Energy 109 (2016) 641–649

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Building occupancy diversity and HVAC (heating, ventilation, and air conditioning) system energy efficiency

Zheng Yang, Ali Ghahramani, Burcin Becerik-Gerber*

Department of Civil and Environmental Engineering, University of Southern California, Los Angeles, United States

A R T I C L E I N F O

Article history:
Received 10 February 2016
Received in revised form
22 April 2016
Accepted 23 April 2016

Keywords:
HVAC system
Energy efficiency
Building information modeling (BIM)
Occupancy diversity
Simulation
Loads

A B S T R A C T

Approximately forty percent of total building energy consumption is attributed to HVAC (heating, ventilation, and air conditioning) systems that aim to maintain healthy and comfortable indoor environments. An HVAC system is a network with several subsystems, and there exist heat transfer and balance among the zones of a building, as well as heat gains and losses through a building's envelope. Diverse occupancy (diversity in terms of when and how occupants occupy a building) in spaces could result in increase of loads that are not actual demands for an HVAC system, leading into inefficiencies. This paper introduces a framework to quantitatively evaluate the energy implications of occupancy diversity at the building level, where building information modeling is integrated to provide building geometries, HVAC system layouts, and spatial information as inputs for computing potential energy implications if occupancy diversity were to be eliminated. An agglomerate hierarchical clustering-based iterative evaluation algorithm is designed for iteratively eliminating occupancy diversity. Whole building energy simulations for a real-world building, as well as virtual reference buildings demonstrate that the proposed framework could effectively quantify the HVAC system energy efficiency affected by occupancy diversity and the framework is generalizable to different building geometries, layouts, and occupancy diversities.

1. Introduction

In the United States, people spend more than 90% of their time indoors [1] and approximately 40% of all energy consumption is attributed to the 120 million buildings [2]. Sustainability and energy conservation have become increasingly important topics, as nearly 50% of the energy consumed by buildings is wasted, and the total energy consumption by the building sector is projected to increase by 15.7% between 2013 and 2035 [3,4]. In commercial buildings, nearly 40% of the energy is used by HVAC (Heating, Ventilation, and Air Conditioning) systems to maintain comfortable and healthy indoor thermal environments [3,5]. Occupancy (when and how occupants occupy a building) is one of the most influential factors to determine the actual demands for an HVAC system, thus matching HVAC system controls with actual occupancy is an effective approach to reduce energy consumption without sacrificing occupant comfort and system functionality. In general, when a space is not occupied, loads in that space do not need to be fully addressed by the HVAC system. Occupancy could be incorporated with HVAC system controls to reduce the loads for heating and cooling. It has been demonstrated in our previous research [6] and by others [7,8] that if an HVAC system is controlled based on actual occupancy, energy efficiency could be significantly improved. Commercial buildings usually have multiple zones that are the basic thermal control units. The loads at the zone level are the sum of loads in all spaces of that zone. Diversity in occupancy among different spaces could lead to reduction in energy efficiency as the loads from an unoccupied space might still be considered as demands by the HVAC system [9]. In addition, there exist heat transfer and balance among the zones, as well as heat gains and losses through a building's envelope. Given the fact that different zones may have same supply air, loads exchange, shared or similar boundary conditions [10], occupancy diversity among those zones could result in diverse distributions of loads for the HVAC system, hindering system efficiency.

The objectives of this paper are to quantify the heating/cooling loads associated with occupancy diversity and to provide a generalizable framework to evaluate energy efficiency affected by eliminating the diversity. Occupancy is stochastic in nature with varied patterns, creating diverse schedules and requirements for heating and cooling. In this paper, occupancy diversity is analyzed from two perspectives of real-time occupancy and long-term occupancy.

* Corresponding author.
E-mail address: becerik@usc.edu (B. Becerik-Gerber).

http://dx.doi.org/10.1016/j.energy.2016.04.099
0360-5442/

Real-time occupancy is the time-sequenced occupancy status at each time point, representing how an occupant occupies a space for a specific time. Long-term occupancy is the probability of how an occupant typically occupies a space as a function of time, representing occupancy patterns. An HVAC system usually responds to the heating/cooling loads through the control of setpoints, which determine the desired temperature ranges for spaces. Therefore, in this paper, setpoint is used as the medium to control the heating/cooling loads based on occupancy. To quantify the energy implications of diversity, we compare the loads before and after the load rearrangement (based on long-term occupancy) using an occupancy driven setpoint control (based on real-time occupancy). Specifically, occupancy driven setpoint control allows the setpoint to float to another temperature (setback), when the space is unoccupied for more than a certain waiting period and then is restored to setpoint, when the space becomes occupied again. An agglomerate hierarchical clustering algorithm is designed to cluster occupants based on their presence similarities while considering the connectivity between the clusters. Since the process of eliminating occupancy diversity is restricted to hierarchical constraints of the ways how occupants use a building, an iterative evaluation algorithm is developed. The algorithm integrates BIM (building information modeling) to support the understanding of hierarchical constraints, and therefore, aims to increase the quality of evaluation. Whole building energy simulation is used to validate the effectiveness and generalizability of the framework in quantifying the HVAC system energy efficiency affected by occupancy diversity at the building level through a well-informed analysis of occupant–space relationships. Specifically, for the effectiveness validation, a real-world testbed building with actual occupancy is used to examine the performance of the proposed methodology for eliminating occupancy diversity and analyzing corresponding load reduction. For the generalizability validation, virtual reference buildings are used to examine the consistency of the proposed methodology for other buildings with different building geometries, layouts and occupancy diversities. The numbers of building models, simulations and trials of eliminating diversity are determined based on the distributions and patterns of results.

The paper is structured as follows. Section 2 introduces the importance of occupancy diversity and how to measure it. Section 3 describes the methodology to eliminate the occupancy diversity based on hierarchical constraints for quantifying the energy implications of diversity, and its integration with BIM. Section 4 presents the validation of the proposed framework by using whole building simulation for a testbed building. Section 5 tests the generalizability of the proposed framework using virtual reference buildings, representing different commercial buildings. Section 5 discusses the limitations and concludes the paper.

