Lawrence Berkeley National Laboratory

Lawrence Berkeley National Laboratory

Title Building Performance Simulation

Permalink https://escholarship.org/uc/item/1xp7s1b4

Author Hong, Tianzhen

Publication Date 2013-06-01

XXXXXX



ERNEST ORLANDO LAWRENCE BERKELEY NATIONAL LABORATORY

Building Performance Simulation

Tianzhen Hong¹, Hung-Wen Lin¹, Wen-Kuei Chang¹, Liping Wang¹, William Turner¹

Da Yan², Dandan Zhu², Xin Zhou², Chuang Wang², Chen Peng², Xiaoxin Ren²

¹Environmental Energy Technologies Division, LBNL ²Department of Building Science and Technology, Tsinghua University, China

June 2013

This report is a summary of research work conducted by LBNL and Tsinghua University, China in 2011 and 2012 under the 5-year research program of the U.S.-China Clean Energy Research Center for Building Energy Efficiency. The LBNL's research was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231. Tsinghua's research was supported by the Ministry of Housing and Urban-Rural Development and the Ministry of Science and Technology of China, under Contract No. 2010DFA72740-02. Some joint research work was also sponsored by Energy Foundation.

Disclaimer

This document was prepared as an account of work sponsored by the United States Government. While this document is believed to contain correct information, neither the United States Government nor any agency thereof, nor The Regents of the University of California, nor any of their employees, makes any warranty, express or implied, or assumes any legal responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by its trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof, or The Regents of the University of California. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof, or The Regents of the University of California.

Ernest Orlando Lawrence Berkeley National Laboratory is an equal opportunity employer.

Table of Contents

Introduction 1
The U.SChina Clean Energy Research Center 1
Research Background 2
Research Team and Collaboration5
Research Objectives and Technical Tasks 6
Research Objectives
Technical Tasks
Task 1 – Key drivers of energy performance of buildings 6
Task 2 – Occupant behavior 6
Task 3 – Comparison of building energy modeling programs 7
Research Findings
Summary7
Building Operation
Building Maintenance 11
Weather Impact 16
Occupant Behavior 17
Description of occupant behavior 17
Integration of behavior model with energy modeling programs
Statistical model of occupancy patterns 19
Markov-chain model of occupant moving 22
Quantitative description and simulation of human behavior in residential buildings 23
Comparison of EnergyPlus, DeST and DOE-2.1E23
Introduction
Building loads
HVAC systems
Future Research
Acknowledgement
Appendix A – List of Publications
Appendix B – List of Workshops and Major Activities
Appendix C – Selected Publications

Introduction

U.S. and China are the world's top two economics. Together they consumed one-third of the world's primary energy. It is an unprecedented opportunity and challenge for governments, researchers and industries in both countries to join together to address energy issues and global climate change. Such joint collaboration has huge potential in creating new jobs in energy technologies and services.

The U.S.-China Clean Energy Research Center

In November 2009, President Barack Obama and President HU Jintao announced the establishment of the \$150 million U.S.-China Clean Energy Research Center (CERC, http://www.us-china-cerc.org/, http://www.cerc.org.cn/). The Protocol formally establishing the Center was signed at ceremonies in Beijing by U.S. Energy Secretary Steven Chu, Chinese Minister of Science and Technology Wan Gang, and Chinese National Energy Agency Administrator ZHANG Guobao.

The CERC builds upon over 30 years of U.S. and China science and technology collaboration. Under the Science and Technology Cooperation Agreement of 1979 and its 1991 amendment, our two countries have cooperated in a diverse range of fields, including basic research in physics and chemistry, earth and atmospheric sciences, a variety of energy-related areas, environmental management and more.

The CERC facilitates joint research and development on clean energy technology by teams of scientists and engineers from the United States and China. It is a flagship initiative funded in equal parts by the United States and China, with broad participation from universities, research institutions and industry. U.S. funds will be used exclusively to support work conducted by U.S. institutions and individuals only, and Chinese funds will support work conducted by Chinese institutions and researchers.

CERC has three research themes: (1) CERC Building Energy Efficiency (CERC-BEE) focusing on research and development of building technologies, tools, and policy to improve design and operation of buildings to reduce energy use in buildings, (2) CERC Clean Vehicles focusing on research and development of new technologies for electric vehicles and alternative fuels to reduce air pollution and carbon emissions from the transportation sector, and (3) CERC Advanced Coal Technology focusing on research and development of technologies to improve efficiency and reduce air emissions of coal power plants and new technologies for carbon capture and storage.

The CERC-BEE Consortium conducts R&D on building energy efficiency technologies and practices in the United States and China. CERC-BEE's vision is to, "To build a foundation of knowledge, technologies, tools, human capabilities, and relationships that position the United States and China for a future with very low energy buildings resulting in very low CO2 emissions."

BEE develops innovative technologies and strategies for use in new and existing buildings to improve efficiency, save energy, reduce greenhouse gas emissions, increase indoor comfort, and reduce stress on the electric grid. As new construction proceeds around the globe, collaborative BEE research efforts are helping to lock in tremendous potential energy savings for the long term via a more efficient and low carbon built infrastructure. Figure 1 shows the five research areas and projects for the first two years under the CERC-BEE.



Figure 1 CERC-BEE Research Areas and Projects

Research Background

Buildings in the US and China consumed about 40% and 25% of the primary energy in both countries in 2010 respectively. Worldwide, the building sector is the largest contributor to the greenhouse gas emission. Better understanding and improving the energy performance of buildings is a critical step towards sustainable development and mitigation of global climate change.

Buildings demonstrate very diverse performance based on measured energy use. Figure 2 shows site energy use intensities (EUIs) of 100 LEED-NC certified buildings from the 2008 New Building Institute Study, *Energy Performance of LEED for New Construction Buildings*. At the same LEED certification levels, energy use of green buildings varies by a factor of up to 4 even excluding outliners. An ICF study shows similar divergence exists even for same type of buildings; Figure 3 shows the EUIs of big-box retails in the US and Canada. Measurements done by Tsinghua University, by China (Figure 4) have disclosed large differences in energy use of campus buildings in similar climates between the US and China, even though the buildings in the US were designed to meet more stringent energy codes than those in China.



Figure 2 – Measured Energy Use Intensities (kBtu/ft²) of LEED-NC Certified Buildings (courtesy New Building Institute)







Figure 4 – Measured Electricity Use Intensities of Campus Buildings in the US and China (courtesy Tsinghua University, China)

As identified in the IEA ECBCS Annex 53: Total energy use in buildings – assessment and analysis methods, there are six driving factors that determine the energy performance of buildings (Figure 5): climate, building envelope, building equipment (energy and water services systems), operation and maintenance, occupant behavior, and indoor environmental conditions. Understanding how these factors affect the energy performance of buildings and which factors play more significant role under certain conditions can provide insight into the large variations of building energy use. This is also a crucial step to improve the design and operation of buildings for lower energy use and lower carbon emissions.



Figure 5 – Six driving factors of energy performance of buildings (courtesy IEA ECBCS Annex 53)

Measurement and simulation are the two approaches to obtaining the energy use data of buildings. While measurement can provide solid and more accurate data, it can be time consuming and costly. On the other hand, simulation is a quick and more cost effective way to get more detailed energy use data, but the simulated/predicted energy use usually is not as accurate as measured data. Both approaches are needed as one supplements the other and usually both are used in a project.

Measurements of real buildings tend to show large discrepancies between simulated and measured energy use of buildings. Figure 6 shows the measured and simulated site EUIs of LEED-NC certified green buildings. Averaged across all buildings, simulated energy use is within a reasonable range from the measured data, but looking at the individual building, simulation over-predicted energy use by up to 120%, and underpredicted by up to 65%. More astonishingly, simulation seemed to always under-predict the energy consumption of low energy buildings, with site EUI of 40 or lower representing about 50% better energy performance than the 2003 CBECS average commercial buildings in the US (EUI of 90 kBtu/ft²). This can be observed by the fact that no points fall into the shaded triangle in Figure 6. Besides how the six driving factors are captured in the simulations, the energy modeling tool used, the simulation user, and the simulation process can have strong impact on the predicted energy use of buildings.



Figure 6 – Measured vs. Simulated Energy Use Intensities (kBtu/ft²) of LEED-NC Certified Buildings (adopted, courtesy New Building Institute)

Computer-based building performance simulation has been widely and successfully used to: (1) evaluate design alternatives during the design of new buildings and evaluate retrofit measures of existing buildings, (2) demonstrate code compliance, and (3) calculate performance ratings. Although less common in the past and gaining momentum nowadays, simulation is also used to predict energy performance of buildings.

Among the six factors, the occupant behavior is the least studied and gets too simplified during the design and operation of buildings. How occupants interact with building systems have direct and decisive impacts on energy performance of buildings.

In this project, building performance simulation will be used to provide insight into the following important questions:

- 1. Why buildings of same type in the US and China have such large differences in measured energy use?
- 2. Why buildings of same type in similar climates between the US and China have such large differences in measured energy use?
- 3. Why the measured and simulated energy use of buildings have such large discrepancies?
- 4. How to describe and model human behavior to better understand and quantify its impact on building energy performance?
- 5. How building simulation can be improved to better capture the influences of the six factors in order to better guide the design and operation of buildings for high performance?
- 6. With various building energy modeling programs to choose, which is the right one to use?
- 7. How and why do simulation results vary so much from using different energy modeling programs?

Research Team and Collaboration

The joint research team (Table 1) includes the LBNL team, the U.S. industry partners, the Tsinghua team and the China industry partners. Tianzhen Hong of LBNL led the U.S. side research and Da Yan of Tsinghua University led the China side research. Richard Karney and Yi Jiang served as the senior technical advisors for the project.

