CIFE CENTER FOR INTEGRATED FACILITY ENGINEERING

Improving Facility Performance Prediction by Formalizing an Activity-Space-Performance Model

By

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Abstract:

The design, construction, and operation of high-performing facilities depends on the ability of planners and designers to predict the future performance of a facility with reasonable accuracy and granularity, and tailor the performance to support the facility users' business and operational requirements and activities. However, today's design and engineering methods are not able to predict, document and communicate the performance of facilities with sufficient accuracy and granularity to allow the users to select the building design that works best for them. Thus, we developed a logical framework that enables planners and designers to connect users, their activities, and spaces to generate activity-space pairs. We then formalized the relationships between activity-space pairs and two performance metrics (i.e., space utilization and energy consumption) to provide space-level prediction of these metrics. Our model provides the rationale for tailoring functional performance by providing information of activity-space pairs and by shedding light on who this information affects other performance, such as space utilization and energy consumption.

Keywords: User activity; Space; Performance; Space-use analysis; Energy consumption analysis;

1. Introduction

Improving the methods of predicting the performance of a complex system, such as a facility where a mix of technical systems and user activities shapes the performance, depends on appropriate models to represent the design choices and analyze the performance impacts of these choices. Since a facility's performance depends on the performance of its technical systems in connection with the users' and operator's activities, a model that differentiates between the product, organization, and process aspects of a facility is needed. Such models exist for the prediction of a facility's first monetary cost (Staub-French et al. 2003), but they do not exist for the use phase of a facility.

Therefore, we represented users' activities, spaces, and performance and formalized the relationships among them, in a model called the Activity-Space-Performance (ASP) model, to help planners and designers better predict, document, and communicate the performance of facilities throughout the lifecycle of a facility. By allocating user activities in their spaces, planners and designers would be able to predict, document, and communicate the performance of a facility in a level of granularity that is suitable for providing feedback to the design and operation choices, i.e., at the space level (Figure 1). As more data about the users and their activities in facility spaces becomes available (e.g., through installing and collecting sensor data), our ASP model would be able to use those data to calibrate itself.

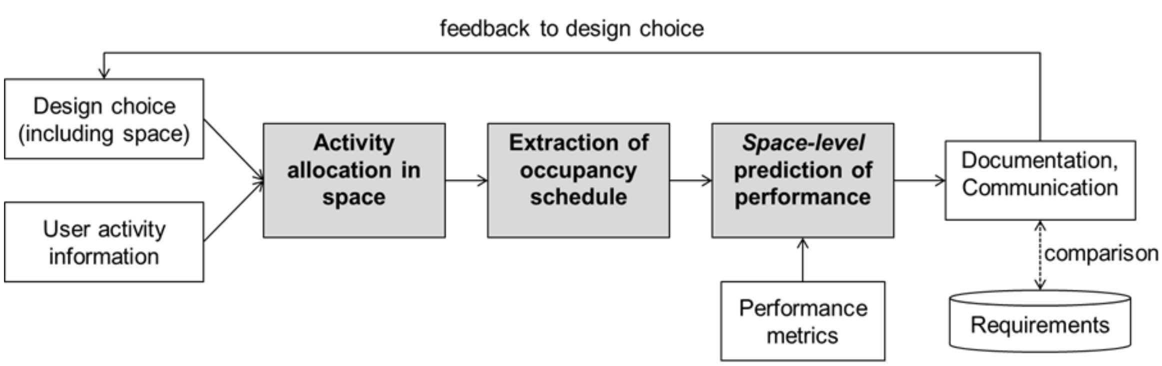

Figure 1. Vision of the research: formalizing activity-space-performance relationships to increase accuracy and granularity of performance analysis.

Although many research efforts integrate user activities and spaces to generate occupancy schedules (Ioannidis et al. 2012; Pennanen 2004; V. Tabak 2008), they do not automatically generate activity-space pairs in support of automated performance analysis methods. Therefore, in this paper, we first developed a logical framework that enables planners and designers to connect users, their activities, and spaces to generate activity-space pairs. We then formalized the relationships between activity-space pairs and two performance metrics (i.e., space utilization and energy consumption) to provide space-level prediction of these metrics. Our research contributes to the broad CIFE vision of VDC and the specific focus of 2011-12 Seed Fund, sustainability, by representing user activity models and integrating them with facility performance to help realize a facility of better functionality with less space and less energy consumption, i.e., more sustainable facility. Building less space with higher performance contributes to sustainable design and construction because most of the life cycle primary energy of a facility is consumed during its use phase, e.g., by HVAC and electricity, in proportion to the area of the facility (Scheuer 2003). However, having less space without a clear rationale can diminish the functional performance of a facility. The dysfunctionality of the facility then directly and continuously makes users struggle to perform their activities (Vischer 2007; Vischer 2008). In this context, our ASP model provides the rationale for tailoring functional performance by providing information of activity-space pairs and by shedding light on who this information affects other performance, such as space utilization and energy consumption.

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2. Motivating case

The ASP model can make a difference in current practices of both space-use analysis and energy consumption analysis by allowing planners and designers to understand the space and energy use from different perspectives, e.g., per user and per activity-hour. Furthermore, by explaining the relationships between activities, spaces, and performance of the facility, the ASP model allows planners and designers to easily and rapidly capture changes in users (having different user profiles) or different user activities (having a mix of activities) and perform the analyses to understand the impact of those changes on the space allocation and energy consumption of the facility. This section first shows how the current space-use analysis can be improved by the ASP model.

During facility planning, planners should ask and seek to answer various space-use questions. These questions vary from simple questions such as ‘how many students eat lunch?’ to rather complex questions such as ‘how good is the healthcare service given a set of spaces?’ When developing a space program, planners repetitively ask and answer these questions to speculate about the requirements for space-use and develop the space program to fulfill the requirements. Planners also try to answer these questions to assess the suitability of existing spaces or space program when a given user or user activity information changes. However, current practice of space-use analysis does not provide answers to these questions because it does not explicitly model user activity and integrate it with other required information such as space and performance.

For example, Kim and Fischer (2011) describe the planning practice of a publishing company building project. In 2010, a publishing company consulted with an architect (planner) because the company wanted to build a new building to provide more space for employees and to provide the president with a gallery space for her paintings. Although the company had built its own building before, it had abandoned the building because of functional inconvenience. Therefore, the company tried to develop the space program very carefully for the new building. At the first meeting, they determined the target gross area (660 m2) in accordance with the company’s financial plan and identified the needs for various spaces including storage for books, a gallery, and a commemorative room for successive presidents of the company. The planner converted the needs to space requirements using his architectural knowledge. When he was uncertain about the size of a space, he used test drawings to define the size. Figure 2 illustrates the current practice of space programming.