2. Occupancy diversity analysis

Load is the quantitative measure to describe the demands of energy for HVAC systems to maintain thermal conditions in buildings. The majority of the energy consumed by an HVAC system is to satisfy the loads from interior sources (e.g., due to occupant metabolisms and device/equipment related heat gains) and exterior sources (e.g., due to conduction and convection). Occupancy is associated with heating/cooling schedules and effects, which determine the amount of loads and energy efficiency of an HVAC system. Extensive research has been conducted to model building occupancy [11–13] and a range of occupancy driven setpoint control strategies has been developed [6,14,15]. The basic principle is that energy efficiency could be improved by not considering the loads in vacant zones as demands for HVAC systems. Substantial energy savings have been reported by prior research by not maintaining static setpoints in unoccupied zones. Instead, zone temperatures were allowed to float within a certain range [16–18]. However, since zones usually consist of more than one space, if only one space in a zone is occupied, heating/cooling is required for the entire zone, and the loads of the zone are the sum of loads in all spaces of that zone. Studies have found different spaces may have different or in some cases inverse occupancies that undermine the effects of occupancy driven setpoint control strategies [12,19,20]. Simply aggregating disparate occupancy information of different spaces might create an inaccurate representation of how each zone is occupied, which may lead to unnecessary heating/cooling loads and further reduce energy efficiency.

In addition, a building usually has multiple zones and there exist heat transfer and balance among the zones. Loads in one zone could increase because of the different thermal conditions of neighboring zones resulting from occupancy diversity. Several researchers have studied this issue and analyzed occupancy diversity at the building level from the supervisory control perspective [17] with a focus on global controller optimization, from the occupant classification and segmentation perspective [21] with a focus on constructing energy-use scores and behavior interventions, from the human-building interaction perspective with a focus on different levels of thermal preferences [22], and from the system operation scheduling perspective [23] with a focus on energy performance for single zones. However, a quantitative study for measuring the amount of heating/cooling loads that are associated with occupancy diversity is still needed [24], and it is still not clear how occupancy diversity at the building level quantitatively influences the energy efficiency of an HVAC system. In this paper, we introduce a framework to analyze energy implications of diversity at the building level with the following factors being considered: (1) HVAC layout. Commercial buildings may be segmented and served by different sets of HVAC systems or secondary systems (e.g., air handling units). HVAC layout determines the zones with shared supply air [25,26]. (2) Zone adjacency: adjacent zones share boundaries and there are load exchanges through heat transfer and balance among the zones when there is temperature difference or mutual ventilation [27]. If the adjacent zones have distinct schedules and requirements for heating/cooling, excessive energy might be consumed due to the thermal circulation. (3) Orientation: zones with the same orientation usually have similar boundary conditions and are therefore impacted similarly by the outside environment [28].

3. Methodology for eliminating occupancy diversity

The objective of quantifying the energy implications of occupancy diversity is to rearrange heating/cooling loads by virtually rearranging occupancies until the diversity is eliminated. Occupancy profile, the typical presence probability as a function of time, representing long term occupancy patterns, is used as a measure to calculate the level of diversity. There might be more than one profile representing one space (e.g., different profiles for an occupant for different days of the week). If so, for each time point, the highest probability among the profiles is chosen to account for the majority of the time. The process is restricted by hierarchical constraints, which represent how a building is utilized. After higher-level constraints are satisfied, the lower-level constraints are included. If there is a conflict between the two sets of constraints, higher-level constraints are given the priority. In this paper, primary constraints are individual requirements, e.g., different room sizes for different occupants, and group requirements, e.g., occupants of the same department should be spatially close. To be clear, individual requirements are for individual spaces and mainly consider physical conditions and preferences, such as orientation while group requirements are for connections between spaces and the functionality of spaces, such as the offices of administration for a department should be next to each other. The secondary constraint requires occupants with similar occupancy profiles to be virtually placed in the same zones so that the occupants of a zone could have similar presence patterns, eliminating the occupancy diversity at the zone level. The third constraint requires similar occupancy profiles in the connected zones, including zones under the same (secondary) HVAC systems, zones adjacent to each other, and zones with same orientation, to further eliminate the occupancy diversity at the building level. It is important to note that the consideration of these influential factors does not change the HVAC layout, zone adjacency, and orientation, but it guides the virtual change of occupant–space relationships for rearranging the loads associated with occupancy diversity.

An agglomerative hierarchical clustering algorithm is designed to cluster occupancy profiles based on their similarities while considering the connectivity between the clusters. Occupancy profiles are derived from real time occupancy information [29] by analyzing the patterns of observable contextual information, such as CO_2 concentration, temperature and lighting levels [30]. In our previous work, four techniques including ARMA (AutoRegressive-Moving-Average) time series model, ANN (Artificial Neural Network) pattern recognition model, MC (Markov Chain) stochastic process model, and GLM (Generalized Linear Model) were tested. ARMA yielded the best results for modeling personalized occupancy profiles by analyzing the ambient environment and previous occupancy information [29], and outperformed other methods (e.g., survey and observation) commonly used in practice and research in terms of both statistical approximation and load approximation. Therefore, the ARMA algorithm is used in this paper to prepare occupancy profiles. Actual occupancy has time continuity, which could be undermined by the outliers in the ground truth and by the impacts of irregular occupancies. In addition, conditioning effects of heating/cooling are not spontaneous and it takes time to reach the desired temperature. Therefore, occupancy profiles should be further adjusted on a time-window basis in order to be more representative. Specifically, sliding windows are defined to segment the profiles by time windows with overlaps. The averaged presence probability within each window is then used as the feature for this window to form a new feature vector (updated profile) for calculating the level of occupancy diversity. This logic operation could generalize original feature information but reduce the dimension of the feature vector, which improves the computational efficiency and the reliability to compare the similarity among different occupancy profiles.