The research team had bi-weekly conference calls to discuss project progress and resolve issues. The team organized a series of workshops (Appendix B) to exchange research findings, seek inputs and comments from researchers, practitioners, industry partners, HVAC manufacturers, government agencies, and other stakeholders. The joint research work also made significant contribution to the IEA Annex 53. Exchanged students from Tsinghua University stayed at LBNL for a few months to work on joint technical tasks.

Table 1 – The Joint Research Team

	The U.S. Side	The China Side
Research Team	The LBNL Team	The Tsinghua Team
Principal Investigators	Tianzhen Hong, LBNL	Da Yan, Tsinghua University
Research Team Members	William Turner, Liping Wang, Hung-Wen Lin, Wen-Kuei Chang	Chuang Wang, Dandan Zhu, Xin Zhou, Xiaoxin Ren, Xiaohang Feng, Kaiyu Sun, Chen Peng
Industry Partners	Bentley Systems, C3 Energy, Energy Foundation	The Xinao Group, the CECEP Group
Senior Technical Advisors	Richard Karney, USDOE	Yi Jiang, Tsinghua University

Research Objectives and Technical Tasks

Research Objectives

This project (Project A2 in Figure 1) aims to improve and expand the use of building simulation to support the design and operation of low energy buildings through better understanding and predicting the energy performance of buildings. The research objectives are to: (1) develop methods and models to identify and evaluate the six key factors to improve understanding of the energy performance of buildings in China and US, (2) develop methods to describe and model occupant behavior in buildings, and integrate the behavior models with the energy models to simulate the impact of occupant behavior on building performance, and (3) evaluate and compare capabilities of EnergyPlus, DOE-2.1E and DeST to better understand their commons, differences, strengths, weakness and limitations, and to guide simulation users how to choose an energy modeling tool for a specific application.

Technical Tasks

To achieve the three aforementioned research objectives, three research tasks were designed and completed.

Task 1 - Key drivers of energy performance of buildings

This task developed simulation methods and models, and performed sensitivity and scenario analysis to quantify the impact of operation practice, maintenance practice, occupant behavior, and weather on energy performance of typical office buildings in the U.S. Integrated consideration of these influencing factors in a holistic system approach during the design and operation of buildings is the most critical key in achieving high performance buildings.

Task 2 - Occupant behavior

Occupant energy-related behavior in buildings has two aspects: (1) occupant needs of comfort: thermal, acoustical, visual and indoor air quality (IAQ), and (2) occupant responses by interacting with building systems to restore comfort if their needs are not

met. The usual occupant interactions include opening/closing windows, operating blinds (or other shading devices), switching or dimming lights, adjusting thermostat, turning HVAC on/off, turning on/off computers, monitors and portable devices, and adjusting clothing. Occupant behavior includes occupant movement – how often and for how long an occupant moves around, and personal habit. ASHRAE Standard 55 defines comfort range for typical occupants at various activities and environments. The latest additions to the standard allow the cooling setpoint of the indoor air temperature to be adjusted upper if indoor air velocity is elevated or based on the adaptive comfort model. ASHRAE Standard 62.1 defines minimum outdoor air needed for healthy ventilation. Differences in occupant behavior can lead to huge variations of energy use in buildings. On the other hand, changes to human behavior at no-cost have demonstrated energy savings of 5 to 30% in office and residential buildings.

Current simulation programs, including EnergyPlus, DOE-2.1E and DeST, have limited capability to model human behavior considering its multidisciplinary and inherent complexity and uncertainty. This task will: (1) identify key energy related behavior of building occupants based on measured and survey data, and literature review, (2) develop algorithms to model occupant behaviors, (3) integrate the behavior models with energy models: EnergyPlus and DeST, and 4) assess the impact of occupant behavior on energy use in selected buildings in the US and China.

Task 3 – Comparison of building energy modeling programs

EnergyPlus is a computer program developed by USDOE to simulate the energy performance of buildings. It was started to combine the best features of two former energy modeling programs: DOE-2 and BLAST, but has since evolving as a powerful simulation engine to calculate building performance. DeST is a simulation program developed by Tsinghua University since the early 1990s and has been getting more and more use in China. DOE-2 was developed by LBNL in the early 1980s through mid 1990s to simulate energy performance of buildings. This task will compare the three programs, evaluate their capabilities, identify their commons and differences, strengths, weakness, and limitations in energy modeling. This provides guidance and support the simulation use in the building energy code development, code compliance, and performance rating and labeling.

Research Findings

This section summarizes the key research findings. Detailed description of research work, technical approaches, and results were published in 11 journal articles, 11 conference papers, and two technical reports (Appendix A). Selected publications were included in Appendix C.

Summary

 Building operation, maintenance, occupant behavior, and weather data are key drivers of energy performance of buildings. Various practices of building operation and maintenance, various types of occupant behavior, and long-term actual yearly weather data should be used in building simulations when evaluating energy savings of building designs and technologies in order to understand and quantify the sensitivity of such savings. Technologies sensitive to these factors may not work well when they are applied to real buildings.

- Different building operation practices lead to different building performance, and such differences can be greater than those caused by different design efficiency levels of buildings. Good operation is crucial to achieving low energy buildings, providing comfort for occupants, and extending equipment life.
- Building maintenance has strong influence on energy performance of buildings. Different maintenance practices lead to large differences in energy use. Good maintenance is another key to achieving low energy buildings, providing comfort and extending equipment life.
- Yearly variation of weather is significant and has strong impact on building performance. Energy savings and peak electric demand reduction of energy technologies calculated using traditional weather data TMY can be significantly over or under-estimated for actual weather. When evaluating design alternatives and retrofit measures, long-term actual yearly weather data should be used. This is now feasible and convenient considering the availability of historical AMY weather data and computing power of typical laptop and desktop computers nowadays.
- Technologies alone may not lead to high performance buildings if occupant behavior is ignored. Occupant behavior is complex, stochastic, and multi-disciplinary. Methods were developed to describe and model occupant behavior and to evaluate its impact on energy use in buildings. Various types of occupant behavior should be considered during the building design and operations. Changes to occupant behavior can be a no-cost measure to save energy.
- Markov-chain models were developed to describe occupant movement. Statistical models were developed to describe occupancy patterns in single-occupied offices.
- Occupant behavior, related to opening/closing windows, turning on/off TVs and air conditioners, and turning on/off lights, was identified and models were developed for residential buildings by mining measured data.
- Simulation methods were developed to compare the energy performance of four office buildings in the U.S., China, Hong Kong, and Taiwan to identify and analyze driving factors to the discrepancies of energy use of these buildings. The methods can be used for benchmarking analysis of building performance by simulations.
- An in-depth comparative study was conducted to analyze the three building energy modeling programs: EnergyPlus, DOE-2.1E and DeST. Comparison methods and suites of test cases were developed to identify and quantify the discrepancies of the results from the three programs. In general three programs can provide consistent simulation results if inputs to them are the same or equivalent. Due to its limitations, DOE-2.1E can have large errors if adjacent spaces have very different load profiles and operating schedules. For HVAC simulations, the largest discrepancies again came from discrepancies in user inputs, followed by HVAC equipment control strategies. There is no simple rule of which program is the best; it all depends on the application. It is recommended to apply a program within its application scope and observe its limitations.

Building Operation

Energy use of buildings varies in a wide range. Large office buildings in Chicago and built after 2000 were selected from the 2003 CBECS database and the high performance building database. These buildings' measured total source energy use intensities (EUIs) were graphed at the top portion of Figure 7. The size of the bubble represents the EUI. These buildings were compared to the DOE commercial reference large office building (baseline building) compliant with ASHRAE 90.1-2004 in Chicago, and their relative performance in EUI were calculated as a percentage (compared to the simulated EUI of the baseline building which is 1.39 MJ/m^2) and shown in Figure 7.



Figure 7 – Impact of building design and operation for a large office building in Chicago

As Figure 7 shows, the source EUIs of the seven large office buildings from the CBECS vary by a factor of four. The only one high performance large office building found from the HPB database consumed about half the total source energy compared to the baseline building. Why would the energy performance of these buildings of same type (large office) in same climate (Chicago) built in same era (after 2000) vary by a factor of eight? A rational assumption is these buildings use different technologies with different energy efficiency levels (insulation or walls and roofs, windows, lighting power, COP of chiller etc.) and these buildings are operated very differently. To understand the impact of building operation and building design on energy use, key parameters (Table 2) were selected to represent the building design and operation.

Table 2 – Design and operation parameters

Design parameters	Operation parameters
WWR (Window-wall-ratio) Window Wall insulation Internal loads (lighting + plug-load) Economizer Chiller efficiency Boiler efficiency	Daylighting control Shading control Infiltration rate Infiltration schedule VAV box damper setting Heating thermostat Cooling thermostat Heating setback during unoccupied hours Cooling setback during unoccupied hours Supply air temperature reset Lighting schedule Plug-load schedule

Typical values (Figure 8) of the design parameters are grouped into three categories: (1) high efficiency design, based on ASHRAE Standard 90.1-2010 requirements and best design practice, (2) standard design compliant with ASHRAE Standard 90.1-2004, and (3) low efficiency design based on characteristics of old office buildings. Typical values of the operation parameters are grouped into three categories too: (1) good operation practice, (2) standard operation practice, and (3) poor operation practice. These various design and operation practices were applied to the baseline building and simulated with EnergyPlus.

When the three levels of building design efficiency were combined with the three types of operation practices, their compound effects on the building total source energy were simulated. The bottom portion of Figure 9 shows the simulated source EUIs of the nine combined cases (the middle bubble represents the baseline building).

It can be seen that:

- The design efficiency plays a significant role. Under standard operation practice, the low efficiency building consumed 4.5 times of the total source EUI of the high efficiency building. Under the good and bad operation practices, the ratio is about 3.7 and 4 respectively. The ratios are not very different.
- The operation practice is as important. Under the standard design efficiency, the bad operation practice consumed 2.6 times of the total source EUI of the good operation practice. Under the high and low design efficiency levels, the ratios are 3 and 3.2 respectively.
- Combined together, the building with the low design efficiency and the bad operation practice consumes 12 times of the source energy of the building with the high design efficiency and the good operation practice. Although these ideal combinations may not exist in real word, it fully explains why the actual/measured energy performance of building varies by a factor of 8.