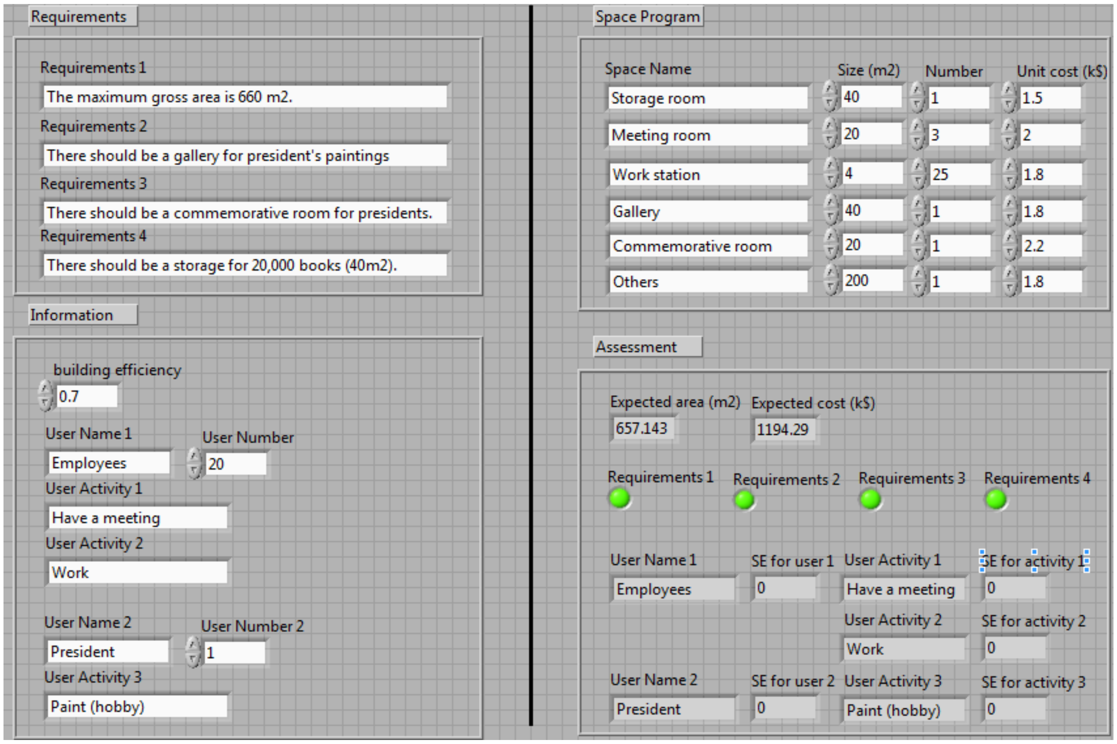

Figure 2. Space programming for a publishing company example. Considering user information and space requirements, a planner develops a space program that satisfies the requirements. Green lamps mean that all requirements in this example are fulfilled by the space program.

During facility planning, the company wanted to increase the size of the storage room to hold an additional 10,000 books (from 20,000 to 30,000 books). However, because the project had already exceeded the budget, in order to increase the size of the storage, the company had to reduce the size of other spaces (Figure 3). Multiple options were discussed to evaluate this trade-off, including reducing the gallery area and work station area. Therefore, the planner had to answer following questions including space (e.g., gallery and meeting room) and user activity (e.g., meeting):

- “How many meetings of employees happen daily in average?”
- “How long is the meeting in average?”
- “Which user activities are affected when reducing the size of the gallery area? And how?”
- “Which user activities are affected when reducing the number of meeting rooms? And how?”

However, without any analytic tool for answering these questions, the impact of the options could not be adequately assessed and compared. With great hesitation, the company eventually decided to reduce the number of meeting rooms (from 3 to 2) without clear understanding of the impact of the decision on the space-use.

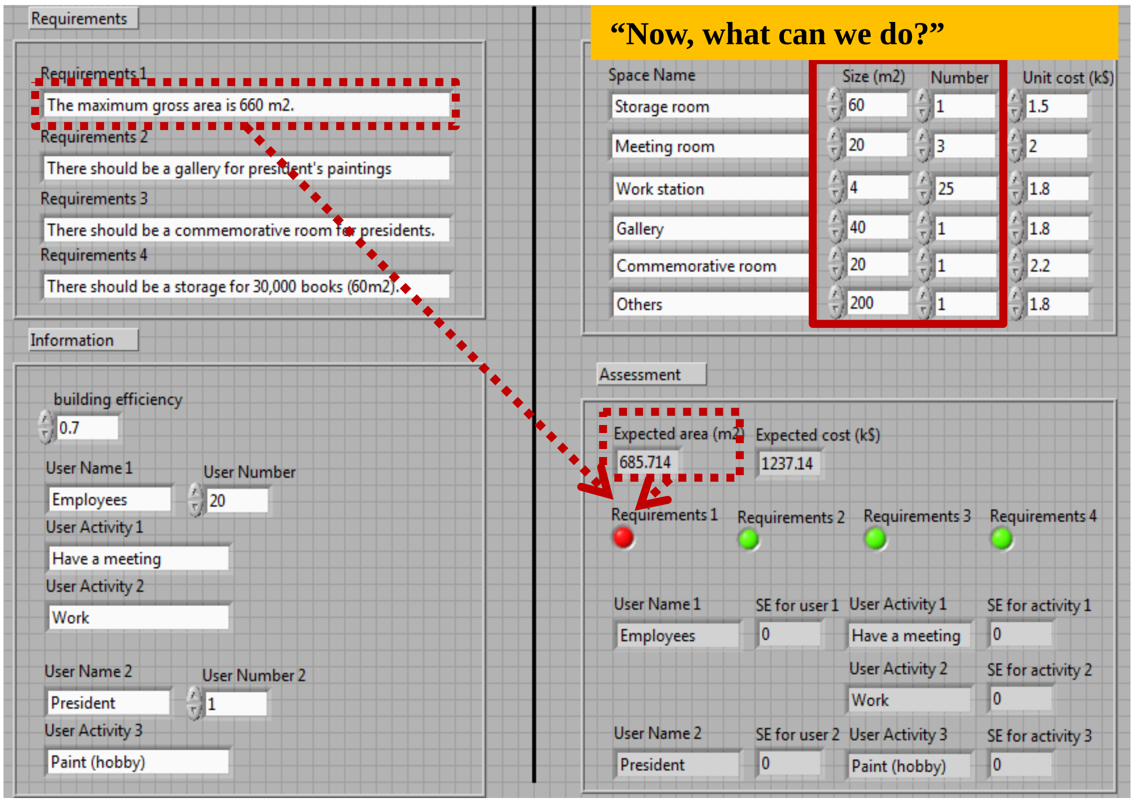

Figure 3. Challenges in space-use analysis. The planner had difficulty understanding the change in space-use when making a decision about a space program to satisfy the requirement of the maximum gross area.

The ASP model must address these problems because it represents activity, space, and performance models and formalizes their relationships. In this example, when the number of meeting rooms is reduced, the ASP model must be able to automatically find all activities that are related with the space 'meeting room' and to predict the impact of the change using space-use metrics of the performance model (Figure 4). Consequently, planners must be able to easily and rapidly answer various space-use questions whenever they acquire new information on user activities or whenever they change their space program.

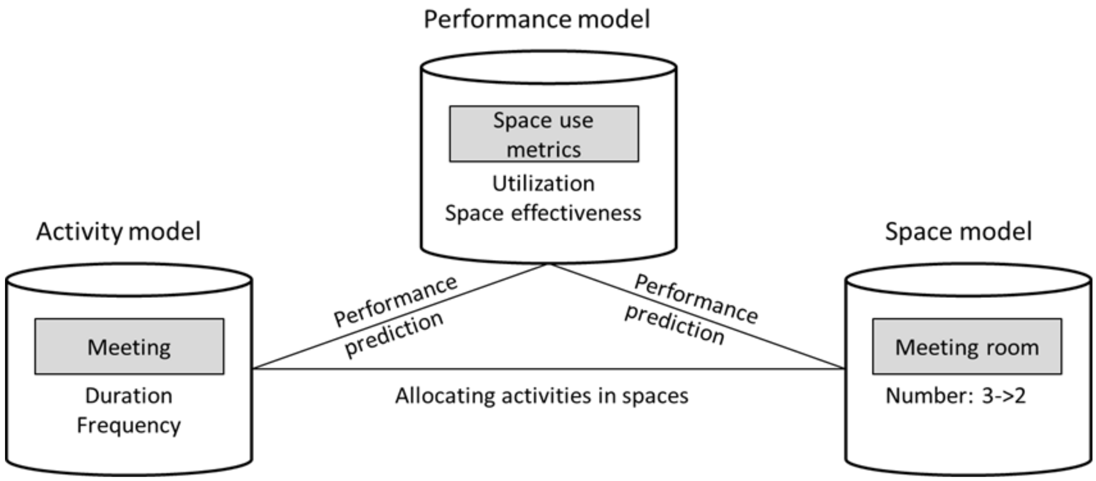

Figure 4. Contribution of the ASP model to the space-use analysis. When the number of meeting rooms is reduced from 3 to 2, based on the formalized relationships among user activity, space, and performance models, it automatically calculates the space-use metrics of impacted activities and the changed space.