The clustering process starts by assigning each updated profile to an individual cluster, each containing only one profile. The Minkowski distance is used to calculate the similarity between two profiles, as it is used as a general function to measure distance in clustering [31].

$$\text{Minkowski distance } d_{ij} = \sqrt[r]{\left(\sum_{k=1}^{n}\left|x_{ik} - x_{jk}\right|^{r}\right)}$$

In which, d_{ij} is the distance between profile i and profile j; n is the vector dimension, depending on the length and overlap of the sliding window; x_{ik} is the averaged probability of window k for the profile i, and x_{jk} is the averaged probability of window k for the profile j. r is selected as 2 in this study to make the Minkowski distance the Euclidean distance. Since the primary constraints for group requirements may change the distances between profiles for addressing the second and third level constraints, the implicit information from primary constraints is used to improve the accuracy and reduce the computational complexity. A data structure is built using a heap to efficiently update the distance between the profiles. There are three parts in this structure: the first two are the names of the profiles and clusters to be paired, and the third one is the Minkowski distance of the pair. The data structure can be presented as a distance list with three columns for the three parts. First based on the group requirements, if two profiles belong to the same group, which means they must be close to each other, the distance between them is set to 0 and the two profiles are combined in the distance list as a new cluster. Single linkage, also called the nearest-neighbor, is then applied to calculate the distances of other profiles without group requirements and combine them as new clusters, in which the shortest distance of any inter-cluster profile pairs is considered as the distance between the two clusters. All remaining pairs are searched to find the closest pair of clusters to be merged into a single cluster. Following this procedure, there is one cluster less. Each time when a new cluster is formed, all the related clusters and distances on the distance list are updated. The distance list is updated iteratively until all of the profiles are clustered into a single cluster. The implementation of this data structure enables the calculation of the distances of all profile pairs on the first step and then updates the distances between clusters in the following clustering process.

Based on this hierarchical clustering structure, an iterative evaluation algorithm is then designed to complete the load rearrangement through virtually changing occupancies, depending on the hierarchical constraints to eliminate diversity (Fig. 1). First, all of the profiles are assigned into initial clusters based on the individual requirements (I cluster). This step might vary case by case. Meanwhile, all profiles are also gathered into initial clusters based on the group requirements (G cluster). The following steps are executed independently for the intersections of I cluster and G cluster and the remaining. Initially, the profiles with the distances of 0 are merged based on the group requirements and randomly placed to the zones that could satisfy both the individual requirements and group requirements. The heap based distance list is then used to merge two clusters one at a time according to their profile similarities. Since the capacity of each zone (numbers of spaces and occupants in the zone) does not change before or after the load rearrangement, if the new cluster contains the cluster merged in the previous step, the subsequent profiles are placed to the same zones of the existing profiles or connected zones depending on whether the zone capacity has been reached and how the third level constraints (zone adjacency, orientation, and HVAC layout) define the divisions of connected zones. Otherwise, the subsequent profiles are placed to the zones containing the profiles that are relatively most similar to them. As long as two clusters are merged to one cluster, profiles within one zone are adjusted to ensure the profiles on the zone boundaries are similar to the profiles on the boundaries of the connected zones. Finally, all occupancy profiles are virtually traversed and one trial of eliminating diversity is completed. Since the initial assignment for loads rearrangement is randomly selected, the entire process described above, is iterated with different initial assignments until the ratio between inter-zone distance (average profile distance within each zone) and inner-zone distance (average profile distance from other zones) reaches the maximum.

Another contribution is the integration of BIM, with the aid of its unique representation of the spatial relationships of occupants, and its ability in improving the understanding of hierarchical constraints and load rearrangement for eliminating the diversity. The algorithm relies on BIM as a source of building information and spatial information. BIM provides digital repository for information exchange and interoperability to facilitate design, construction, and facilities management, and nowadays more buildings have BIMs. Moreover, building information is important to feed into building energy model and could further provide contextual interpretation of energy performance.

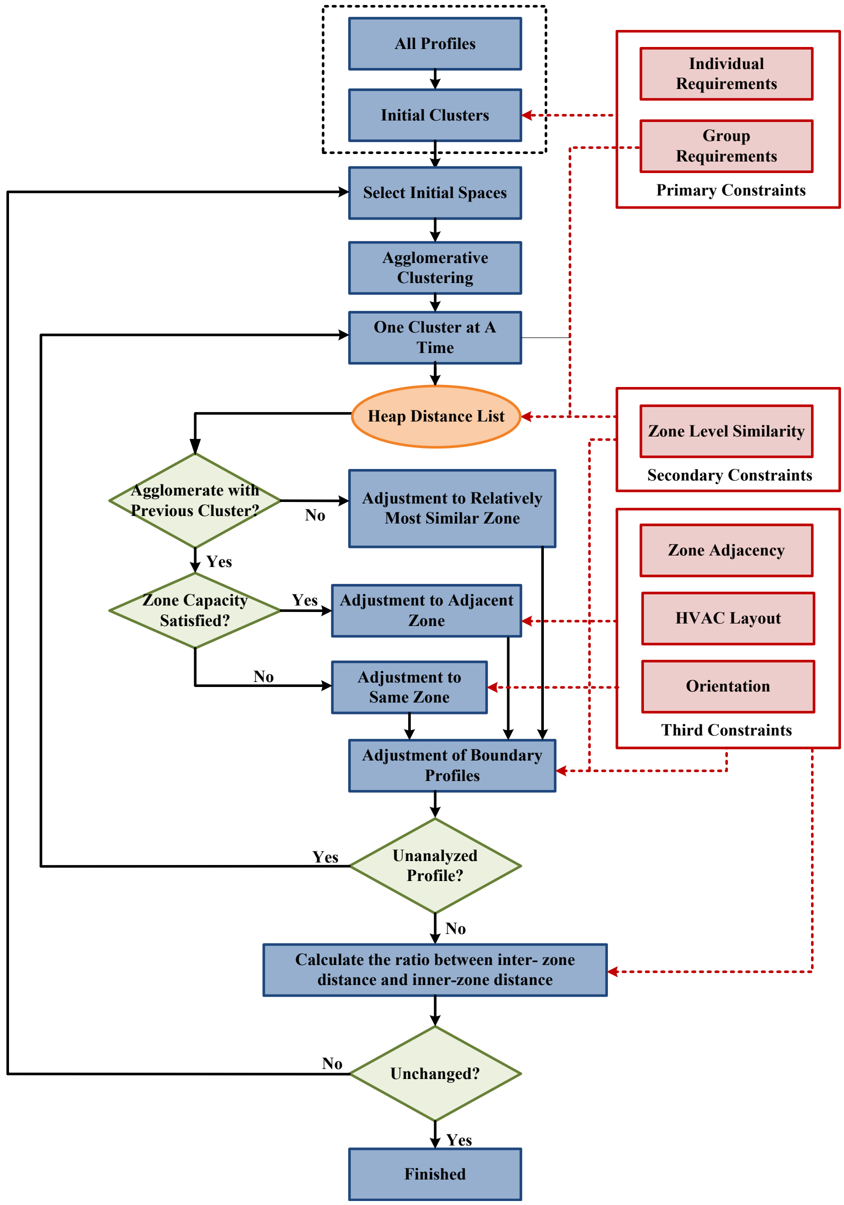

Fig. 1. Iterative evaluation algorithm for hierarchical clustering and elimination of occupancy diversity.

