energy usage.

CONCLUSIONS

The primary purpose of this paper was to introduce and test the $OESP_G$ framework, a data framework grounded in the emerging area of signal processing on graphs and capable of analyzing occupant behavior in three core dimensions: *spatial, temporal,* and *social.* Extending previous data-driven occupant based analysis frameworks (Azar and Menassa 2015; Gulbinas et al. 2015), a major contribution of the $OESP_G$ framework is its ability to simultaneously analyze data across the three key dimensions of occupant energy use within a commercial building. By using the physical locations and organizational or team identity of individuals and their workstations, we define a graph with edges between nodes that are weighted based on these spatial and social dimensions. Using power draw signals from the occupant workstations, the $OESP_G$ framework analyzes the variability of the signal across the constructed graph, identifying in real time situations in which occupants behave differently from other occupants closely related by space and social structure. These incongruities are detected as spikes in the high frequencies of the frequency plot, which indicate high variability across one or more dimensions. In both a simulated and real case study example, we demonstrate how our $OESP_G$ framework can be utilized to provide insight into which occupants are responsible for this high variability across the graph, and, using this information, can yield simple recommendations to more closely align individuals and enable more energy efficient operations of building systems.

In addition to addressing the multi-dimensionality problem associated with commercial building energy data, the $OESP_G$ framework was designed to be scalable to very large buildings with thousands of occupants. The underlying graph structure and computational efficiency of the single eigendecomposition lends itself efficient to the real time analysis of large commercial buildings with thousands of occupants and even multiple buildings. As a result, the proposed OESP_G framework is a building block for more efficient data-driven management of building systems, better recommendations for occupant behavior, and even better design of building layouts for improved energy efficiency.

By utilizing new energy use data streams, a deeper understanding of the complexity of interactions among the various dimensions of occupant energy use in buildings has the potential to yield significant energy savings in commercial buildings and enhance occupant comfort of spaces. Given the large role of buildings in the energy use landscape, data-driven efficiency strategies for commercial buildings will prove to be invaluable in addressing modern day environmental crises and meeting our sustainability goals.

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APPENDIX: EMPIRICAL PLUG LOAD DATA AND OCCUPANT BEHAVIOR

This Appendix validates the notion that variations in typical office behaviors can have a substantial impact on metered plug load power draw. We utilized a HOBO Onset plug load logger to capture power draw at 20-minute intervals (the same interval as the plug load monitor used in this study) for a typical office set up, including a laptop charger, monitor, and coffee maker. Notes were kept during the 24-hour data collection period, to understand how recorded behavior correlated with power draw variations. Fig A-1 summarizes the findings. It clearly indicates how activities such as leaving the desk for a meeting or class can lead to highly noticeable changes in power draw at the workstation. The $OESP_G$ framework introduced in this manuscript leverages these changes in its analysis.

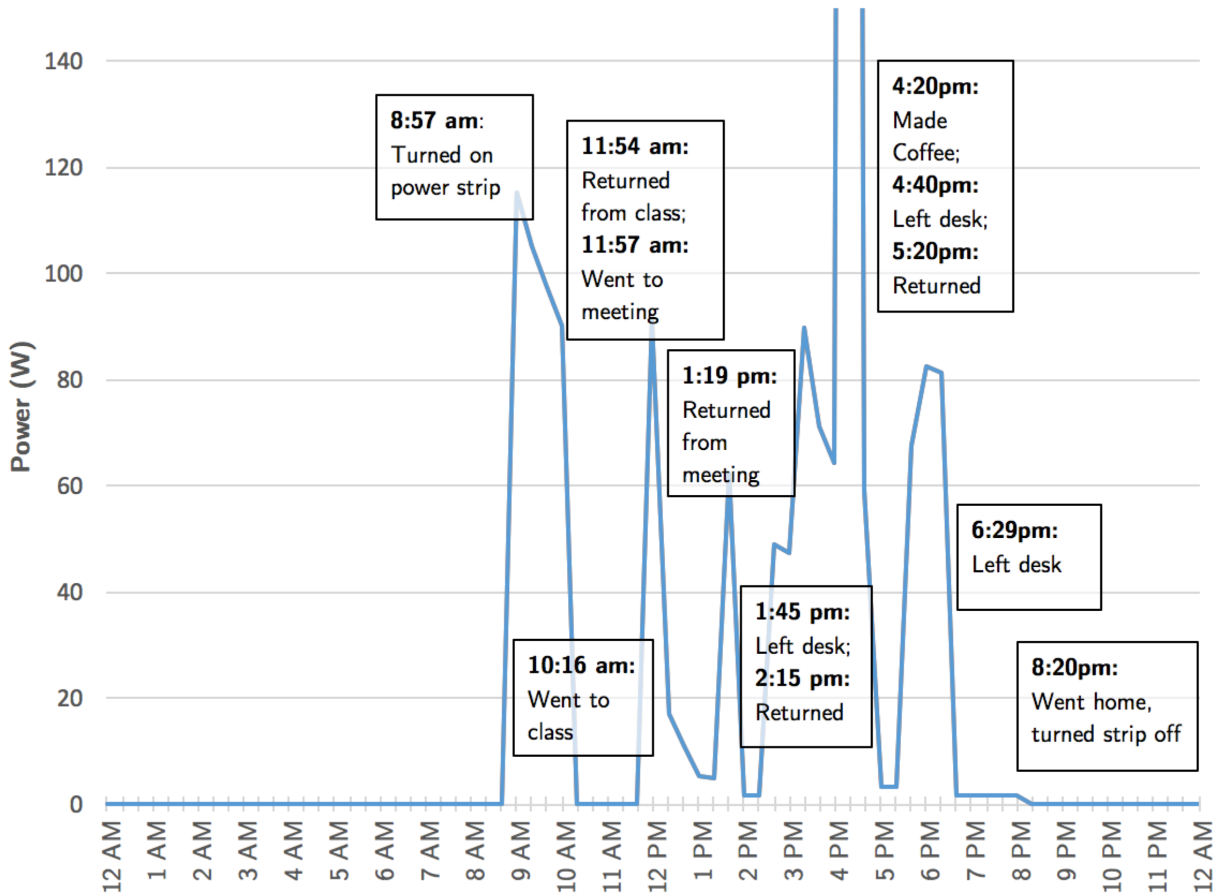

Fig. 8. Empirical plug load power data

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