3. Points of departure

Theories of user activity modeling, space-use performance models, and energy consumption performance models serve as points of departure for our research. Although the importance of modeling user activity and predicting facility performance during facility planning and design has been emphasized in several theories, activity modeling is not represented and integrated with other elements to predict and document facility performance with sufficient accuracy and granularity.

3.1. Prior research on user activity modeling

The most common way of documenting user activity information in a construction project is recording it using natural languages, such as English. However, natural languages are not appropriate for expressing knowledge for use in computer models because of their ambiguity and traceability issues (Brachman and Levesque 2004; Jain et al. 1989). In contrast, ontological modeling, a systematic approach for representing knowledge in ontologies, enables analyzers to clearly express project-specific knowledge and enables computer models to interpret the knowledge for their own purposes (Wang et al. 2011).

To this end, many researchers in the construction industry have developed ontologies for representing construction activities for various purposes, such as planning (Aalami et al. 1998; Darwiche et al. 1989), time-space conflict analysis (Akinci et al. 2002), cost estimation (Staub-French et al. 2003), and field instruction generation (Mourgues et al. 2008). However, these ontologies cannot be directly used in representing building user activities because of the following two reasons: (1) a user activity ontology mainly serves the purpose of describing activities of building users, while construction activity ontologies mainly serve the purpose of planning activities of field workers. Therefore, in contrast to construction activities, which have specific planned location for their operations, user activities need to be modeled in a way that an activity is accommodated by a space that satisfies certain requirements, e.g., a room that is larger than 20 m^2 and with lighting conditions that allow reading a book. (2) Concepts and their properties in a user activity ontology must be developed on the understandings of the characteristics of user activities, which are different from those of construction activities. For example, Akinci et al. (2002) represent construction activities as <Component><Action><Resources><Work space> tuple and divide the concept <Work space> into four subclasses, i.e., hazard space, crew space, equipment space, and protected space. However, these subclasses cannot be directly used in representing spatial requirements of user activities. Similarly, Staub-French et al. (2003) specify properties of construction activities, such as *cost implication* and *design conditions*, for use in cost estimation; these properties cannot be used in describing user activities for use in space-use analysis.

Research efforts to represent user activities in relation to space-use analysis are yet limited. Users' movement simulation models, whether in an emergency (Pan et al. 2007) or in an normal situation (Dijkstra and Timmermans 2002; Yan and Kalay 2006), only partially represent user activities for use in space-use analysis. Tabak and de Vries (2010) classify user activities into skeleton activities (i.e., user activities that are formed in sequence) and intermediate activities (i.e., physiological or social activities) and model them separately to generate activity schedules. Similarly, Zimmermann (2007) classifies user activities into continuous activities, regular activities, irregular activities, and secondary activities to prioritize activities to generate activity schedules. Ioannidis et al. (2012) model user activities as linked to organization information (i.e., roles and organizational units) to take into account multi-level organization-related information in predicting occupancy presence. Pennanen (2004) models user activities as having properties for utilization computation, including *user group*, *temporal load*, and *group size*. However, these models do not specify spatial requirements of user activities, and therefore, they are not formal enough to be used in automated generation of activity-space pairs.

3.2. Space-use performance models

Space-use analysis is defined as the prediction of how much each space in a facility will be used by users and their activities. Space-use has three different perspectives: space perspective that questions if there is too much space, user perspective that questions if all users can work as they expect, and activity perspective that questions if a building supports the activities an organization needs to do for its business. Since these perspectives of space-use are interrelated, space utilization has been developed and used as a metric of space-use that embraces different perspectives simultaneously. According to Cherry (1999), for example, 100% utilization of a space implies that it is unacceptable from user and activity perspectives due to scheduling inflexibility and long queues for activities in the space, while 0% utilization of a space implies that it is unacceptable from space perspective due to building costs. Space utilization is similar to capacity utilization in the manufacturing industry, which is a ratio of the actual output to a sustainable maximum output, i.e., capacity (Corrado and Mattey 1997). However, while capacity utilization is targeted at the point where marginal costs equal average costs in manufacturing, space utilization is targeted at the point that is predetermined by a planner or an architect (Cherry 1999; Pennanen 2004). In this paper, we use space utilization (or utilization) as a metric of space-use.

Although the importance of space-use analysis has been recognized widely (Gibson 2000; Pendlebury 1990), conventional methods that have been used in analyzing space-use, such as architectural programming (Ann et al. 2008; Cherry 1999; Peňa and Parshall 2001) and post-occupancy evaluation

(Preiser et al. 1988; Whyte and Gann 2001; Wilson et al. 2003; Zimmerman and Martin 2001), provide limited formalization of the analysis because of the following two reasons: (1) these methods do not specialize in space-use analysis, but serve broader purposes upon a client's demand or an analyzer's intention. Therefore, although generally accepted steps for conducting these methods exist, it is difficult to formalize detailed information (e.g, input, output, control, and mechanism) for each of the steps. These methods heavily depend on the analyzer's experience and expertise. (2) Although space, user, and user activity are interrelated and thus must be taken into account simultaneously, the relationships among these concepts are not formalized in these methods. Consequently, user activity information in these methods is often gathered and analyzed on an ad hoc basis, which makes space-use analysis inconsistent and time-consuming.

Workplace planning has been developed and applied in practice by a Finnish company named Haahtela (Pennanen 2004; Whelton 2004). Based on the value generation concept of lean production theory (Koskela et al. 2002), workplace planning attempts to reduce waste of spaces, i.e., spaces that are not needed by value-adding activities. Therefore, it sets target utilization for each space and determines an "appropriate" number of spaces where utilization does not exceed target utilization but is maximized. To do so, it needs the following information: the number of user groups, activities that are linked to a user group and a set of spaces, temporal load of activities, and target utilization of spaces. When a planner provides this information to a workplace planning system, this system computes the total load of each space, i.e., an aggregated value of temporal loads of activities that are mapped onto this space. Then the system determines the "appropriate" number of this space that makes utilization as large as possible within the boundary of target utilization. Workplace planning provides the operational knowledge for computer-assistive space-use analysis. However, despite this advance in the formalization of space-use analysis, it does not model user activity and its relationship with space at a sufficient level of detail for answering various space-use questions.

3.3. Energy consumption performance models

To plan and execute consumption reduction policies and programs effectively, a sound understanding of the determinants that drive household electricity consumption (such as floor area, average outside temperature, and number of occupants) is needed (Haas 1997). However, because of lack of easily-accessible, high-resolution consumption data, underlying determinants of energy use and energy-related behaviors have hardly been examined before (Abrahamse et al. 2005). Therefore, we need a bottom-up model that can make use of high-resolution electricity consumption data and a large set of information about the households. Existing models cannot support the use of high-resolution data due to:

- Use of aggregate (low-resolution) consumption data: Most studies in the past have used monthly billing data, mainly because the advanced metering technologies of today were not easily accessible (Aigner et al. 1984; Aydinalp et al. 2003; Caves et al. 1987; Hsiao et al. 1995; Goldfarb and Huss 1988; LaFrance and Perron 1994; Lins et al. 2003; Parti and Parti 1980; Swan and Ugursal 2009). However, Masiello and Parker (1992) show that residential electricity consumption has strong temporal variation, which is not captured with low-resolution consumption data such as monthly bills.
- Partial set of explanatory variables: A large number of previous studies have analyzed only a partial set of residential electricity consumption determinants; e.g., only appliance stock, weather conditions, or behavioral factors (Cayla et al. 2011; Sütterlin et al. 2011). However, the interaction between different factors (e.g., the relationship between weather, appliance load, lighting load, and heating load) offer considerable potential for improving energy efficiency (Abrahamse et al. 2005). Another limitation of some of the previous studies is the use of "bundle" variables (such as zip code) that combine (hence obscure) the effect of several underlying determinants.
- No distinction between "idle" consumption of the house and peak consumption: Most studies in the past have either looked at peak consumption (mostly at the utility level) or the total electricity

load. However, understanding the lower limit of electricity consumption (i.e., the part of consumption that is almost constant, regardless of active end uses) enables policy makers and planners to quantify the potential for energy efficiency. In this paper we also show that the distinction between idle and maximum consumption distinguishes the ways in which different factors impact electricity consumption.