- To achieve high performance building, using latest products and technologies to improve design efficiency is necessary, but as important is the improving of good operation practice.
- When evaluating energy savings of energy efficiency technologies, various operation
 practices should be considered, at least as sensitivity analysis to look the persistency
 and variation range of the calculated energy savings.



Similar trends were observed in other US climates.

Figure 8 – Typical values of design and operation parameters and their impact on total source energy use

Building Maintenance

Different practices of HVAC system maintenance can result in substantial differences in building energy use. If a piece of HVAC equipment is not well maintained, its performance will degrade. If sensors used for control purpose are not calibrated, not only building energy usage could be dramatically increased, but also mechanical systems may not be able to satisfy indoor thermal comfort. Properly maintained HVAC systems can operate efficiently, improve occupant comfort, and prolong equipment service life.

The maintenance practices are categorized into three levels depending on the maintenance effort and coverage: 1) proactive, performance-monitored maintenance; 2) preventive, scheduled maintenance; and 3) reactive, unplanned or no maintenance. Table 3 summarizes the three practices of HVAC maintenance and their implications on equipment operating efficiency and energy use, equipment life, short term maintenance cost, and life cycle cost

including maintenance cost, energy cost, and equipment replacement or repair cost. The good practice will lead to lowest life cycle cost, while the bad practice seems to save short term maintenance cost, it will result in the highest life cycle cost.

Maintenance Practice	Description	Equipment Efficiency	Operating Energy	Equipment Life	Short-Term Costs	Life Cycle Costs
Reactive (Bad)	Deferred or no maintenance, "run to fail".	Low	High	Short	Low	High
Preventive (Average)	Scheduled maintenance, periodic inspection, cleaning, and adjustment.	Medium	Medium	Medium	Medium	Medium
Predictive (Good)	Use periodic measurements to detect evidence that equipment is deteriorating and to avoid failing.	High	Low	Long	High	Low

Table 3 - Three types of HVAC maintenance practices

A list of maintenance issues, including cooling tower fouling, boiler/chiller fouling, refrigerant over or under charge, temperature sensor offset, outdoor air damper leakage, outdoor air screen blockage, outdoor air damper stuck at fully open position, and dirty filters are investigated in this study using field survey data and detailed simulation models. The energy impacts of both individual maintenance issue and combined scenarios for an office building with central VAV systems and central plant were evaluated by EnergyPlus simulations using three approaches:

1) Direct modeling with EnergyPlus (Direct Modeling)

Maintenance issues are directly modeled using existing inputs (either design input parameters or performance curves) in the current version of EnergyPlus. This modeling approach can be applied to such maintenance issues as supply air sensor offset, zone thermostat offset and outdoor air damper leakage. This approach is also applied to model simplified maintenance issues such as chiller or boiler fouling by introducing a degradation factor to the chiller or boiler efficiency inputs to the EnergyPlus models. The advantage of this approach is easy implementation.

2) Using the energy management system (EMS) in EnergyPlus

EMS is an advanced feature of EnergyPlus and designed for users to develop customized high-level, supervisory control routines to override specified aspects of EnergyPlus modeling in the EMS program. The EMS feature in EnergyPlus is flexible to allow users to simulate equipment operating with some maintenance issues by overwriting or adding algorithms in EnergyPlus within the specified aspects of current EMS capability. Use of EMS feature may require advanced knowledge of EnergyPlus and computer programming. EMS is used to model maintenance issues like dirty filters which increase pressure drop across the filter with operating hours.

3) Modifying EnergyPlus source code (Modified Code)

Modifying the existing EnergyPlus source code, the third modeling approach, is used when both direct modeling and EMS approaches cannot be applied to simulate any particular equipment or system deficiencies. This approach requires users to have a thorough understanding of the existing EnergyPlus source code and to write your own custom computer program based on existing code. Such HVAC maintenance issues as cooling coil fouling, outdoor air and return air temperature sensors offset adopt the third approach. Table 4 shows a list of common HVAC maintenance issues with their potential impacts and modeling approach according to maintenance types, including sensor calibration, filter replacement, heat exchanger treatment, mechanical repair and refrigerant charge, are investigated using detailed simulation models. A description of the implement model for selected maintenance issues is as follows.

• Temperature sensor offset

Control sensors such as supply air temperature (SAT) sensors, zone thermostats, and outdoor air temperature (OAT) sensors may be out of calibration over a long term operation period. In this study, it is assumed that temperature sensors are offset by $\pm 2^{\circ}$ C. For example, if a SAT sensor is offset by $\pm 2^{\circ}$ C and a designed supply air temperature to control is 13° C, the actual supply air temperature due to sensor offset is 11° C.

• Dirty filter

In terms of filter replacement for reactive maintenance, it is assumed that filters in air handler units have not been replaced over a year. Therefore, pressure drop for air handler units has been increased and the maximum additional pressure drop is 500 Pa.

• Fouled cooling tower

Cooling towers can become fouled due to unfavorable conditions. The study assumes certain fouling condition that overall heat transfer coefficient is reduced to 85% of design value.

• Fouled Chiller/Boiler/Coils

Fouling on heat transfer surfaces of boiler and chiller increases the thermal resistance and leads to reduced heat transfer. For the scenario of chiller/boiler fouling, both chiller COP and boiler efficiency are assumed to be reduced by 10%. For fouled cooling/heating coils, overall heat transfer coefficients are assumed to be reduced to 50% of design UAs.

• Outdoor air damper (OAD) leakage

In the study, it is assumed that OAD leakage level is 30%. When the commanded outdoor air fraction is smaller than the leakage level, leaky damper cannot effectively control the air intake.

• Stuck outdoor air damper (OAD)

Stuck OAD due to control and mechanical failure is another common fault in field. In this study, OAD is assumed to get stuck at fully open position. Cooling and heating energy penalties are introduced when outdoor air is not favorable for free cooling.

• Clogged OA screen

Outdoor air intake screens may get clogged due to unfavorable locations or weather condition. The maximum percent of intake fresh air is assumed to reduce to 70%.

• Stuck outdoor air damper (OAD)

Stuck OAD due to control and mechanical failure is another common fault in field. In this study, OAD is assumed to get stuck at fully open position. Cooling and heating energy penalties are introduced when outdoor air is not favorable for free cooling.

Table 4 – A list of HVAC maintenance issues

Maintenance	nce Maintenance Simulated		Simulated	Modeling
Types	Issues	impacts	Scenarios	Approach
Sensor Calibration	Supply air temperature sensor (SAT) offset Zone temperature sensor offset Outdoor air temperature	controls, heating and cooling energy	temperature sensors are offset by ±2°C	Direct modeling, adjust SAT setpoint Direct modeling , adjust thermostat settings Modified Code, modify the
Filter replacement	sensor offset Dirty filter	pressure drop, fan energy, airflow	additional 500Pa of air pressure drop	controls EMS, adjust fan power for VAV systems
	Fouled cooling tower	efficiency	overall heat transfer coefficient is reduced to 85% of design UA	Direct modeling, adjust cooling tower UA
Heat exchanger	Chiller: fouled tubes	efficiency	chiller COP is reduced by 10%	Direct modeling, adjust chiller efficiency
cleaning/treatme	Boiler: hard water scale	efficiency	boiler efficiency is reduced by 10%	Direct modeling, adjust boiler efficiency
	Fouled heating /cooling coil	efficiency, comfort	overall heat transfer coefficient is reduced to 50% of design UAs	Modified Code, adjust coils UA
	Outdoor air damper leakage	heating and cooling energy	30% OAD leakage	Direct modeling, adjust minimum OA flow
Mechanical repair	Stuck outdoor air damper (OAD)	heating and cooling energy	OAD is stuck at fully open position	EMS, set constant OA flow
	Clogged OA screen	outdoor air flow is less than 100% during economizer mode thus increasing cooling energy	maximum percent of intake fresh air is reduced to 70%	Direct modeling, set maximum OA flow
Refrigerant charge	Chiller: over or under 10% refrigerant charge	efficiency	chiller COP is reduced by 10%	Direct modeling, adjust chiller efficiency

Clogged OA screen

Outdoor air intake screens may get clogged due to unfavorable locations or weather condition. The maximum percent of intake fresh air is assumed to reduce to 70%.

The energy penalty introduced by HVAC maintenance issues varies by a few factors including building and HVAC systems types, vintage (design efficiencies), and climates. In the study, the USDOE commercial building reference model for a large-size office building in compliance with ASHRAE Standard 90.1-2004 is used as a baseline representing good maintenance practice. The large-size office building consists of one basement level and 12 floors above ground served by 4 built-up VAV systems with 2 water-cooled chillers and one natural gas hot-water boiler.

The results, shown in Figure 9, demonstrated the energy penalty introduced by the reactive maintenance practice for the built-up VAV system located in Chicago. The percentages are derived by comparing the total source/primary energy use of HVAC systems for the reactive maintenance practice to those of the good practice (baseline reference model). The maintenance issues with significant energy impacts for Chicago are OA damper stuck at 100% position, blocked OA screen, supply air temperature offset, boiler/chiller fouling, and chiller refrigerant under/overcharge. Although there is no significant energy impact due to heating/cooling coil fouling, the numbers of unmet thermal comfort hours for both heating and cooling are significantly increased due to reduced system cooling and heating capacities. Two combined scenarios (#1 and #2) with different temperature sensor offsets were simulated in the study. The overall energy penalty by combining the sampled maintenance issues including sensor offset by +2 °C can reach 85% of overall HVAC energy consumption for Chicago climate.