4. Validation: quantifying energy implications of occupancy diversity

In order to validate the effectiveness of the proposed framework in quantifying the HVAC system energy efficiency affected by occupancy diversity at the building level, the heating/cooling loads after implementing the framework were compared with other possible trials of eliminating diversity in a testbed building. The building is a typical office building facing north on the USC (University of Southern California) campus in Los Angeles, California. It is a three-story building with a footprint of 3735 m^2 with 89 mechanically ventilated rooms that have spaces of varying sizes and functions. Most of the rooms in the building are enclosed single occupancy offices; other rooms are classrooms, conference rooms, and auditoriums. The building is served by a centrally controlled HVAC system with a VAV (Variable Air Volume) box for each zone. The occupancy profiles were acquired using the cross-space occupancy modeling algorithm and ARMA profiling method introduced in Section 3. Since the sampling rate for the occupancy modeling was 3 min, the original occupancy profile was 480-dimensional. The logic operation was determined to segment the 480 dimensions by a 30-min time window with 15-min overlap based on the analysis of degree of statistical approximation for different window/overlap combinations. The period from 6:00 AM to 9:00 PM was chosen to form a 60-dimensional vector. Each number in the vector was the averaged presence probability for the corresponding 30-min time window.

A VB.NET script was prepared in order to implement the iterative evaluation algorithm with a DLL (Dynamic Link Library) file compiled for extracting information from the BIM through API (Application Programming Interface). The spatial information was encoded for implementing the hierarchical clustering and elimination of diversity in Matlab. Whole building energy simulation was then used to calculate the heating/cooling loads before and after diversity elimination. Building geometry was built using Google Sketchup. Construction thermal properties and HVAC systems were added using OpenStudio. Equipment/appliance schedules were assumed to be the same as occupant presences. Lighting fixtures were assumed to be used if a space was occupied and when artificial lighting is used (based on light sensor) during 6:30–10:00 and 15:30–18:00 (after 18:00 lighting fixtures were assumed to be used if occupant presence is positive). All these inputs were written into *idf* file using Matlab for the EnergyPlus simulations. Based on the availability of occupancy data, only one floor was used to validate the proposed framework. However, conduction, convection and longwave radiation, heat transfer and loads exchange between two floors (above the ground) are relatively less significant compared to the walls, therefore, their influence on the elimination of diversity at the building level is assumed to be limited. However, the same framework could be implemented to quantify the heating/cooling loads associated with diversity for both single-floor buildings and multi-floor buildings across floors.

Primary constraints were set for individual requirements and group requirements. The individual requirement was about space size, which cannot change by more than 20% for a given occupant, while the group requirement was about having occupants of the same departments to be spatially close to each other. It is important to note that the selection of specific primary constraints does not influence the way of eliminating occupancy diversity, and can be varied case by case. The secondary constraint was to move the similar occupancy profiles into the same zones. Occupancy profile for each room was calculated for the period of simulation (12 months from March 2014 to March 2015). The third level constrain required the occupancy profiles in the connected zones to be similar. Considering the zone adjacency, zone orientation (North, South, East, West – no Core Zone in this building), and HVAC layout, the third floor of the testbed building was divided into six connected zones (Fig. 2). The capacity of each zone was not changed before or after implementing the evaluation algorithm.

First, the proposed framework was implemented, and compared with other 100 trials of eliminating diversity simply based on primary constraints and random occupant-space combinations through running occupancy driven setpoint control. During the on-hour period (6:30 AM – 9:30 PM on workdays, and 7:00 AM – 9:30 PM on weekends), a setpoint (i.e., 73 F) was maintained and allowed to float until reaching a setback (i.e., 78 F) when the zone was unoccupied for more than 15 min (e.g., during lunch breaks, etc.). If the space was occupied again, the setting went back to the setpoint. During the off-hour period, no cooling or heating services were provided. Only minimum airflow was maintained to satisfy the ASHRAE compliance [32]. The benchmarks for comparison were the heating/cooling loads for occupancy driven setpoint control without any occupancy-space rearrangement. The increment percentages, after occupancy-space rearrangement compared to the benchmarks in both heating and cooling loads, were calculated. Their relative performances (Fig. 3) indicate whether the proposed framework could effectively eliminate diversity and quantify the energy implications of diversity.

It can be seen from the results (Fig. 3) that there was no complete superposition of any two trials, indicating generally the diversity was closely associated with heating/cooling loads. When hearing or cooling being analyzed separately, there was only one trial that generated slightly less loads. All of the 100 random trials consumed more energy in both heating and cooling than the proposed framework (Fig. 3). There was no random trial that could outperform the iterative evaluation algorithm in eliminating the diversity. The loads for HVAC system as actual demands at the building level were reduced (11.3% for cooling and 6.5% for heating).

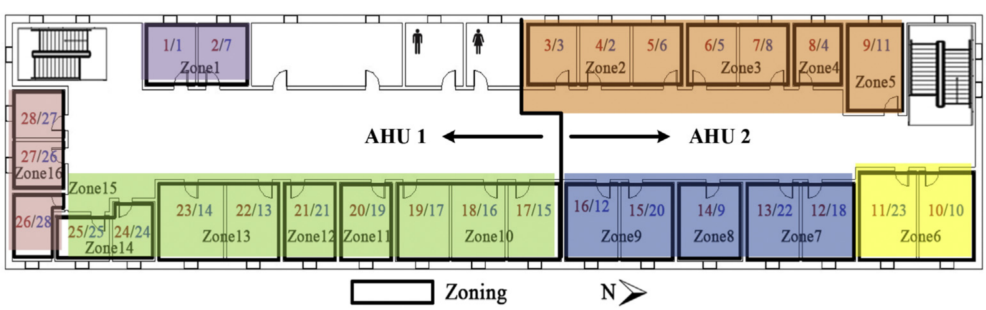

Fig. 2. Iterative evaluation algorithm for eliminating the occupancy diversity (different colors represent connected zones defined by the third level constraints).