- Using energy intensity as the only indicator for analyzing electricity consumption: Most studies have used energy intensity (kWh per square foot) as the metric to measure residential electricity consumption (Baltagi 2002; Haas and Schipper 1998; Halvorsen 1975; Hirst 1978; Houthakker 1980; Kamerschen and Porter 2004; Dubin and Mcfadden 1984). This designation implies that, for example, a refrigerator in a 2000 sq.ft house will consume twice as much as the same refrigerator in a 1000 sq.ft house, even when all other factors are held constant. Instead, we scale only those factors whose consumption is dependent on floor area by the area of the house (e.g., lighting and heating loads), and use the actual kWh value for other factors.

4. Automated activity-space pairing

This section describes the ontological relationship between user activity and space we formalized to support automated pairing of user activities (i.e., user model) onto spaces (i.e., product model). We represent user activities as a tuple of <User>, <Action>, and <Spatial requirements>, or <UAS> tuple, where spatial requirements are defined as “properties of a space that a user activity requires for occupying the space.” Examples of user activities from one case study we analyzed are (1) <Employees><Have a meeting><In a meeting room that is larger than 15m^2>, (2) <Editors><Edit a book><In any room with quiet conditions>, and (3) <A company president><Paints as her hobby><In an art room>. In this model, a user activity is mapped onto a space when all spatial requirements of the activity are met by the features of the space (Figure 5).

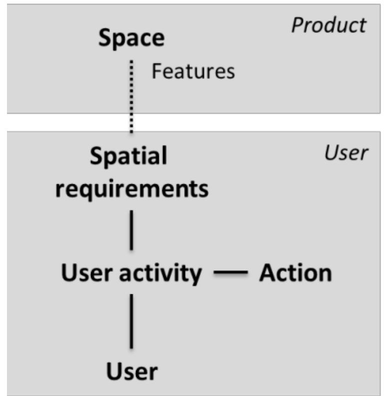

Figure 5. Ontological relationships between user activity and space. Dotted line between space and spatial requirements means that a user activity is linked to a space when features of the space satisfy all spatial requirements of the user activity.

We defined the following classes for automated generation of activity-space pairings:

- User activity: An action of users that requires occupying spaces. Therefore, user activity is defined not only by its action, but also by its users and its requirements. It is represented by a tuple of <User>, <Action>, and two <Spatial requirements> instances, i.e., preferences and constraints.
- User: A subject of a user activity, e.g., students and employees. In this paper, user and user group are interchangeable because we do not consider individual users and their personal needs, e.g., Tom works well with Jane, so he wants to study near her. User has two subclasses: (1) <Regular user> that requires satisfying the *constraints* of his or her activities, and (2) <Important user> that requires satisfying the *preferences* of his or her activities.
- Action: What is being performed by a user activity. We assume that a user activity has only one action and has no workflow because it is difficult and often vague to represent all user activities as workflows.
- Spatial requirements: Conditions of a space that a user activity requires for occupying the space. Since some activities require occupying a whole room, while others need only part of a room, spatial requirements have the following two subclasses: (1) <Whole room use requirements> that

characterizes the required conditions of a whole room, and (2) <Equipment use requirements> that characterizes the required conditions of part of a room, i.e., equipment.

- Space: A physical element of a building by which user activities are accommodated. Building Information Model (BIM) provides a foundation for representing spaces in a computer-interpretable form for automated activity-space pairing. Maile (2010) introduces a building object hierarchy that combines the spatial and thermal aspects of a facility to improve the energy consumption prediction and comparison. This structure includes relationships between different levels of detail of building objects and allows for aggregation or disaggregation of building energy consumption data into units appropriate for estimation. Since our ASP model has a product aspect for energy consumption analysis, this building object hierarchy can be used to inform our research regarding space-level energy consumption analysis.

5. Improved space-use performance prediction using ASP model

Activity-space pairings, automatically generated by formalized relationship between user activity and space, must be connected to performance metrics that are heavily affected by the pairing information. We took the model-driven approach to predict space utilization because many aspects of the analysis have been formalized by our work (Section 4) and previous work on space-use analysis (see Section 3.2).

5.1. The implication of space utilization

Utilization of a space is calculated by dividing activity loads in the space by open time of the space. For example, if an activity A occurs three hours and an activity B occurs one hour in a space that has eight-hour open time, the utilization of the space is 50%. Based on the previous work that suggests the implication of the utilization (Cherry 1999; Pennanen 2004), we categorized the utilization of non-designated spaces or equipment into 4 groups and the utilization of designated spaces or equipment into 2 groups, as shown in Table 1. In space-use analysis, the categories are color-coded to visualize the implication. Space utilization is computed in light of the pairs of a user activity and a space.

Table 1. The implication of the utilization

Non-designated spaces or equipment			
Range of utilization	Implication	Description	Color-code
utilization <=50%	No wait	Activities can be done without waiting.	Green
50%< utilization <=75%	Adequate	Activities may need to be scheduled.	Yellow
75%< utilization <=100%	Inconvenient	Activities need to be relocated.	Red
100%< utilization	Infeasible	Activities cannot be physically accommodated.	Gray
Designated spaces or equipment			
Range of utilization	Implication	Description	Color-code
utilization <=100%	No wait	Activities can be done without waiting.	Green
100%< utilization	Infeasible	Activities cannot be physically accommodated.	Gray

5.2. Space-use analysis process

We defined functions of the automated space-use analysis process using the ASP model. The functions consist of “building the knowledge base,” “mapping user activities onto spaces,” “computing utilization,” and “visualizing the results.”

(1) Building the knowledge base:

The “building the knowledge base” function takes input from the architectural design, user profiles, and the external database to provide the knowledge base for a specific project as an output. Table 2 explains the information that needs to be gathered for building the knowledge base. The ontology for space-use analysis is needed as a control. Data collecting templates, another control, can help analyzers input the necessary information even without knowing the ontology for space-use analysis. Gathering data and building the knowledge base are two mechanisms in this function.