Figure 9 - Impact of poor HVAC maintenance on HVAC source energy use of a large office building in Chicago

Modeling and simulation of building maintenance can help practitioners and building operators to gain the knowledge of maintaining HVAC systems in efficient operations, and prioritize HVAC maintenance work plan.

Weather Impact

Yearly variations of weather are significant, which can even change the climate zone classification of a location. Figure 10 shows the variations of weather data on the ASHRAE climate zone map for the 17 representative cities based on the AMY (Actual Meteorological Year) data from 1980 to 2009. It can be seen that most cities do not belong to only one climate zone. For the 30-year period, the climates of some cities vary across two zones and some even across three or more zones.

Yearly variations of weather have strong impact on energy performance of buildings. The simulated energy savings and peak electrical demand reduction from the use of energy efficiency technologies are sensitive to the weather data used in the simulation, this is in contrary to the traditional thinking of weather data only impacts the absolute energy use but not the relative performance between two different designs. Figure 11 shows the variations of peak demand reduction (in %) and the HVAC and building total source energy savings (in %) by comparing the performance of the prototype office buildings designed to meet the ASHRAE standard 90.1-2010 with those meeting the 90.1-2004, using the TMY3 and the 30-year AMY weather data across the 17 climates. In Figure 11, the green bars represent the variation in the demand reduction and source energy savings, using the 30-year AMY weather data. The red marks represent the corresponding results using the TMY3 weather data.

Generally the weather impact on the peak demand reduction is much greater than on the HVAC source energy savings. For HVAC source energy savings, larger weather impacts occur for the mixed to cold climates, from San Francisco to Fairbanks. The savings based on TMY3 weather files are usually within the ranges of savings based on the AMY weather files, except for over-estimates in San Francisco, Albuquerque, Boise, Vancouver, and Helena, where the red marks are usually at the very right end or outside of the green bars. The peak demand reduction can vary significantly year-over-year for most climates. The differences in demand reduction can be as high as 15% for Chicago and Fairbanks across the 30-year period for the large office building.

With the availability of long-term AMY weather data and sufficient computational power of personal computers, it is feasible and necessary to run simulations with AMY weather data covering multiple decades to fully assess the impact of weather on the long-term performance of buildings, and to evaluate the energy savings potential of energy conservation measures for new and existing buildings from a life cycle perspective. Main findings are: (1) annual weather variation has a greater impact on the peak electricity demand than on the energy use in buildings; (2) simulated building energy use using the TMY3 weather data is not necessarily representative of the average energy use using the AMY data, across the 30-year period. The TMY3 results can be significantly higher or lower than those from the AMY data; (3) the weather impact is greater for buildings in cold climates; (4) the weather has the greatest impact on the medium-size office building, followed by the large office and then the small office; and (5) simulated energy savings and peak demand reduction by energy conservation measures using the TMY3 weather data can be significantly lower or higher when compared to the results using the AMY data. These findings can support energy policy making, energy code development, building technologies evaluation, and utility incentive programs planning.







Figure 11 – Variations of percentage reduction of peak electricity demand, and percentage savings of HVAC source energy and total source energy of the ASHRAE 90.1-2010 models over the ASHRAE 90.1-2004 models. (a)-(c) large office; (d)-(f) medium office; (g)-(i) small office.

Occupant Behavior

Description of occupant behavior

Occupant behavior refers to an occupant's movement and responses to discomfort when his/her comfort needs are not met by interacting with building systems, including windows, shades, lights, appliances, thermostat, and HVAC systems. An occupant's comfort needs include thermal, acoustic, visual, and indoor air quality. Occupant's behavior varies with time, space, and individual. It is stochastic, complex, and multidisciplinary. A framework is developed to describe occupant energy-related behavior (Figure 12), which captures the three key elements: Drivers, Needs, and Actions. Drivers determine the needs which further determine the actions.



Figure 12 – A framework to describe occupant energy-related behavior

The framework will be represented in an XML schema to provide a standard definition of occupant behavior. Typical occupant behavior, actions on building systems, personal habit, and adjustment of personal clothing, moving, etc, will be represented as mathematical models suitable for simulation with energy modeling programs such as EnergyPlus and DeST.

Integration of behavior model with energy modeling programs

Typical occupant behavior in single occupancy private offices was studied, including how an occupant sets comfort criteria (cooling and heating thermostat), operates lights and office equipment, and turns on/off HVAC systems. The behavior is categorized into three workstyles (Table 5): (1) austerity – occupants are proactive in saving energy, (2) standard – average occupants, and (3) wasteful – occupants don't care about energy use.

The three types of occupant behaviors were modeled using EnergyPlus for a singleoccupancy office room. The simulation results demonstrate the impact of occupant behavior on building energy use is significant, and even so at the energy end use levels such as lighting, space cooling and heating. Compared to the standard or average workstyle, the austerity workstyle reduces energy use by 50%, while the wasteful workstyle increases energy use by up to 90% (Figure 13).

Occupant behavior	Austerity workstyle	Standard workstyle	Wasteful workstyle
Cooling setpoint (°C)	26	24	22
Heating setpoint (°C)	18	21	23
Follow ASHRAE Adaptive Comfort Model	Yes	None	None
Occupancy controls	If unoccupied, turn off lights and HVAC, turn down plug-load 30%	Scheduled	Leave everything on: lights, HVAC, and plug-load
Daylighting Control	3 Steps Dimming	None	None
HVAC operation time	Turn on 1 hour late and turn off 1 hour early: 9am to 4pm	Scheduled on: 8am to 5pm	Same as the whole building schedule: 6am to 10pm
Cooling startup control	Cooling turns on when space air temperature reaches 28°C, then maintains at 24°C. Cooling turns off when unoccupied.	Follow HVAC operation schedule (8am to 5pm) to maintain 24°C. Same as above.	Follow HVAC operation schedule (6am to 10pm) to maintain 24°C. Same as above.
Combined	All above behavior	All above behavior	All above behavior

Table 5 - Occupant behavior categorized into three workstyles



Figure 13 – Impact of occupant behavior for a private office

Three methods were used to model occupant behavior depending upon the complexity: (1) use EnergyPlus directly, (2) use the advanced feature of EnergyPlus - Energy Management System, and (3) modify source code of EnergyPlus. A software module is being developed to allow its co-simulation with EnergyPlus for various types of occupant behaviors.

Statistical model of occupancy patterns

Two important aspects of the occupant behavior research are: (1) measure indoor and outdoor environmental parameters and occupant's interactions with building systems and personal movement, (2) analyze the measured data to identify occupant behavior

and develop mathematical models for such behavior. Occupancy profile is one of the driving factors behind discrepancies between the measured and simulated energy consumption of buildings. The frequencies of occupants leaving their offices and the corresponding durations of absences have significant impact on energy use and the operational controls of buildings. Statistical methods were used to analyze the occupancy status, based on measured lighting-switch data in five-minute intervals, for a total of 200 open-plan (cubicle) offices. Five typical occupancy patterns were identified based on the average daily 24-hour profiles of the presence of occupants in their cubicles. These statistical patterns were represented by a one-square curve, a one-valley curve, a two-valley curve, a variable curve, and a flat curve (Figure 14). The key parameters that define the occupancy model are the average occupancy profile together with probability distributions of absence duration, and the number of times an occupant (Figure 15 and Figure 16) is absent from the cubicle. The statistical results also reveal that the number of absence occurrences decreases as total daily presence hours decrease, and the duration of absence from the cubicle decreases as the frequency of absence increases. The developed occupancy model captures the stochastic nature of occupants moving in and out of cubicles, and can be used to generate more realistic occupancy schedules (Figure 17 and Figure 18). This is crucial for improving the evaluation of the energy saving potential of occupancy based technologies and controls using building simulations.



Figure 14 - The occupancy patterns: (a) single-square curve, (b) one-valley curve, (c) two-valley curve, (d) variable curve, (e) flat curve



Figure 15 - The curves of occurrences, probability distribution function (PDF), and cumulative distribution function (CDF) of Pattern 1: (a) number of daily absences; (b) absence duration



Figure 16 - The curve of cumulative distribution function (CDF) of daily absence section for Pattern 2





Figure 18 - Three generated weekday occupant schedules for Pattern 2

Markov-chain model of occupant moving

Building occupancy is an important basic factor in building energy simulation but it is hard to represent due to its temporal and spatial stochastic nature. A novel approach for building occupancy simulation based on the Markov chain was developed. In this study, occupancy is handled as the straightforward result of occupant movement processes which occur among the spaces inside and outside a building. By using the Markov chain method to simulate this stochastic movement process, the model can generate the location for each occupant and the zone-level occupancy for the whole building. There is no explicit or implicit constraint to the number of occupants and the number of zones in the model while maintaining a simple and clear set of input parameters. From the case study of an office building, it can be seen that the model can produce realistic occupancy variations in the office building for a typical workday with key statistical properties of occupancy such as the time of morning arrival and night departure, lunch time, periods of intermediate walking-around, etc. Due to simplicity, accuracy and unrestraint, this model is sufficient and practical to simulate occupancy for building energy simulations and stochastic analysis of building HVAC systems.

Quantitative description and simulation of human behavior in residential buildings

This study gives a quantitative description of human behavior in residential buildings. The quantitative description method can be used to forecast the impact of the human behavior on the indoor built environment and energy use. Human behavior influences the energy use directly and indirectly by changing window openings, air-conditioner usage, lighting, etc. The quantitative description method describes these behavioral effects. Behavior can be divided into several types according to the usage with time related, environmentally related and random modes used to quantitatively describe the behavior. The method is then applied to describe a household in Beijing with comparison to on-site observations of the occupant behavior and measurements of energy use to validate the method. The results show that the human behavior in the real world can be quantified by the quantitative description method. These simulation tools can greatly facilitate building energy conservation by describing the influence of human behavior on building performance and energy use.