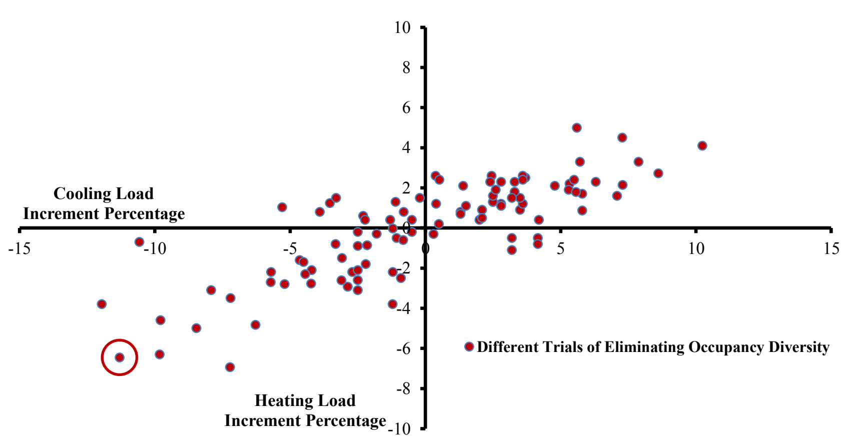

Fig. 3. Load increments (%) of different trials for eliminating occupancy diversity (the dot with red circle is the trial resulting from the proposed framework). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

To further evaluate the importance of eliminating diversity at the building level, the three factors of HVAC system layout, thermal zone adjacency and orientation for defining the third constraint were added gradually for implementing the iterative evaluation algorithm. The number of factors being considered was varied, and at least fifty simulations were conducted for each number of factors to reduce the variability. In Fig. 4, the x-axis represents the load increment percentages compared to eliminating occupancy diversity at the zone level, while the y-axis displays the number of simulations for the certain percentage of load increment. It can be seen that the loads were generally reduced as more factors were added. It is necessary to define connected zones as third constraints for eliminating occupancy diversity at the building level to improve HVAC system energy efficiency.

For a more detailed analysis, eight possible combinations ("none", "HVAC layout", "zone adjacency", "orientation", "HVAC layout and zone adjacency", "HVAC layout and orientation", "zone adjacency and orientation" and "HVAC layout and zone adjacency and orientation") were explored. Each time one combination was considered as the third constraint to generate 20 trials of eliminating diversity at the building level. The average load increment percentage of each combination was then compared with the benchmark introduced previously (heating/cooling loads for occupancy driven setpoint control without any occupancy-space rearrangement). As presented in Fig. 5, the x-axis represented the combinations of factors to be considered as the third constraints, while the y-axis showed the load increment percentages, compared to simply implementing occupancy driven setpoint control.

"Zone adjacency" had the most significant influence on load increments associated with diversity. It is because adjacent zones share boundaries and there are load exchanges through heat transfer and balance among the zones and adjacent zones are usually supplied by the same conditioned air. If two factors were considered, the combination of "zone adjacency" and "orientation" was more influential than any other combinations. One possible reason is that zones with the same orientation have similar boundary conditions and are impacted similarly by the outside environment. If all the three factors were incorporated, the loads were significantly reduced (9.6%), demonstrating that all three factors were important to form the third constraints for eliminating occupancy diversity and improving HVAC system energy efficiency.

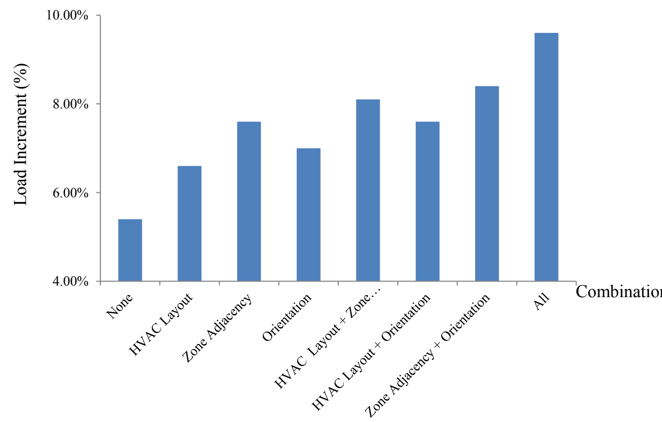

Fig. 5. Load increments (%) of different combinations.

5. Generalizability analysis

In order to test the generalizability of the iterative evaluation algorithm, virtual reference buildings were created based on the enhanced reference buildings provided by the Department of Energy [33] and architectural logic/shape grammar [34] for representing different commercial buildings in the United States. Five basic building shapes, including I, L, H, U, and T, were studied [35,36] (Fig. 6).

We assumed the virtual reference buildings to have the same occupants and number of rooms as the third floor of the testbed building. The layouts of rooms and original occupancy for each room were formed by a LPP (Layout Planning Process) program (explained in the appendix of this paper), by which each occupant could be assigned to a specific room as the original plan for each building. HVAC system configuration was also kept the same as the one in the testbed building to eliminate the possible disturbances from different HVAC system parameters. Zoning also remained the same with the same number of zones and zone capacities. For each building shape, twenty different plans were generated using the LPP program by relocating the 28 rooms. One-story virtual reference buildings were then created based on the plans using Sketchup. Corridors, the same size as in the testbed building, were added. Other building features, such as window fraction, construction materials (e.g., wall U-factor), and internal loads (e.g., average lighting power density), were determined according to the enhanced reference office building models (covering 80% of the commercial building floor area in the U.S.) and ASHRAE 90.1 [33,37,38]. The same weather data for the testbed building was

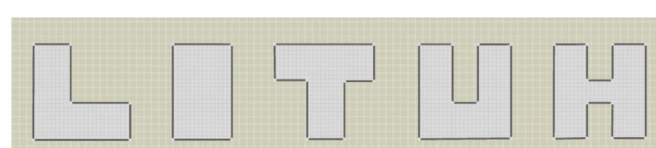

Fig. 6. Basic building shapes for mass modeling.