Table 2. Required information for building the knowledge base for space-use analysis

Concept for space-use analysis	Required information
User	Name, The number of users, Regular users or important users
User activity	User, Action, Preferences (spatial requirements), Constraints (spatial requirements), Ratio[a], Frequency[b], Typical or atypical
Action	Group size, Duration[c], space criteria
Spatial requirements[d] (In case of whole room use requirements)	The name of space, The number of space, The minimum size of space, The type of space, Conditions of space,
Spatial requirements[d] (In case of equipment use requirements)	The name of space, The name of equipment, The number of equipment, The minimum size of equipment, The type of equipment, Conditions of equipment
Space	Size, Type, Number, Conditions, Open hour, Inaccessible user group, Equipment set if the space is non-occupiable
Equipment set	Equipment, The number of equipment, Conditions of equipment, Open hour of equipment, Inaccessible user group
Equipment	Size, Type

[a] what percentage of users are involved in this activity – 1.0 means all of the user group are involved
[b] how many times a user is involved in this activity per day
[c] how many hours an action continues per occurrence
[d] values for all the properties are not mandatory

(2) Mapping user activities onto spaces

The "mapping user activities onto spaces" function takes the knowledge base as an input to provide the pairs of user activities and spaces or equipment sets as its output. The mapping is conducted not manually by analyzers but automatically by a set of rules. The rules consist of metrics necessary for the mapping and space mapping heuristics, which are controls of this function. Calculating the metrics, finding spaces, and mapping user activities onto the spaces are three mechanisms in this function. We defined the following three metrics for the mapping:

- *Event quantity* refers to the number of groups for a given activity; it is calculated by dividing the number of users by the size that the activity requires to have, i.e., group size

  Event quantity = (the number of users of the activity × the ratio of the activity) ÷ the group size of the action of the activity

- *Load* refers to hours that an activity demands from spaces

  Load = event quantity of the activity × the frequency of the activity × the duration of the action of the activity

- *Space-use area* refers to the area that a group of users requires for an activity

  Space-use area = the group size of the action of the activity × space criteria of the action of the activity

We divided space mapping heuristics into two groups: "mapping activities requiring designated spaces" and "mapping activities not requiring designated spaces." As for "mapping activities requiring designated spaces," there should be rules to find spaces. Activities of important users should satisfy their preferences, while activities of regular users should satisfy their constraints. If the preferences or constraints are whole room use requirements, then the activities should be mapped onto occupiable spaces. If the preferences or constraints are equipment use requirements, then the activities should be mapped onto equipment sets and non-occupiable spaces that contain the equipment sets. Then, (1) if the number of spaces that occupy the activity is larger than the event quantity of the activity, the spaces should be divided into two entities; the number of the first entity is equal to the event quantity, and the number of the second entity is the remaining number. The first entity should be mapped with the activity and flagged as “designated”, while the second entity is not. (2) If the number of spaces is equal to the event quantity, the spaces should be mapped with the activity and be flagged as “designated”. (3) If the number of spaces is less than the event quantity, the spaces should be mapped with the activity, be flagged as “designated”, and store the number of lacking spaces (the event quantity minus the number of spaces) in the *lack* property of the spaces. In terms of “mapping activities not requiring designated spaces,” knowledge systems do not need to calculate the difference between the number of spaces and the event quantity. These systems only need to find spaces that are not designated and satisfy the spatial requirements of an activity and map the activity onto the spaces (Figure 6).

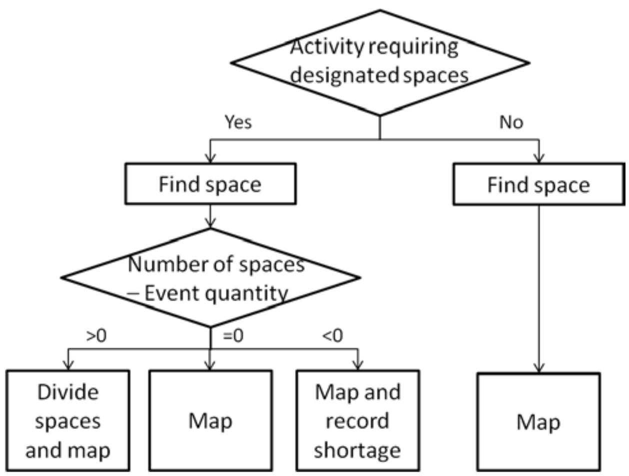

Figure 6. Space mapping heuristics

(3) Computing utilization

The “computing utilization” function takes the knowledge base (i.e., output of the first function) and the mapping results (i.e., output of the second function) to compute the utilization based on the utilization theory. Computing the utilization is a mechanism of this function, which has the following four steps:

- Step 1: For all user activities, sum up the number of spaces or equipment that occupy the activity and record the value in the activity.

- Step 2: For all user activities, compute the load per space or equipment by dividing the load of the activity by the recorded value in Step 1.
- Step 3: For all spaces or equipment sets, compute the total loads by summing up all the loads per space or equipment of activities that occupy the space or the equipment set.
- Step 4: For all spaces or equipment sets, compute the utilization by dividing the total loads by open time.

(4) Visualizing the results

The "visualizing the results" function takes outputs of "mapping user activities onto spaces" and "computing utilization" functions to provide visualized results of space-use analysis. The policy on utilization, one of the controls in this function, was defined in Table 1. We propose the visualization method of activity-loaded spaces, which is another control of this function, as shown in Figure 7. This visualization shows which activities occupy a space (by black area and the name of the activities), how long the activities occupy the space (by loads per space in the x-axis), how much of the space the activities occupy (by space-use area in the y-axis), and how many area-hours of the space cannot be used even if the space is vacant (by gray area).

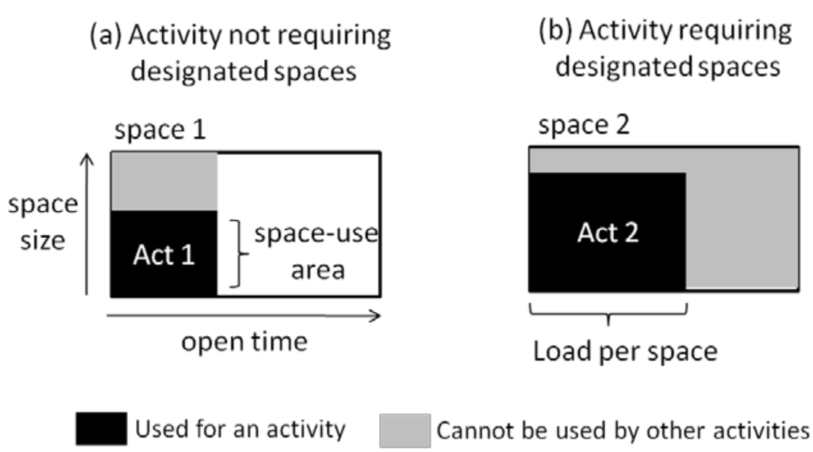

Figure 7. Visualization method of activity-loaded spaces: (a) activity-loaded space where activity 1 does not require designated spaces, (b) activity-loaded space where activity 2 requires designated spaces

This function has three outputs: activity-loaded spaces, the activity-space mapping diagram, and the utilization summary. Since automated space-use analysis makes spaces in the architectural design "activity-loaded," analyzers can see the visualization of an activity-loaded space easily by selecting the space in the design. The activity-space mapping diagram illustrates the links between user activities and spaces so that analyzers can see the automated mapping results at a glance. The utilization summary allows analyzers to see and document the utilization of each space by providing color-coded spaces in the architectural design based on the policy on utilization and by providing a table that lists spaces, their utilizations and the implications thereof.

5.3. Validation: Case studies

We compared our method to the workplace planning method, which is the existing state-of-the-art method we have found (please see Section 3.2 for further information). we conducted three case studies on which we hypothetically tested these methods to see how these methods would deal with the tests. The three cases are the Jerry Yang and Akiko Yamazaki Environmental and Energy (Y2E2) Building located at Stanford University, United States of America, the Cygnaeus High School located in Jyväskylä, Finland, and the H Publishing Company located in Seoul, South Korea (Table 1).

Table 1. Summary of case studies.