Comparison of EnergyPlus, DeST and DOE-2.1E

Introduction

Building Energy Modeling (BEM) programs play a significant role in the design of energy efficient envelopes and HVAC systems for new buildings and retrofit of existing buildings, the development and compliance of building energy codes, and implementation of building energy rating/labeling programs. However, the issue that large discrepancies exist in simulation results between different BEM programs, even for the same building modeled by the same person, leads to many users and stakeholders lack confidence in building simulation methods and the results from simulations. This is a major barrier for the wider adoption and effective application of building energy simulation, and represents a challenge to the industry. The large discrepancies of simulation results from different BEM programs mainly come from three factors (Figure 19): first is the simulation engine which is the unchangeable core; second is the GUI to the simulation engine that usually simplifies, hides or hard-wires some inputs that can be important; third is the fact that users may model the building or system inaccurately as they may not be familiar with the chosen BEM program, or input poor data due to constraints of budget and resources. In order to address the issue of large discrepancies between different BEM programs, the impact of the above three factors must be identified and quantified.



Figure 19 - Top three influencing factors of the discrepancies in simulation results

EnergyPlus, DOE-2.1E and DeST were selected for the in-depth comparative analysis to qualitatively and quantitatively assess the main influencing factors driving the discrepancies of simulation results. EnergyPlus was chosen because it is widely used and continuously being developed and supported by USDOE. DOE-2.1E was chosen as it is still widely used in the U.S. DeST was chosen due to its popular use in China and a few Asian countries. Top-level key features of DOE-2.1E, DeST and EnergyPlus are summarized in Table 6.

Due to the complexity of BEM programs and the intention of isolating influencing factors, two separate comparisons were made: the building loads and the HVAC systems.

Feature	DOE-2.1E	DeST	EnergyPlus
Developer	LBNL/DOE, US	Tsinghua University, China	DOE/LBNL et al. US
Development Started	Early 1980s	1989	1996
Development and Support	No more development or support	On-going	On-going
Users	Worldwide	Mostly China	Worldwide
Inputs	Text, BDL	Database, Microsoft Access	Text, IDF
Outputs	Summary & hourly reports	Summary & hourly reports	Extensive summary & detailed reports with user specified time steps
GUI	Simulation engine only; 3 rd party GUIs available	Coupled with AutoCAD	Simulation engine only; 3 rd party GUIs available
Algorithms	Surface heat transfer: CTF; Zone weighting factors	Zone heat balance: State Space Method	Surface heat balance: CTF; Zone heat balance
Time Step	1 hour, fixed	1 hour, fixed	1 to 60 minutes
Weather Data	Hourly	Hourly	Hourly or sub-hourly
HVAC	28 pre-defined systems	A few pre-defined systems	User configurable with some limitations
User Customization	User functions	N/A	Energy Management Systems
Co-Simulation	N/A	N/A	External Interface
Language	Fortran 77	C++	Fortran 2003
Limitations	Lack zone air heat balance, linear systems	Limited user customization, linear systems	Potentially long run-time for large models
Licensing	Free download; Source code available	Free download; Source code not open to public	Free download; Open source

Table 6 - Comparison of top-level key features of DOE-2.1E, DeST and EnergyPlus

Building loads

Detailed comparison of the building thermal load modeling capabilities and simulation results of the three BEM programs was made with the goal to identify and quantify the influences of the simulation engines and input values or algorithms. Test cases, with modifications to the ASHRAE Standard 140 tests, were designed to isolate and evaluate the key influencing factors responsible for the discrepancies in results between EnergyPlus and DeST. This included the loads algorithms and some of the default input parameters. It was concluded that there is little difference between the results from EnergyPlus and DeST (Figure 21) if the input values are the same or equivalent despite there being many discrepancies between the heat balance algorithms. DOE-2.1E can produce large errors for cases when adjacent zones have very different conditions, or if a zone is conditioned part-time while adjacent zones are unconditioned. This was due to the lack of a strict zonal heat balance routine in DOE-2.1E, and the steady state handling of heat flow through interior walls and partitions.

This comparison study did not produce another test suite, but rather a methodology to design tests that can be used to identify and isolate key influencing factors that drive the building thermal loads, and a process with which to carry them out. Figure 20 summarizes the method used to develop the tests and perform the comparisons. For all test cases, EnergyPlus Version 7.0, DeST Version 2011-11-23 and DOE-2.1E114 were used. For all EnergyPlus tests, the CTF (Conduction Transfer Function) method was used with a simulation time-step of 15 minutes.



Figure 20 - Methodology to build the tests and perform the comparisons



Figure 21 - Annual cooling and heating loads from the ASHRAE Standard 140-2007 tests

HVAC systems

For comparison of HVAC systems modeling, a comparative test method is used mainly for the inter-program comparison. First, the HVAC system module calculations for each program are summarized, analyzed, and compared to identify differences in the solution algorithms and main assumptions (Table 7). The component models are important parts of the HVAC system calculations and have an important influence on the HVAC calculation results. The calculation methods and the main assumptions of several of the main components are discussed and compared in detail. As the HVAC control strategies of supply air temperature, supply air volume, and other parameters affect the operation of HVAC systems, they have large impacts on the simulation results. The basic simulation methods for the control strategies in the three BEM programs (Table 8) are summarized and the differences are discussed. Secondly, the limitations of existing HVAC system calculation tests are discussed, and additional tests are designed to allow the HVAC systems to be compared in depth. CAV (constant air volume) and VAV (variable air volume) systems are tested in this study to analyze the HVAC system performance and control strategies under different heating/cooling load ratios. All inputs for the test cases are kept constant where possible. For the parameters that cannot have the same values, equivalent conversions are made, in the interest of consistency. The tests include the system-side and plant-side, so that the test process is similar to the real cases. Analytical tests are first conducted to make the load-side calculations consistent, so the differences in the following calculation results can only come from the HVAC system module. Through the CAV tests under full load and part load conditions, the component models and their influence on the calculation results are compared. Then, based on the VAV test cases, the control strategies used by the three BEM programs are analyzed in detail. Finally, a case study based on a real office building is presented and differences in the simulation results between the three BEMPs are analyzed. Based on the load calculation results, drivers of the differences in the HVAC side are analyzed and discussed. Figure 22 shows the method used for the HVAC system simulation comparison.



Figure 22 Methodology of the HVAC calculation comparison

Theoretical comparison

The three BEMPs are reviewed in terms of HVAC simulation methods, and their advantages and disadvantages are summarized. Then, focusing on the main HVAC components and HVAC control strategies, the differences between simulation methods (including solution algorithms, modeling assumptions, and simplifications) are discussed and analyzed in detail.

Integrated test cases

Based on the review of existing HVAC system tests, an integrated test method is proposed and used. Due to the similarity of EnergyPlus and DOE-2 in the use of steady-state HVAC models, the test process is only applied to EnergyPlus and DeST. Two types of HVAC systems (CAV and VAV) are tested under different load conditions. Comparisons of each component model and control strategy are made and analyzed in detail.

Case study with a real building

Based on the findings of the previous two comparisons, a real building case study is conducted using the three simulation programs. The differences in the load-side calculations are compared first. Then, on the foundation of the load-side results, the errors in the HVAC system energy consumption results are compared and analyzed to ascertain the differences between measured and simulated results, for each program.

Features	EnergyPlus	DeST	DOE-2.1E	
Time-step	Sub-hourly, auto-adjusted from zone time step	Fixed hourly	Fixed hourly	
Advanced features	Energy Management Systems (EMS)	None	User functions	
Simulation structure	Integrated solution. BUILDING, SYSTEM, PLANT are integrated and controlled by the integrated solution manager. Uses a predictor- corrector approach.	DeST separates the heating and cooling station from the supply side, dividing them into two modules: equivalent user terminal and heating/cooling station. The two modules iterate to calculate results.	DOE-2 is a program with sequential simulations. It has one subprogram for the translation of users' inputs (BDL processor), and four simulation subprograms (LOADS, SYSTEMS, PLANT and ECON). LOADS, SYSTEMS and PLANT are executed in sequence. Their outputs are used as inputs to the ECON subprogram.	
Algorithm	All the equipment models are forward, quasi-steady models that use equipment/system performance curves			
Limitations	For complex system configurations, convergence sometimes is an issue	For new types of HVAC systems, the equivalent user terminal is limited	Cannot model new HVAC system types; When the SYSTEM subprogram cannot meet the loads, space temperatures are estimated.	
System configurations	Flexible, user definable, HVAC templates covering most traditional designs	Predefined HVAC templates: VAV, CAV, FCU, VRF, PTAC, PTHP	25 fixed system types with optional components	

Table 7 Summary of HVAC systems simulation

Pressure calculation	Two types of pressure drop curves	Characteristics of equivalent user terminal	User inputs
Terminal model	Take terminals as different equipment models to get the information about flow rate, return water temperature and so on	Use the equivalent user terminals to reflect the average of terminal flow rate and thermodynamic state	Take terminals as different equipment models and the inputs are based on average parameters, then the overall features can be achieved
Interaction between the HVAC equipment and the building loads	successive substitution iteration to reconcile all elements using the Guass-Seidell philosophy of continuous updating with predictive system energy balance method	equivalent user terminal curve	The zone temperatures from the previous hour calculation are used to approximate the heat flow across internal walls. Temperature histories are used in the calculation of equipment capacities.
Handling of given types of equipment with multiple sizes	According to the control strategy defined by the users	According to the control strategy defined by the users	Model them as if all the sizes operating were combined together into one large unit.