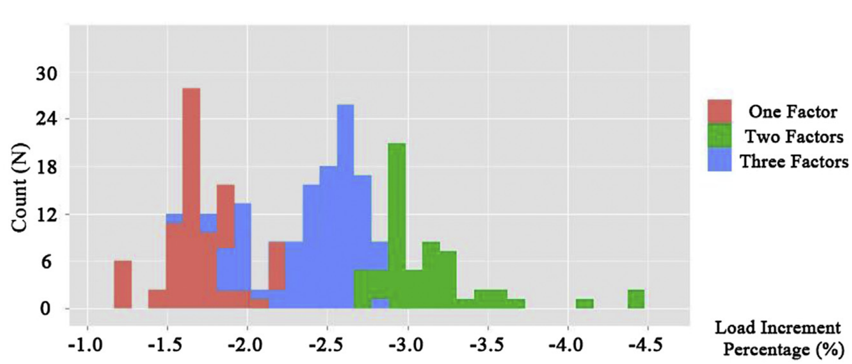

Fig. 4. Load increments (%) of different number of factors for determining connected zones as the third constraints.

used, downloaded from the website of Department of Energy for simulations. Total of 100 building models (20 different plans for each of the five building shapes) were generated for the validation. For each of the model, 4 types of simulations were performed and results were compared to evaluate the generalizability of the iterative evaluation algorithm (Fig. 7).

1) *Baseline control:* The existing setpoint control without any change was simulated for each virtual reference building. The existing control assumed all thermal zones in the building to be always occupied under the on-hour mode (6:30 AM – 9:30 PM on workdays, and 7:00 AM – 9:30 PM on weekends), and a constant temperature setpoint of 73 F was maintained;
2) *Occupancy driven setpoint control with occupancy diversity:* The occupancy driven setpoint control without any change to occupancy was simulated for each virtual reference building. During the on-hour mode, a constant temperature setpoint of 73 F was enforced for occupied zones. If a zone was vacant for a minimum of 15 min, the setback of 78 F was triggered until it was occupied again;
3) *Occupancy driven setpoint control after eliminating occupancy diversity at the zone level:* Occupancies were virtually changed based on primary constraints and secondary constraint for load rearrangement. The occupancy driven setpoint control after occupancy diversity was eliminated at the zone level.
4) *Occupancy driven setpoint control after eliminating occupancy diversity at the building level*: All of the primary, secondary and third constraints were considered for eliminating diversity. The occupancy driven setpoint control was simulated for each virtual reference building after occupancy diversity was eliminated at the building level.

Based on the results, 96% of the models had the same increasing trend of load increment percentage, from simulation 1 to simulation 4, indicating that energy efficiency was consistently affected by diversity both at the zone level and building level. Heating/cooling loads, associated with diversity, were reduced by load rearrangement. Ranking of the influence of diversity on heating/cooling loads for different building shapes was the following (from less to more): I shaped, L/T shaped, and H/U shaped. The more complicated the building geometry was, the more connections the zones had and the influence of outside environment was more significant, therefore, the influence of diversity on heating/cooling loads was more significant (approximately 3.5% difference between I shaped and L/T shaped, and 3% difference between L/T shaped and H/U shaped). Since the loads that were the actual demands for HVAC system were significantly reduced for all of the models, the influence of diversity on HVAC system energy efficiency was consistent over different building shapes, different layouts and different occupancy diversities (Table 1). By running occupancy driven setpoint control, 11.5–14.4% of the energy efficiency could be improved if occupancy diversity was eliminated at the zone level. The improvement range could move up to 16–18% if occupancy diversity was eliminated at the building level. In addition, the method was generalizable.

6. Conclusions

Occupancy diversity may increase the loads that are not actual demands for an HVAC system, leading to energy inefficiencies. In this paper, an iterative evaluation algorithm, based on agglomerative hierarchical clustering, was introduced to eliminate occupancy diversity based on three levels of constrains. A testbed building and virtual reference buildings were used for validation. The

Table 1
Influence of occupancy diversity on HVAC system energy efficiency for five building shapes and four types of simulations.

	Simulation 1	Simulation 2	Simulation 3	Simulation 4
I Shape	0% (Benchmark)	7.27%	12.62%	16.67%
L Shape	0% (Benchmark)	7.76%	14.64%	18.76%
T Shape	0% (Benchmark)	6.91%	14.44%	18.84%
U Shape	0% (Benchmark)	6.23%	12.08%	18.31%
H Shape	0% (Benchmark)	6.18%	11.77%	18.27%

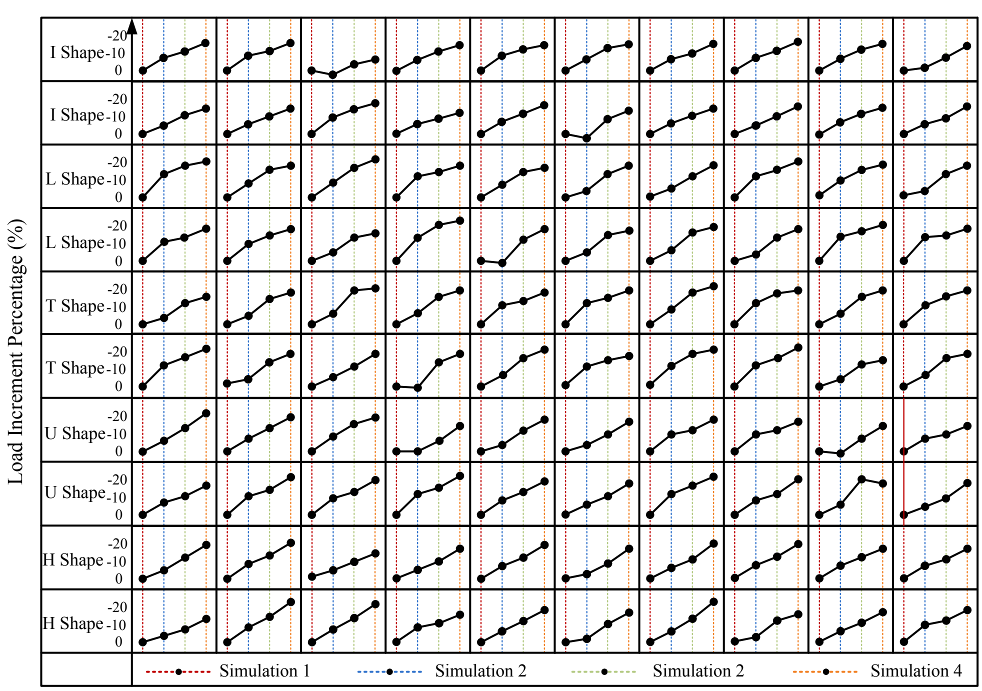

Fig. 7. Comparison of results for four types of simulations across 100 virtual reference buildings.

agglomerative hierarchical clustering process was improved using heap to reduce the time and computational complexity for updating distances among clusters. When using a real-world testbed building, the iterative evaluation algorithm outperformed other possible trials of eliminating diversity, and was effective to quantify the energy implications of diversity. The method could reduce the loads that are not the actual demands for HVAC systems to leverage the effects of occupancy driven setpoint control. The performance of the proposed framework was also consistent over different building geometries, different building layouts and different diversities when using virtual reference buildings. The more complicated the building geometries were, the more significant the influence of diversity on HVAC system energy efficiency was.