	Y2E2	Cygnaeus	H Publishing
The number of space types	9	6	3
The number of user groups	5	4	3
The number of user activities	13	5	4
The number of hypothetical tests	2	3	3

5.3.1. The Y2E2 Building, Stanford University

We applied our method into the select areas in the Y2E2 Building (educational building) to demonstrate its effectiveness in analyzing and visualizing utilization of this building (Kim et al. 2012). Based on this case study, we conducted the following two hypothetical tests:

T1: Changes in space configuration

We increased the number of small conference rooms from 2 to 3 while maintaining the gross area of the building by reducing the size of a large conference room (546 ft2 to 389 ft2). Since workplace planning relies on a fixed relationship between spaces and users, which is manually constructed by a planner, it computes the utilization of each space based on the same activity-space mapping. Thus, the total load of each small conference room is reduced due to the increased number of this space, and sequentially, the utilization of this space is also decreased from 0.99 to 0.66. The utilization of other spaces remains unchanged. However, in our method, activities are mapped onto spaces based on their spatial requirements, and reduced size of a large conference room triggers changes in activity-space mapping. In this case study, links from two activities ("grads having class" and "undergrads having class") to the space "large conference room" are deleted because these activities require any space that is larger than 400 ft2. This change then affects utilization of other spaces. The utilization of small conference rooms is decreased from 0.99 to 0.82.

T2: Changes in space usage

In this test, we prevented undergraduate students from using small conference rooms and required them to find other conference rooms for their individual study activity while maintaining the results of previous test T1. To respond to this change, workplace planning requires a planner to delete all activities of undergraduate students from small conference rooms, find other conference rooms in the space list, and map these activities onto the found conference rooms. In contrast, our method formulates spatial requirements of each activity as the knowledge base, and therefore, an analyzer has to change spatial requirements of undergraduate students' activities. An analyzer also needs to add "undergraduate students" into the "block" property of the space "small conference room" to prevent them from using this space. Thus, although the computation of utilization is based on the same theory, workplace planning and our method map activities onto spaces in a different way.

5.3.2. The Cygnaeus High School

Pennanen (2004) describes the Cygnaeus High School project (educational building) in Finland to demonstrate the effectiveness of workplace planning. This case is described also in Whelton's work (2004). Based on this case study, we conducted the following three hypothetical tests:

T3: Unsatisfied requirements

This case study describes a discussion about an auditorium where the auditorium was removed due to its low utilization and three 80m2 classrooms were planned to be utilized for the activity "final examination before graduation." To accommodate the activity, these classrooms need to have portable walls with good sound insulation. Based on this discussion, we developed a test where the good sound insulation requirements are not satisfied (or specified) during the design process. In this case, workplace planning does not change the utilization of any space because the mapping between activities onto spaces remains the same regardless of whether or not the requirements are fulfilled by design. In contrast, since our method represents spatial requirements and their relationships to the mapping, it automatically deletes the link from the "final exam" activity to "flexible classrooms" when the design does not satisfy the spatial requirements of this activity.

T4: Changes in user information

In this test, we doubled the number of teachers (from 70 to 140) and saw how two methods react to this change. Given that the utilization of 70 workstations for teachers is 18% according to this case study, workplace planning would change the utilization from 18% to 36%, which is still fairly low according to Cherry (1999) and Pennanen (2004), since the total load for each workstation is doubled. However, because all 140 teachers would like to have their own workstations, this doubling in the number of teachers would result in the lack of workstations. Workplace planning does not represent the designation of a space, and therefore, an analyzer has to explain this "real" meaning to the client on an ad hoc basis.

In contrast, our method takes into account the designation in the analysis, and therefore, maintains the utilization of 18% and notifies the analyzer that 70 workstation are lacking (Figure 8).

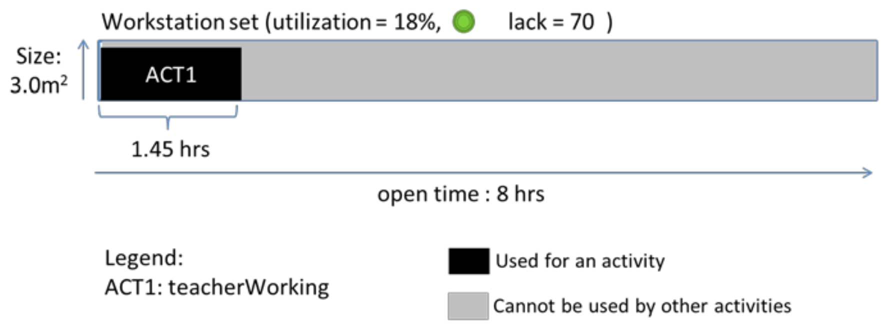

Figure 8. Activity of workstation set example in T4.

T5: Addition of a space type

This case describes that the school added a club for the student association at the request of the association. We investigated how two methods deal with this addition into their systems. workplace planning does not automatically analyze the impact of adding the club on space-use because it depends on fixed relationships between activities and spaces. A planner must map activities that can be accommodated by the club onto this space on an ad-hoc basis. On the other hand, our method automatically finds activities that can be accommodated by the club (i.e., activities whose spatial requirements are satisfied by the club), such as “student meeting” and “student association meeting,” and links these activities to the space.

5.3.3. The H Publishing Company

We examined the planning and design phase of a publishing company building (office building) in Korea. This building set 660 m2 as its gross area for 20 employees of the company. However, after an architect developed the space program, this company wanted to refine the space program to increase the size of a storage room to hold additional books without exceeding its space budget (660 m2). To make a decision to address this trade-off, this company needed to be informed of space-use of each space and the impact of each option on the space-use. For detailed information, please read (T. Kim and Fischer 2011). Based on this case study, we conducted the following three hypothetical tests:

T6: Changes in space configuration

In this test, we reduced the number of meeting rooms from 3 to 2 to increase the size of the storage room. In this case, both workplace planning and our method are able to rapidly provide consistent utilization information in response to this change. However, these methods work in a different way. workplace planning updates the utilization of meeting rooms immediately because it relies on the activity-space mapping that is predetermined by a planner. In our method, an analyzer predetermines spatial requirements of activities rather than the activity-space mapping itself. Thus, our method first re-evaluates the relationships between activities and spaces before computing utilization whenever it finds any modification in user, user activity, and space information.

T7: Changes in space usage

There was an art room that was designated for the president of the company to use for the activity of painting. In this test, we allowed this art room to be used for activities other than the painting activity to reduce the utilization of meeting rooms. To respond to this change, workplace planning requires a planner to manually update the mapping because (1) the designation that was originally needed by the painting activity is not represented, (2) rules for activity-space mapping regarding the designation are not formalized, and (3) spatial requirements of other activities, such as employees' meeting and editors' editing books, are not represented. In contrast, when an analyzer changes the designation property in the spatial requirement of the painting activity, our method automatically updates the activity-space mapping, i.e., it adds a new link of “editors' editing books” activity to “art room” space.

T8: Generation of multiple options

In space-use analysis, there is a need for generating and testing multiple options to find the best space configuration or usage solution that fits client's needs and business purposes. We generated the following three space usage options regarding where "editors' editing books" activity can be accommodated: (1) a quiet room, (2) a workstation placed in an office area, and (3) a workstation placed in any space. To test and compare these options in terms of the utilization of spaces, workplace planning planner must manually find spaces that satisfy the required condition and link the "editors' editing books" activity to these spaces to compute utilization for each option. However, since our method can generate and represent different options in explicit knowledge bases, a planner can easily and efficiently test these options simply by generating many spatial requirements and changing requirements linked to the "editors' editing books" activity. For example, using F-Logic (Angele et al. 2009), a knowledge representation and reasoning language, the three options in this test can be represented by:

Constraint1:WholeRoomUseRequirement [space -> anySpace, number -> 1, conditions -> quiet].

Constraint2:EquipmentUseRequirement [space -> officeArea, equipment -> workstation].

Constraint3:EquipmentUseRequirement [space -> anySpace, equipment -> workstation].

6. Improved energy consumption performance prediction using ASP model

We took the data-driven approach to predict energy consumption because mechanisms to connect the performance and the information of activity-space pairings are yet unclear to be modeled, and there are large data sets of residential smart meter data available.

6.1. Model development

Through a review of the residential electricity consumption models and building sciences literature (Haas 1997), we identified four major categories of residential electricity consumption determinants:

- Weather and location. Examples: daily outdoor temperature and climate zone; these determinants are normally outside the scope of influence of the household.