Table 8 Comparison of VAV system control strategies

Program	Control	Description
EnergyPlus	Heating	Supply airflow rate stays at a constant minimum value for normal acting dampers and modulates higher for reserve acting dampers, supply air temperature may vary
(normal acting damper)	Cooling	Supply air temperature may vary, supply airflow rate varies
DeST	Heating & cooling	An optimization technique is employed to search for the best supply air temperature; when the range of best supply air temperature (SAT) exists, determine the supply air volume (SAV) to make sure the air flow rate minimum; otherwise, determine the SAT to make deviation minimum
DOE-2	Heating	The actions are sequential: 1) increase supply air temperature, 2) increase the baseboard output if exist,3) increase reheat coil output;3) increase supply air volume
	Cooling	The actions are sequential:1) reduce supply air temperature;2) increase the airflow rate

Based on the comprehensive test cases and results analysis, the main findings are summarized as follows:

- 1. EnergyPlus, DOE-2.1E, and DeST all have fundamental capabilities and appropriate modeling assumptions for HVAC system simulations. The results from the comparative tests on component models show small differences, which are mainly due to the input settings and algorithms used in each program. Differences between the total energy consumption calculation results of HVAC systems from DeST and EnergyPlus can be limited to 5%, if all component models are similar, and the same or equivalent inputs for the HVAC systems are used. It is found that the main influencing factors on HVAC discrepancies between DeST and EnergyPlus are the algorithms used for the HVAC component models and their control strategies. For the case that simulates the real building, using design and default values for the inputs of each simulation program, the errors in both load calculations and HVAC system calculations are within 15% of the measured values. This demonstrates good agreement between the simulation programs and the real building.
- 2. EnergyPlus has more comprehensive component models than DOE-2 and DeST. The three programs have consistent component models for pumps, fans, and boilers. The coil models in EnergyPlus and DeST are based on engineering equations while the coil model in DOE-2 is based on assumptions and empirical data. The influences of load ratio, condenser inlet water temperature, and evaporator outlet water temperature on the chiller efficiency are considered in all three programs. Three chiller performance curves with user-specified coefficients are used in EnergyPlus and DOE-2, while one hard-wired performance curve is used in DeST. In EnergyPlus and DOE-2.1E, the fan power of the cooling tower is related to the load ratio, so the fan can cycle during a particular hour if the load is small. In DeST, the fan power draw remains constant whenever the cooling tower has a load for any particular hour.
- 3. To complete a comprehensive comparison of the three different simulation programs, several requirements are needed: 1) the test cases should be broad enough to cover most modeling features; 2) the test cases should be detailed enough to isolate influencing factors; 3) special cases should be designed to test the unique limitations of the programs. Based on the current development of HVAC system tests, a testing concept is introduced in this report to develop a better method of comparison. As each component in a HVAC system is connected and influenced by one another, the whole HVAC system should be considered when the comparison is conducted. This means that both air-side and plant-side components should be tested together. Imposing steady-state conditions makes it possible to compare each component model in detail and calculate the analytical results. Considering the whole system makes the test process more practical.

Future Research

The research findings from the project directly feed into the two new CERC-BEE Simulation Projects: Integrated Design and Operation for Very Low Energy Buildings, and Human Behavior. Both projects aim to further understanding driving forces of building performance, integrated building design and operation, and occupant energy-related behavior, and to create new scientific knowledge, toolkit, guideline, and case studies for building designers, engineers, researchers and policy makers to improve design and operation of high performance buildings.
Acknowledgement

This work was sponsored by the U.S. Department of Energy under the U.S.-China Clean Energy Research Center for Building Energy Efficiency, and the China Ministry of Housing and Urban-Rural Development and the Ministry of Science & Technology. The energy modeling program comparison work was sponsored by the China Sustainable Energy Program, Energy Foundation. Special thanks to the U.S. and China CERC-BEE management, our industry partners, the Industry Advisory Board, and the Technical Advisory Committee for the strong support on the project.

This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Building Technologies Program, of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

Appendix A – List of Publications

Journal Articles

- 1. T. Hong, W.K. Chang, and H.W. Lin. A Fresh Look at Weather Impact on Peak Electricity Demand and Energy Use of Buildings Using 30-Year Actual Weather Data, Applied Energy, Vol.111, 2013.
- H.W. Lin, T. Hong. On Variations of Space-heating Energy Use in Office Buildings, Applied Energy, Vol. 111, 2013.
- D. Zhu, T. Hong, D. Yan, C. Wang. A Detailed Comparison of Three Building Energy Modeling Programs: EnergyPlus, DeST, and DOE-2.1E. Journal of Building Simulation, 2013.
- 4. W.K. Chang and T. Hong. Statistical Analysis and Modeling of Occupancy Patterns in Open-Plan Offices using Measured Lighting-Switch Data, Journal of Building Simulation, 2013
- 5. X. Zhou, D. Yan, T. Hong, and D. Zhu. Building energy modeling programs comparison: Research on HVAC systems simulation, Journal of HV&AC, 2013. In Chinese.
- D. Zhu, D. Yan, C. Wang, T. Hong. Comparison of Building Energy Simulation Programs: DeST, EnergyPlus and DOE-2. Building Science, 28(S2):213-222. 2012. In Chinese.
- 7. H.W. Lin, M.S. Zhen, T. Hong. Analysis of impact of occupant behavior on variations of energy use in office buildings. Journal of Energy & HVAC Engineering, 76:31-37. 2012. In Chinese.
- 8. C. Wang, D. Yan, Y. Jiang. A novel approach for building occupancy simulation. Journal of Building Simulation, 2011.
- 9. C. Peng, D. Yan, R. Wu, C. Wang, X. Zhou, Y. Jiang. Quantitative description and simulation of human behavior in residential buildings. Journal of Building Simulation, 2012.
- 10. X. Zhou, D. Yan, X. Ren, T. Hong. Data analysis and model study about lighting energy consumption in large offices. Submitted to the CERC-BEE issue of Building Research and Information, 2012.
- 11. X. Ren, S. Hu, D. Yan, C. Peng. Development of energy models for residential appliances based on measured data. Building Science, 28(S2), 2012. In Chinese.

Conference Papers

- 1. T. Hong, WK Chang. A Sensitivity Study of Building Performance Using 30-Year Actual Weather Data. IBPSA Building Simulation, France, 2013.
- 2. W.K. Chang, T. Hong. Statistical Analysis of Occupancy Behavior in Open Office Spaces Using Measured Lighting Switch Data. First Asia Building Simulation Conference ASim, Shanghai, 2012.

- L. Wang, T. Hong. Modeling and Simulation of HVAC Faulty Operations and Performance Degradation due to Maintenance Issues. First Asia Building Simulation Conference ASim, Shanghai, 2012.
- H.W. Lin, T. Hong. Occupant Behavior: Impact on Energy Use of Private Offices. First Asia Building Simulation Conference ASim, Shanghai, 2012.
- X. Zhou, D. Yan, X. Ren, T. Hong. Data analysis and modeling of lighting energy use in large office buildings. First Asia Building Simulation Conference ASim, Shanghai, 2012.
- H.W. Lin, T. Hong. An In-Depth Analysis of Space Heating Energy Use in Office Buildings. ACEEE Summer Study on Building Energy Efficiency, Asilomar, 2012.
- 7. M. Levine, W. Feng, K. Jing, T. Hong, N. Zhou. A Retrofit Tool for Improving Energy Efficiency of Commercial Buildings. ACEEE Summer Study on Building Energy Efficiency, Asilomar, 2012.
- 8. D. Zhu, C. Wang, D. Yan, T. Hong. A Comparison of DeST to EnergyPlus. Annual China HVAC Simulation Conference, Beijing, 2011. In Chinese.
- Q. Shen, J. Xia, Y. Jiang. A case study on energy performance and retrofitting technologies for a high standard resort hotel. the 7th International Symposium of Heating, Ventilation and Airconditioning, Shanghai, 2011.
- 10. X. Ren, D. Yan, X. Zhou. A Study of Lighting Energy Consumption Model of Office Buildings. First Asia Building Simulation Conference ASim, Shanghai, 2012.
- 11. G. Deng, D. Yan, Y. Rui. Commissioning and analysis of usage patterns of water-source heat pump system based district heating systems. Annual China HVAC Simulation Conference, 2012. In Chinese.

Technical Reports

- X. Zhou, T. Hong, D. Yan. Comparison of building energy modeling programs: HVAC Systems. 2013. LBNL Report, submitted, 2013.
- D. Zhu, T. Hong, D. Yan, C. Wang. Comparison of building energy modeling programs: Building Loads. LBNL Report 6034E, 2012.

Appendix B – List of Workshops and Major Activities

Workshops/Activities	Date and	Summary			
	Location				
CERC Conference	1/19-20/2011,	CERC Kickoff meeting			
	DOE, USA				
CERC-BEE	3/24-25/2011,	Research teams from both countries and CERC			
Conference	Tsinghua, China	management attended to discuss the research plan and scope of work etc.			
Project Kickoff Meeting	7/21/2011, LBNL, USA	About 24 people attended the meeting, including the LBNL and Tsinghua research teams, industry partners, DOE, and researchers from other institutes. Research objectives, plan and deliverables were presented and discussed.			
Industry Advisor Board Meeting	8/16/2011, LBNL, USA	The LBNL Team presented research progress a addressed comments and questions from IAB.			
CERC Management visited Tsinghua	9/21/2011, Tsinghua, China	The Tsinghua Team reported research progre and had broader discussion with US CE directors, Robert Marley and Michaela Martin, plan and improve the next step.			
Project Progress Meeting	12/27/2011, Tsinghua, China	The LBNL and Tsinghua research teams had a one- day meeting to exchange and discuss research progress and address issues.			
China CERC-BEE Annual Review	1/10/2012, ShenZhen, China	China CERC-BEE Annual Review. The Tsinghua Team presented the research work and addressed comments and questions from reviewers.			
US CERC-BEE Technical Review	2/14/2012, DOE, USA	The LBNL Team presented joint research progress and addressed comments and questions from CERC reviewers and management.			
Industry Advisor Board Meeting	3/20/2012, LBNL, USA	The LBNL Team presented joint research progress and addressed comments and questions from IAB.			