The contribution of this research is to increase our knowledge about the impact of occupancy diversity on HVAC system energy efficiency, which could bring about potential energy savings and could facilitate better-informed decision making for energy-efficient HVAC system control strategies. The investigations, presented here, do not aim to provide any specific solution to eliminate diversity for a specific building or for a specific HVAC system or in a specific climate. Although centrally controlled HVAC VAV systems were used in the testbed building and virtual reference buildings for validation, the proposed framework could be applied to other buildings and HVAC systems as the essence of the framework about occupancy–space relationships and control of setpoint remain the same. However, the work has limitations which could be addressed in future research. First, the occupancy data from the testbed building was used for both validations, which might not be representative for all cases. The lack of available occupancy ground truth is a common issue not only with this research but also for any occupant related study. We will continue to collect occupancy data from a large range of buildings for larger scale validations. Second, if occupants could be reassigned to spaces or occupants are moved to new buildings in the future. Third, if changing occupancy–space relationship is not feasible, occupancy driven setpoint control should be optimized globally to reduce the loads caused by occupancy diversity, by allowing different zones to have different values of setback and different waiting time to trigger the setback, as well as different supply air flow temperatures and rates.

Acknowledgments

This material is based upon the work supported by the National Science Foundation under Grant No. 1351701. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. The occupancy data and building performance data were collected under Grant No. DE-EE0004019. Computation for the work described in this paper was partly supported by the University of Southern California's Center for High-Performance Computing (hpc.usc.edu).

Appendix

In order to create the virtual reference buildings for validation, a computer application program was developed using Java to assist the Layout Planning Process (LPP) for different building shapes (Fig. A1). The layout of rooms and original occupancy for each virtual reference building could be formed following certain rules that already existed in the testbed building by extracting building information as an add-on to BIM. The individual and group requirements of primary constraints, which required the occupants have new spaces with similar sizes and occupants from the same department to be spatially close to each other, were included in the program.

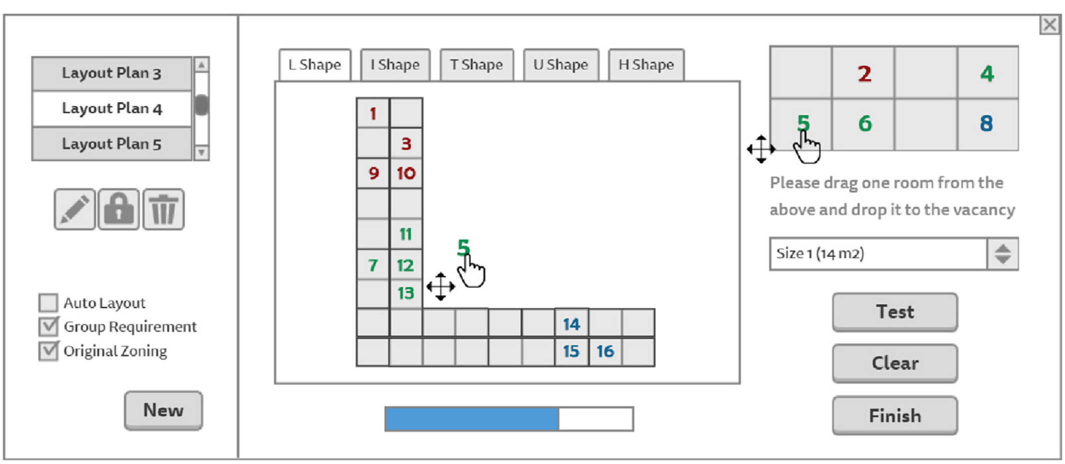

Fig. A1. Computer application program interface for layout planning.

as long term occupancy patterns may change over time, a piecewise occupancy profile might be more reliable to calculate the similarities among occupants for diversity measurement.

As an extension to the proposed research, findings from the two-stage validation could provide some recommendations for real-world applications. First, for building design with more complex geometries, occupancy diversity should be considered for reducing the excessive loads, and spaces with diverse occupancies could be put to different orientations depending on dominant heating or cooling requirements. Second, for buildings equipped with ambient sensor network, real-time and long-term occupancy information could be calculated and recorded for energy efficiency

The user interface of the program is divided into two panels. The left panel is the set up menu, in which the existing layout plans can be viewed, edited, locked, and deleted. Before creating new plans, the user decides whether he/she wants the program to generate the plan automatically based on the primary constraints and random number coding, and whether the group requirement and HVAC zoning information are shown during the planning process. The right panel of the GUI is the configuration window, in which the user can drag a room from the right top repository and drop it to a vacant space in the building. The number of rooms unassigned can be tracked by the progress bar. There are three options of TEST to check whether the current plan is same as the existing ones, CLEAR to erase the current plan and start over, and FINISH to save the current plan. For each building shape, there are four additional unassigned spaces for two stair cases and two restrooms. If the group requirement checkbox is checked, the room numbers under the same group are color coded to point out where the next rooms should be placed. When the original zoning is selected, the default zoning information based on the testbed building is shown by enclosing the rooms of the same zone. Although the zoning is not exactly the same, the number of zones and the zone capacities remain the same.