- Physical characteristics of the building. Examples: level of insulation and fuel use for water heating; modifying these determinants is normally considered long-term investments.
- Appliance and electronics stock. Examples: the number of refrigerators or computers; modifying these determinants is normally considered medium to short-term investments.
- Occupancy and occupants' behavior towards energy consumption: determinants in this category have different levels of effort and impact span. Some behavioral modification determinants such as proper management of thermostat settings are of short-term effort and impact. Another group of determinants are associated with long-term effort and impact (such as purchasing energy-efficient appliances). Finally, some determinants in this category are outside the scope of interest of occupants to change (such as occupancy level during the day).

We then established the following four different features of the hourly electricity consumption data as response variables: daily average, minimum, maximum, and maximum-minus-minimum (also called "range"). For example, daily minimum and daily maximum consumption refer to the lowest and highest values of the hourly consumption data as recorded by the meter (2 extreme values from 24 daily values). Each feature was then used as the response variable in a separate regression model. Such approach enables disaggregating the role of structural versus behavioral determinants of consumption.

We developed a weighted regression model to explain the variation in household electricity consumption. Those determinants whose contribution to electricity consumption has a linear relationship with floor area are multiplied by the floor area of the residence. For example, poor insulation will cause larger houses to waste more energy (through increased envelope surface) compared to smaller houses. On the other hand, a refrigerator has the same consumption level regardless of the size of the house. The majority of previous papers that we reviewed regress energy intensity (kWh/sq.ft) on all end uses. The regression equation of our model is given by:

$$y_j=\beta_{0j}+\sum_{i=1}^{M}\beta_{ij}X_{ij}+A_j.\sum_{i=M+1}^{K}\beta_{ij}X_{ij}+\varepsilon_j, \qquad (1)$$

where y_j is the electricity consumption (*kWh*) of household *j*, X_{ij} is the value of the determinant number *i* for household *j*, and β_{ij} is the regression coefficient for that determinant. *M* is the number of variables (household features) that do not depend on floor area, while *K* is the total number of variables, and ε is the error term.

After selecting the *p* variables that contribute the most to the model fit using forward stepwise model selection (explained above), and multiplying the floor-area-dependent variables by the square foot value of the dwelling, we formed a single matrix *X* and formed the final regression model as:

$$y=X\beta+\varepsilon, \qquad (2)$$

where *y* is the $n\times1$ vector of household consumption values (in *kWh*), *X* is a $n\times(p+1)$ matrix where *p* is the number of selected variables, ε is a $n\times1$ vector of residuals, and β is the $(p+1)\times1$ vector of regression coefficients.

Our model enables working with large data sets of electricity consumption data and large household surveys, by (a) using several indicators (electricity consumption features or load characteristics) in addition to the aggregate load that help understand different aspects of consumption (e.g., long-term steady idle load versus short-term volatile peak load); and, (b) choosing variables that contribute the most to those load characteristics. Our model also introduces a novel approach to understanding the effect of appliances more accurately by (c) properly considering the effect of floor area.

6.2. Data summary for data-driven analysis

We applied our model to a data set of ten-minute interval smart meter data for 1628 households, collected over 238 days starting from February 28, 2010 through October 23, 2010. Detailed data about household characteristics were available via a 114-questions online survey. The survey questions covered a wide range of characteristics including climate and location, building characteristics, appliances and electronics stock, demographics, and behavioral characteristics of occupants. The following sections explain the data in more detail.

Consumption Data

Participant households were selected through a voluntary enrollment in the program, and were provided with a device that recorded the electricity consumption of the household every ten minutes and sent the data to a central server to be stored. The device installation and server costs were covered by the experiment administrators, and participants volunteered to participate merely based on their interest (for more details of the experiment, refer to (Houde et al., 2012).

The consumption data were converted to hourly data (a) to ensure that the fluctuations in electricity consumption are considered, but not obscured by sudden spikes in the consumption; and (b) to compare the results of our models with those of previous studies on smart meter data and electricity market analysis (Lijesen, 2007). Furthermore, we chose not to remove extreme-consumption households from the sample to ensure that the model captures determinants that are associated with a wide range of consumption volumes. Such a model would enable the prediction of likely extreme users in other household samples.

Household data

The smart meter data were supported with a detailed survey of geographical and physical characteristics of dwellings as well as appliance stock, occupant profiles, and attitude of occupants towards electricity usage, for a total of 114 questions. The survey was administered online. After collecting the data, 952 households for which reliable smart meter and survey data were available were selected for the analysis. Less than 3% of survey responses were inconsistent or missing, for which we imputed data using iterative model-based imputation techniques (Courrieu and Rey 2011; Gelman and Hill 2007). The selected households are located in 419 different zip codes, 140 different counties, 26 different states, and are spread across all six climate zones defined by the Department of Energy (US Department of Energy 2011). California has the largest representation (53% of households) of all states in the data set. During the data collection process, the weather conditions in most areas where participant households resided were similar to the 30-year average climatic conditions; however, some areas, especially in the north east of the U.S., experienced slightly higher-than-normal temperatures (NOAA 2010). Average electricity consumption in our sample lies between California and US averages. Some structural determinants such as household size, square footage of the house, and the proportion of single family detached units in our sample are close to US population averages (Houde et al. 2012). Furthermore, to ensure that the homogeneity of socioeconomic status does not reduce the power of our model in explaining behavioral determinants, we performed a factor analysis of the behavioral variables.

All participants in our study had at least a house member working for a high-tech company. As such, the attitudes and lifestyles of these families were more homogeneous than the real sample of US households. In particular, 79% of the participants were engineers, and they were mostly from well-educated, upper and middle class families. More than 50 percent reported income higher than $150,000. However, it is worth mentioning that the mix of households in our study (i.e., well-educated, upper and middle class families who are also early adopters of new technologies such as home energy monitoring systems) are also more likely to respond to energy efficiency programs by investing in energy-efficient products (Ehrhardt-Martinez and Donnelly 2010). Hence, the results of our analysis can be particularly helpful to energy efficiency program managers and policy makers to develop programs specifically targeted towards the households represented by our sample.

We transformed some variables to better reflect the technical characteristics of buildings. For example, we transformed the construction year to a categorical variable that indicated the residential building code that was effective at the time of the construction (i.e., different revisions of ASHRAE 90.2 (US DOE 2011)). We also included a categorical variable for House Size to capture the effects of the floor area that are not completely explained by square footage. For example, when a building's floor area passes a certain threshold, the type of structural and architectural material that is used in the building often changes significantly. Since we do not have a separate variable for floor area and are not dividing the electricity consumption of the dwelling by its floor area, introducing the house size variable does not create a multicollinearity problem. We also examined mathematical transformations of the variables, such as power and logarithm transforms, and included those that showed statistically significant correlation with electricity usage in the regression model.

The household survey captured the attitudes of occupants towards energy consumption using 40 variables, many of which capturing similar behavioral information from different perspectives. Using Factor Analysis as was explained in previous sections, and informed by behavioral sciences research, we formed 22 major factors that collectively explain more than 80% of the information included in the original 40 questions. The 22 variables explain the attitudes of households in three major dimensions, i.e., energy efficiency actions, information seeking behaviors, and home improvements behaviors.

6.3. Findings from energy consumption analysis

After factor analysis and adding a number of transformations of the original variables, the total number of household variables was reduced from 114 to 97. We fit separate models for daily maximum, minimum, maximum minus minimum, and average consumption, both for summer and winter (for the period when the data were available), and ranked the variables by their importance through a forward stepwise model selection procedure.

Through comparison of these different models, we show that the daily minima are most influenced by external conditions or physical characteristics of the building. On the other hand, end uses that are energy-intensive and do not run constantly (e.g., electric water heater) are mostly influenced the daily maxima. This group of end uses mostly depends on the occupancy levels and activities of occupants.