CERC Simulation	7/16/2012,	The LBNL and Tsinghua research teams presented
Workshop	Hong Kong,	the research findings and exchanged ideas with 20
	China	participants from design firms, government
		agencies, and universities.
Joint CERC-BEE	7/18-20, Sanya,	The LBNL and Tsinghua Teams presented the
Annual Conference	China	research results and addressed comments and
		questions from reviewers and CERC management.
CERC Simulation	11/26/2012,	During the first Asia IBPSA Building Simulation
Workshop		Conference, the LBNL and Tsinghua research
	Shanghai, China	teams presented the research findings and
		exchanged ideas with 50 participants from design
		firms, government agencies, universities, and
		other organizations.
Project Progress	11/29/2012,	The LBNL and Tsinghua research teams had a one-
Meeting		day meeting to exchange and discuss research
	Tsinghua, China	progress and address issues.
	12/2/2012	The LDNL research presented the research results
CERC Technical	12/3/2012,	The LBNL research presented the research results
KEVIEW	LBNL. USA	and addressed comments and questions from the
	,	CERC TAC (Technical Advisor Committee).

Appendix C – Selected Publications

Applied Energy 111 (2013) 333-350

Contents lists available at SciVerse ScienceDirect

Applied Energy

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

A fresh look at weather impact on peak electricity demand and energy use of buildings using 30-year actual weather data

Tianzhen Hong^{a,*}, Wen-Kuei Chang^b, Hung-Wen Lin^b

^a Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA 94720, USA ^b Green Energy and Environment Research Laboratories, Industrial Technology Research Institute, Hsinchu, Taiwan, ROC

HIGHLIGHTS

• Weather has a significant impact on both the peak electricity demand and energy use.

• Weather impact varies with building type, building efficiency level, and location.

• Simulated results using TMY3 weather data can under or over estimate those of AMY.

• It is crucial to assess performance of buildings using long-term actual weather data.

• Findings enable building stakeholders to make better decisions on weather impact.

ARTICLE INFO

Article history: Received 20 November 2012 Received in revised form 4 May 2013 Accepted 7 May 2013

Keywords: Actual meteorological year Building simulation Energy use Peak electricity demand Typical meteorological year Weather data

ABSTRACT

Buildings consume more than one third of the world's total primary energy. Weather plays a unique and significant role as it directly affects the thermal loads and thus energy performance of buildings. The traditional simulated energy performance using Typical Meteorological Year (TMY) weather data represents the building performance for a typical year, but not necessarily the average or typical long-term performance as buildings with different energy systems and designs respond differently to weather changes. Furthermore, the single-year TMY simulations do not provide a range of results that capture yearly variations due to changing weather, which is important for building energy management, and for performing risk assessments of energy efficiency investments. This paper employs large-scale building simulation (a total of 3162 runs) to study the weather impact on peak electricity demand and energy use with the 30-year (1980–2009) Actual Meteorological Year (AMY) weather data for three types of office buildings at two design efficiency levels, across all 17 ASHRAE climate zones. The simulated results using the AMY data are compared to those from the TMY3 data to determine and analyze the differences. Besides further demonstration, as done by other studies, that actual weather has a significant impact on both the peak electricity demand and energy use of buildings, the main findings from the current study include: (1) annual weather variation has a greater impact on the peak electricity demand than it does on energy use in buildings; (2) the simulated energy use using the TMY3 weather data is not necessarily representative of the average energy use over a long period, and the TMY3 results can be significantly higher or lower than those from the AMY data; (3) the weather impact is greater for buildings in colder climates than warmer climates; (4) the weather impact on the medium-sized office building was the greatest, followed by the large office and then the small office; and (5) simulated energy savings and peak demand reduction by energy conservation measures using the TMY3 weather data can be significantly underestimated or overestimated. It is crucial to run multi-decade simulations with AMY weather data to fully assess the impact of weather on the long-term performance of buildings, and to evaluate the energy savings potential of energy conservation measures for new and existing buildings from a life cycle perspective.

© 2013 Elsevier Ltd. All rights reserved.

1. Introduction

Buildings consume more than one third of the world's total primary energy. The IEA Annex 53 [1] identified and studied six influencing factors on building energy performance, including climate, building envelope, building equipment, operation and maintenance, occupant behavior, and indoor environmental conditions. Among these influencing factors, climate plays a unique and significant role. Weather contributes directly and significantly to the variations of thermal loads and energy use of HVAC (heating, ventilation, and air conditioning) systems, lighting (for buildings with





AppliedEnergy

^{*} Corresponding author. Tel.: +1 510 4867082; fax: +1 510 4864089. *E-mail address*: thong@LBL.gov (T. Hong).

^{0306-2619/\$ -} see front matter @ 2013 Elsevier Ltd. All rights reserved. http://dx.doi.org/10.1016/j.apenergy.2013.05.019

daylighting controls), and energy production from solar-based renewable systems. In residential and commercial buildings in the US, heating and cooling accounts for more than 40% of enduse energy demand. It is important to understand and estimate the impact of weather on the long-term performance of buildings in order to support policy making, and to allow building operators and owners to respond better to climate changes in terms of building energy supply and demand. Additionally, considering the impact of yearly variations in weather can improve the evaluation of investment risks of energy conservation measures (ECMs) for new and existing buildings by taking into account their life-cycle energy and cost savings.

The accuracy of building energy simulations and economic assessments of renewable energy systems depend on the availability of reliable weather data. There are two primary sources of weather data that are used to generate weather data files used in building simulation: measured weather data using physical sensors and observations, and simulated data using mathematical weather models. Various methods to generate annual hourly weather data have been developed in the past. Such weather data include the Typical Meteorological Year (TMY), the test reference year (TRY), the weather year for energy calculation (WYEC), the design reference year (DRY), as well as the synthetically modeled meteorological year (SMY). However, the lack of long-term weather records usually limits the generation of typical annual weather data files in any format [2].

A TMY weather file contains hourly values of solar radiation and meteorological elements for a 1-year period. The 12 typical meteorological months (TMMs) are selected from various calendar months in a multi-year weather database. The criteria for TMM selection is based on the statistical analysis and evaluation of four weather parameters: the ambient dry-bulb temperature, the dew-point temperature, the wind speed and the global solar radiation. Algorithms are used to smooth discontinuities from the data to avoid drastic changes between two adjacent months selected from different years. The first generation of TMY weather data for the US is derived from the 1952-1975 SOLMET/ER-SATZ database, while the second generation of data (TMY2) is derived from the 1961-1990 National Solar Radiation Database (NSRDB) covering 239 US locations. The latest, third generation data (TMY3) is derived from the 1976-1990 and 1991-2005 National Solar Radiation Data Base (NSRDB). TMY3 covers 1020 US locations. TMY, TMY2 and TMY3 data sets cannot be used interchangeably because of differences in the data structure such as time (solar vs. local), formats, elements, and units. The intended use of TMY weather data is for computer-based building performance simulations of solar energy conversion systems and building systems to facilitate performance comparisons of different system types, configurations, and locations in the US and its territories. Because they represent typical rather than extreme conditions, they are not suited for designing systems to meet the worst-case conditions occurring at a location [3]. For the calculations of peak cooling and heating loads of buildings, and sizing HVAC equipment, design day weather data are used. Designday weather data tend to represent more extreme weather conditions in order to guarantee that HVAC systems can meet peak loads for most of the time during their life cycle. Various methods are used to create design-day weather data [4].

As TMY data may not be available for some cities or sites, SMY weather data provide a practical and useful alternative. SMY weather data can be generated from monthly average or total values of weather parameters using stochastic models and autoregressive moving average processes to represent the seasonal and daily weather variations [5]. Such stochastic weather models can be used to generate AMY weather data for use in deterministic building simulations, or together with a stochastic internal loads

model, can be integrated with a building thermal model to obtain directly the probability distribution of building performance to investigate the uncertainty caused by the random meteorological processes and internal heat gains [6].

A new online weather data service with immediate access to precision, localized weather history, current conditions and forecasts are presented by Keller and Khuen [7]. Localized weather data is created by integrating all available ground station observations with high-resolution datasets from NOAA (National Oceanic and Atmospheric Administration). Both historical and forecast time series data are available for direct user access and application/system access through Web Data Services and API interfaces.

Selecting appropriate weather data to be used in building performance simulation is important. The use of inappropriate weather data can result in large discrepancies between the predicted and measured performance of buildings. In the late 1970s. Freeman [8] evaluated how well TMY represents actual longterm weather data based on simulations of an active residential space solar heating and cooling system for six US climates, Albuquerque, Fort Worth, Madison, Miami, New York, and Washington DC. High variability of the weather and solar heating system performance year to year was noted. Crawley [9] compared the influence of the various weather data sets on simulated annual energy use and cost. Using different weather data sets can cause significant variations in annual energy consumption and cost from simulation results. The results show that the TMY and the WYEC data sets represent the closest typical weather patterns. Simulated results using the TMY weather data provides the average/typical energy use for buildings, but the peak electricity demand predictions and uncertainty analyses based on TMY are often not reliable because a single year cannot capture the full variability of the long-term climate change [10]. In view of the long-term climate change, the time period assigned for TMY selection should include the most recent meteorological data and should be reasonably long to reflect well the weather variations [11]. Most of the available TMY weather data are from weather stations located at airports. It is possible to create a new TMY file localized to a building location by integrating the weather station observations with gridded reanalysis data. However, there are limited complete weather data collected by weather stations over 15-30 years, so TMY data is only available for only 1020 locations. Furthermore, some of the TMY weather data files were created up to 20 years ago. They are less representative of the typical present day climate and do not describe extreme weather conditions. Compared with the TMY weather data, the AMY is created from actual hourly data for a particular calendar year. AMY weather data is particularly useful for modeling years with extremes in weather and verifying the energy performance of buildings. However, as with the TMY weather data, the AMY weather data needs to be chosen as close to the building location as possible.