References

[1] U.S. Environmental Protection Agency. The inside story: a guide to indoor air quality. Available at: http://www.epa.gov/iaq/pubs/insidestory.html#IAQHome2. [accessed 04.20.16].
[2] U.S. Department of Energy. Better buildings, brighter future. 2013.
[3] U.S. Department of Energy. Building energy data book. Available at: http://buildingsdatabook.eren.doe.gov/ChapterIntro3.aspx. [accessed 04.20.16].
[4] Bartlett D. The top ten ways we waste energy and water in buildings. Available at: http://breakingenergy.com/2011/07/26/the-top-ten-ways-we-waste-energy-and-water-in-buildings/. [accessed 04.20.16].
[5] U.S. Department of Energy. Building energy consumption and efficiency-commercial building energy consumption survey. Available at: http://www.eia.gov/consumption/commercial/. [accessed 04.20.16].
[6] Yang Z, Li N, Becerik-Gerber B, Orosz M. A non-intrusive occupancy monitoring system for demand driven HVAC operations. Constr Res Congr 2012:828–37.
[7] Rana R, Kusy B, Wall J, Hu W. Novel activity classification and occupancy estimation methods for intelligent HVAC (heating, ventilation and air conditioning) systems. Energy 2015;93(1):245–55.
[8] Goyal S, Ingley HA, Barooah P. Occupancy-based zone-climate control for energy-efficient buildings: complexity vs. performance. Appl Energy 2013;106:209–21.
[9] Yang Z, Becerik-Gerber B. The coupled effects of personalized occupancy profile based HVAC schedules and room reassignment on building energy use. Energy Build 2014;78:113–22.
[10] Zeng Y, Zhang Z, Kusiak A. Predictive modeling and optimization of a multi-zone HVAC system with data mining and firefly algorithms. Energy 2015;86:393–402.
[11] Wang C, Yan D, Jiang YA. Novel approach for building occupancy simulation. Building simulationvol. 4. Springer; 2011. p. 149–67.
[12] Duarte C, Van Den Wymelenberg K, Rieger C. Revealing occupancy patterns in an office building through the use of occupancy sensor data. Energy Build 2013;67:587–95.
[13] Feng X, Yan D, Hong T. Simulation of occupancy in buildings. Energy Build 2015;87:348–59.
[14] Erickson VL, Carreira-Perpiñán MA, Cerpa AE. OBSERVE: occupancy-based system for efficient reduction of HVAC energy. In: 10th international conference on information processing in sensor networks (IPSN); 2011.
[15] Dong B, Andrews B. Sensor-based occupancy behavioral pattern recognition for energy and comfort management in intelligent buildings. In: 11th international building performance simulation association conference; 2009.
[16] Agarwal Y, Balaji B, Gupta R, Lyles J, Wei M, Weng T. Occupancy-driven energy management for smart building automation. In: 2nd ACM workshop on embedded sensing systems for energy-efficiency in building; 2010.
[17] Oldewurtel F, Sturzenegger D, Morari M. Importance of occupancy information for building climate control. Appl Energy 2013;101:521–32.
[18] Ghahramani A, Zhang K, Dutta K, Yang Z, Becerik-Gerber B. Energy savings from temperature setpoints and deadband: quantifying the influence of building and system properties on savings. Appl Energy 2016;165:930–42.
[19] Davis III JA, Nutter DW. Occupancy diversity factors for common university building types. Energy Build 2010;42(9):1543–51.
[20] Mahdavi A. Patterns and implications of user control actions in buildings. Indoor Built Environ 2009;18(5):440–6.
[21] Gulbinas R, Khosrowpour A, Taylor J. Segmentation and classification of commercial building occupants by energy-use efficiency and predictability. IEEE Trans Smart Grid 2015;6(3):1414–24.
[22] Ghahramani A, Jazizadeh F, Becerik-Gerber B. A knowledge based approach for selecting energy-aware and comfort-driven HVAC temperature set points. Energy Build 2014;85:536–48.
[23] Haniff MF, Selamat H, Yusof R, Buyamin S, Ismail FS. Review of HVAC scheduling techniques for buildings towards energy-efficient and cost-effective operations. Renew Sustain Energy Rev 2013;27:94–103.
[24] Martani C, Lee D, Robinson P, Britter R, Ratti C. ENERNET: studying the dynamic relationship between building occupancy and energy consumption. Energy Build 2012;47:584–91.
[25] Pérez-Lombard L, Ortiz J, Coronel JF, Maestre IR. A review of HVAC systems requirements in building energy regulations. Energy Build 2011;43(2):255–68.
[26] Du Z, Jin X, Fan B. Evaluation of operation and control in HVAC (heating, ventilation and air conditioning) system using exergy analysis method. Energy 2015;89:372–81.
[27] Korolija I, Marjanovic-Halburd L, Zhang Y, Hanby VI. Influence of building parameters and HVAC systems coupling on building energy performance. Energy Build 2011;43(6):1247–53.
[28] Kim H, Stumpf A, Kim W. Analysis of an energy efficient building design through data mining approach. Automation Constr 2011;20(1):37–43.
[29] Yang Z, Becerik-Gerber B. Modeling personalized occupancy profiles for representing long term patterns by using wireless sensor networks. Build Environ 2014;78:23–35.
[30] Yang Z, Becerik-Gerber B. Cross-space building occupancy modeling by contextual information based learning. In: 2nd ACM international conference on embedded systems for energy-efficient built environments; 2015.
[31] Ichino M, Yaguchi H. Generalized Minkowski metrics for mixed feature-type data analysis. IEEE Trans Syst Man Cybern 1994;24(4):698–708.
[32] American Society of Heating. Refrigerating and air-conditioning engineers. ANSI/ASHRAE standard 62.1–2010: ventilation for acceptable indoor air quality. 2010.
[33] Goel S, Rosenberg M, Athalye R, Xie Y, Wang W, Hart R, et al. Enhancements to ASHRAE standard 90.1 prototype building models. Pacific Northwest National Laboratory; 2014.
[34] Mitchell WJ. The logic of architecture: design, computation, and cognition. MIT Press; 1990.
[35] Müller P, Wonka P, Haegler S, Ulmer A, Van Gool L. Procedural modeling of buildings. ACM Trans Graph 2006;25(3):614–23.
[36] Schmitt G. Architectura Et Machina: computer Aided Architectural Design und Virtuelle Architektur. Springer-Verlag; 2013.
[37] Deru M, Field K, Studer D, Benne K, Griffith B, Torcellini P, et al. US department of energy commercial reference building models of the national building stock. 2011.
[38] American Society of Heating. Refrigerating and air-conditioning engineers. ANSI/ASHRAE/IES standard 90.1-2013 for buildings except low-rise residential buildings. 2013.