Overall, locality (usually measured by a proxy such as Zip Code) and House Size demonstrate considerable correlation with residential electricity consumption (Howard 2012), most likely because they are correlated with several other variables that characterize a household. For example, Zip Code is often correlated with weather conditions, building type, type of systems used in the building, building materials, and socioeconomic status of the household. On the other hand, House Size is often correlated with affluence, socioeconomic status, number of residents, and appliance stock. We fitted separate models with and without Zip Code (using the first two digits of zip code to avoid over-fitting) and House Size to (a) study the impact of locality and house size on electricity consumption, and (b) identify the variables that are obscured by zip code and house size through a comparison of the models with and without these two variables. This report only focuses on the effect of occupants (users) we have found. For other findings, please see (Kavousian et al. 2012).

The Effect of occupancy level

Number of Occupants is a significant variable in explaining daily maximum models while it is not a significant variable in daily minimum models, which supports the notion that the presence of occupants primarily impacts the consumption in excess of the daily minimum. Furthermore, the models suggest a non-linear relationship between household electricity consumption and the number of occupants, selecting the Square Root of Number of Occupants over the Number of Occupants. In other words, our model verifies that when the number of occupants double, electricity consumption increases at a slower rate (1.4 in our data), leading to the conclusion that larger households have higher aggregate electricity consumption but lower per capita consumption. A similar concave non-linear relationship between number of occupants and electricity consumption has been reported by (Barnes et al. 2004; Heltberg 2005; Xiaohua and Zhenmin 2003).

Pet Ownership (a proxy for determining whether the house is "active" during the day or not) is a statistically significant factor in all of the models, while the magnitude of its impact is the largest for the summer daily minimum, winter daily maximum, and winter daily maximum-minimum models. We are not aware of any study that has studied the impact of pet ownership on residential electricity consumption; however, previous studies have reported similar results for the impact of occupancy on residential electricity consumption (Guerra Santin et al. 2009).

The Effect of Long-Term Habits and Preferences

Behavioral factors that have long-term impacts (such as Purchasing Energy-Star Appliances and Air Conditioners) or are considered long-term habits (such as Energy Conservation When Using Electric Heater; i.e., adjusting thermostat settings moderately and according to occupancy) are significant explanatory variables for daily minimum consumption.

In the daily minimum model, the behavior of Purchasing Energy-Star Appliances and Air Conditioners has a positive coefficient. This suggests that, in our study sample, contrary to common belief, households that have expressed motivation to buy energy-efficient appliances and air conditioners have higher levels of daily minimum consumption, after adjusting for all other variables. Similar observations have been reported by several previous researchers, leading Sütterlin et al. (2011) to declare that "the green purchaser is not necessarily the green consumer". Some researchers have attributed this behavior to the "rebound effect" where an increase in the efficiency of appliances results in increased use of them (Abrahamse et al. 2005; Beerepoot 2007).

Another long-term habit is Turning Off Lights When Not in Use, which is significant for most winter models. However, the variable that represents the habit of Turning Lights Off When Not In Use manifests a significant geographical pattern, as it becomes insignificant when Zip Code is included in the model. While turning unnecessary lights off reduces consumption, the effect of its associated variable is augmented in our sample by the geographical distribution of the households on the two coasts that have declared environment-conscious behavior, and at the same time benefit from milder climate throughout the year. Therefore, further data are needed to quantify the individual effect of energy-conscious behavior of turning off unnecessary lights.

Effect of Income Level

We did not observe any statistically significant correlation between Income Level and electricity consumption. In our sample, more affluent households tend to have lower daily maximum consumption values in the summer compared to less-affluent households, because they have more energy-efficient appliances on average. This is significant because the most important determinants of the summer daily maximum model are (model coefficients in parenthesis): cooling degree days (0.052), ownership of electric water heater (0.670), ownership of electric clothes dryer (0.344), number of occupants (0.984), and climate zone (five categorical variables ranging from -0.353 to 0122).

Furthermore, since all participants of the study are well-educated and work in a high-tech company, one can conclude that once the consumers pass a certain level of education and awareness of energy efficiency matters, the more affluent they are, the lower their daily maximum consumption is likely to be, mainly because of improved efficiency of high-consumption appliances.

The relationship between household income and energy consumption has been the subject of extensive research. While a large number of studies have concluded that energy consumption increases monotonically with income (Biesiot and Noorman 1999; Cayla et al. 2011; Filippini 2011; Vringer et al. 2007), a number of studies have reported observing an inverted U-path comparing energy consumption and household income. At the same time, the effect of income on household electricity consumption has been shown to be mediated by ownership of appliances: since electricity cost makes up a small percent of households' expenditure, economic factors such as price of electricity and income of the household impact the consumption through affecting the stock (quantity and quality) of appliances rather than having a direct effect. This hypothesis is in agreement with the inverse U-path observation: in the lower-income segment of the inverted U-path which is the monotonically-increasing part, households acquire more energy-intensive appliances as the level of income increases. Then, once the income passes a certain level, in the decreasing segment of the U-path, households purchase more efficient appliances as their level of income increases (Elias and Victor 2005; Foster et al. 2000; Kowsari and Zerriffi 2011; Leach 1992). Our data captures the latter part of the inverted U-path when the energy consumption decreases as the level of income increases, since we have data from well-educated and middle to upper class households.

7. Conclusion

The design, construction, and operation of high-performing facilities depends on the ability of planners and designers to predict the future performance of a facility with reasonable accuracy and granularity, and tailor the performance to support the facility users' business and operational requirements and activities. However, today's design and engineering methods are not able to predict, document and communicate the performance of facilities with sufficient accuracy and granularity to allow the users to select the building design that works best for them. We formalized a facility user's activity model for the design and operation of facilities with the relevant connections to BIM and models describing the organization of people. The focus was on understanding and predicting the performance of a facility with respect to space use and energy consumption.

We developed a framework for automated space-use analysis to enable analyzers to predict and update space utilization simultaneously considering these three perspectives with computational assistance. The framework includes the formalization of the concepts for space-use analysis such as users, user activities, spaces, and equipment, and the automated space-use analysis process. We demonstrated the effectiveness of the proposed framework through three case studies (two educational buildings and one office building). Our results show that the proposed framework can support iterative refinement of the architectural design and its usage by predicting the utilization and visualizing the results automatically.

We also analyzed large data sets of residential electricity consumption to derive insights for policy making and energy efficiency programming. This approach is then applied on a large data set of smart meter data and household information as a case example. Underlying behavioral determinants that impact residential electricity consumption are identified using Factor Analysis. A distinction is made between long-term and short-term determinants of consumption by developing separate models for daily maximum and daily minimum consumption and analyzing their differences. Finally, the set of determinants are ranked by their impact on electricity consumption, using a stepwise regression model. The results show that location, floor area, number of occupants, occupancy rate, and use of electric water heater are the most significant factors in explaining daily maximum (peak) consumption.

This research encompasses relatively new areas of facility planning, design, construction, and operation and therefore, has great possibility of application and expansion. Based on our findings, we will expand our model to include space layout, building system and probability theory so that it can additionally answer questions such as: "What happens to work productivity of researchers if we change the space layout of laboratory?" and "How well do spaces support customers' activities when the number of customers fluctuates daily?" We will also study to integrate user activity with other elements such as facility performance and user performance to enlarge the application of our system so that it can additionally answer questions such as: "What spaces of our building are most required to be fixed? And how?" and "What happens to students' music education quality when the number of music teaching spaces is reduced?" Furthermore, our system can be expanded by future research to using the ability to collect and analyze building sensor data in developing the POP model (Kunz and Fischer 2009) for the usage phase. Our system can be used in properly sensed facilities to collect, analyze and visualize facility performance, and give appropriate feedback both to the facility operators and to the occupants.

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