The potential impacts of various types of weather forecast models, weather data, and building prototypes have been studied from a number of perspectives. A prototypical small office building was modeled operating at three energy efficiency levels, using typical and extreme meteorological weather data for 25 locations, to study various predicted climate change and heat island scenarios [12]. The largest change to the annual energy use due to climate change was seen in the temperate, mid-latitude climates, where there was a swapping of energy use from heating to cooling. The heating energy was reduced by more than 25% and cooling energy was increased by up to 15%. The TMY weather data provides more localized and comprehensive climate indicators to further support the HVAC system design in buildings [3,13]. The space cooling plays a major role in determining the magnitude and timing of peak electricity demand. The archived General Circulation Model (GCM) projections were statistically downscaled to the site scale, which were then used for input to building cooling and heating simulations to study the California specific impact of global warming on building energy consumption [14]. The IPCC's different carbon emission scenarios predict that climate change will lead to a 25-50% increase in space cooling electricity use over the next 100 years. Under the worst case carbon emission scenario the total energy consumption will increase between 8% and 20%. The energy performance of an office building in Hong Kong, using multi-year weather data sets was simulated to investigate the diversity in simulation predictions [15]. The results concluded that the choice of weather data sets was not crucial for the comparative energy studies during the initial design stage. However, it becomes important to select a particular standard weather year data set when absolute energy consumption data are required. Similar studies on office buildings were conducted in five major climate zones in China by using multi-year weather databases as well as TMY data [16–18]. The results showed a decreasing trend for heating loads and an increasing trend for cooling loads due to predicted climate change. The monthly loads and energy use profiles calculated using the TMY and long-term means profiles fell well within the maximum and minimum ranges of the 30-year individual predictions. It was concluded that building performance predictions using TMY weather data can be used in comparative energy efficiency studies.

In recent years, various types of weather data have been used in building simulation to evaluate energy performance and demand response. Accurate estimation of building performance relies on the appropriate selection of accurate weather data. The quality of weather data and their impact on building cooling and heating loads and energy consumption were studied by comparing three weather datasets for a specific location for the calendar year 2010 [19]. The three sources of data included site measured data and AMY weather data provided by two vendors. Key weather variables from the three datasets were compared statistically, and building loads and energy use were simulated using EnergyPlus version 6.0. The study concluded that the maximum difference in individual hourly weather variables can be as high as 90%, annual building energy consumption can vary by ±7%, while monthly building loads can vary by ±40% when using different weather datasets.

Using TMY weather data to calculate the energy use in buildings aims to represent the average or typical values. However, different types of buildings with different energy service systems and operation strategies have different responses to weather. Furthermore, a single set of energy use results from TMY simulations does not provide the range of variations due to the change of weather from year to year. The typical life of a building is more than 50 years; therefore the assessment of long-term building performance becomes very important. TMYs are often recommended to be used in building simulations to evaluate and compare performance of design alternatives under the assumption that energy savings from a design alternative would not vary noticeably with yearly weather variations. This assumption is not necessarily true. Although previous studies have demonstrated actual weather has a significant impact on peak electric demand and energy use in buildings, there are limited studies that focus on investigating the sensitivity of energy savings and peak demand reduction of energy conservation measures to the yearly variation of weather, using multi-decade AMY weather data across a complete coverage of climate zones for typical commercial buildings. This study aims to address that gap in the literature.

This study does not touch the topics of previous studies on impacts of long-term climate change or local heat island effects on building performance; instead it focuses on providing insights to the following important questions:

- (1) How significant is the weather impact on both the peak electricity demand and building energy use?
- (2) Does the simulated building energy use using the TMY3 weather data represent the average or typical energy use over a 30-year period?
- (3) Building simulation results from which climates are greater affected by using different weather data sets?
- (4) What types of office buildings are subject to the greatest impact of weather?
- (5) What are the risks from using the TMY3 weather data in building simulations to evaluate the energy savings and electricity demand reduction of energy efficiency technologies?

Through better understanding of which building technologies and system designs are more sensitive to yearly weather variation, building designers, owners, operators, and policy makers can make more informed decisions on energy efficiency implementations to reduce peak electricity demand and building energy use.

2. Methodology

2.1. Overview

To study the impact of weather on building performance, the most typical commercial buildings located in typical climate zones are the natural starting point. The US 2003 Commercial Building Energy Consumption Survey (CBECS) [20] indicates that office buildings are the most common building type, comprising the largest floor area, and consuming the most energy in the commercial building sector. Therefore, the prototypical office buildings with three different sizes at two design efficiency levels for 17 climates are chosen from the PNNL's prototype buildings. Three building sizes represent large, medium, and small office buildings based on the statistics of the 2003 CBECS. The 17 climates represent all of the ASHRAE climate zones. The two design efficiency levels correspond to the ASHRAE Standard 90.1-2004 and 2010. ASHRAE standard 90.1 is an energy standard providing prescriptive and mandatory requirements for energy efficiency levels of major building systems including building envelopes (opaque construction and fenestration), lighting systems, service water heating, and HVAC systems. The 90.1-2004 standard was published in 2004 and represented the minimum performance of recently built new constructions that comply with the standard. While 90.1-2010 [21] represents more efficient designs, with about 30% energy savings over 90.1-2004 [22].

The TMY3 weather data and 30 years of AMY weather data (1980–2009) are used in the building performance simulations. The simulations were run using EnergyPlus 7.1. There was a total of 3162 simulation runs: 3 office building types, 2 design efficiency levels, 17 climates, and 31 weather files. The HVAC equipment is autosized by EnergyPlus to meet peak cooling and heating loads based on the 2009 ASHRAE design day weather data. The structure of the simulation runs is illustrated in Fig. 1. Performance metrics, including building total source energy (including all end uses), HVAC source energy (including end uses of cooling, heating, and ventilation), and peak electricity demand, of each simulation run were extracted from the EnergyPlus output reports. The performance metrics of each AMY run were then compared with those of the corresponding TMY3 run to calculate the percentage changes, equal to $100 \times (AMY_Results-TMY3_Results)/TMY3_Results, as indicators$ of deviations from the TMY3 results. The ranges of these percentage changes are graphed as key results for analysis and discussions. To filter out the extreme weather years, the variation ranges excluding those of the top three and the bottom three weather years were overlapped on the same graphs. The variation ranges of the percent-



Fig. 1. The structure of simulation runs.

Table 1				
Climate zone classification	based on	ASHRAE	Standard	90.1-2010.

Climate zone	Climate type	Criteria	Representative city
1A	Very Hot-Humid	5000 < CDD10 °C	Miami, USA
1B	Very Hot-Dry	5000 < CDD10 °C	Riyadh, Saudi Arabia
2A	Hot–Humid	3500 < CDD10 °C ≤ 5000	Houston, USA
2B	Hot–Dry	3500 < CDD10 °C ≤ 5000	Phoenix, USA
3A	Warm-Humid	2500 < CDD10 °C ≤ 3500	Memphis, USA
3B	Warm-Dry	2500 < CDD10 °C ≤ 3500	EI Paso, USA
3C	Warm-Marine	CDD10 °C \leqslant 2500 and HDD18 °C \leqslant 2000	San Francisco, USA
4A	Mixed-Humid	CDD10 °C \leqslant 2500 and 2000 < HDD18 °C \leqslant 3000	Baltimore, USA
4B	Mixed-Dry	CDD10 °C \leqslant 2500 and 2000 < HDD18 °C \leqslant 3000	Albuquerque, USA
4C	Mixed-Marine	2000 < HDD18 °C ≤ 3000	Salem, USA
5A	Cool–Humid	3000 < HDD18 °C ≤ 4000	Chicago, USA
5B	Cool–Dry	3000 < HDD18 °C ≤ 4000	Boise, USA
5C	Cool-Marine	3000 < HDD18 °C ≤ 4000	Vancouver, Canada
6A	Cold–Humid	4000 < HDD18 °C ≤ 5000	Burlington, USA
6B	Cold–Dry	4000 < HDD18 °C ≤ 5000	Helena, USA
7	Very Cold	5000 < HDD18 °C ≤ 7000	Duluth, USA
8	Subarctic	7000 < HDD18 °C	Fairbanks, USA

age changes of building total source energy, HVAC source energy and peak electricity demand give a clear picture on how the AMY results differ from the TMY3 results. The smaller the range of difference, the closer of TMY3 results to AMY results.

To investigate the weather impact on energy savings and demand reduction of building technologies, two office models under two design efficiency levels (ASHRAE standard 90.1-2004 and 90.1-2010) were simulated using the TMY3 and 30-year AMY weather files. The energy savings and demand reductions of the 90.1-2010 models over the corresponding 90.1-2004 models were determined using the same TMY3 or AMY weather files.

Furthermore, values of key weather parameters, such as annual average ambient air temperature, global horizontal solar radiation, and heating and cooling degree days, were extracted from the EnergyPlus weather statistics (stat) files and used to identify potential variation patterns and trends.

In this study, source energy (also referred to as primary energy) is used because it considers the energy loss during energy generation, transmission, and distribution. EnergyPlus calculates the source energy by multiplying the calculated site energy with corresponding source factors, which depend on types of energy sources and building location.

2.2. Weather data

In general, two kinds of weather data packaged in weather files are used in building performance simulation. One is the TMY

weather data and the other is the AMY weather data. The TMY weather data is usually used for annual energy simulations during the building design process, either to evaluate the energy and cost effectiveness of design alternatives, to demonstrate code compliance, or to calculate credit points towards building rating systems or utility incentive programs. The AMY weather data, containing measured data for a particular year, is usually used in simulations post occupancy to verify and diagnose the actual building energy performance. The AMY weather data can be obtained from several sources, including Weather Bank, National Climatic Data Center (NCDC), Weather Source, Weather Analytics, and Meteonorm. Weather Bank maintains hourly and daily historical data records from every National Weather Service reporting station in the United States, as well as other locations around the world. The weather data are archived on a real-time basis and updates are made hourly. NCDC is the world's largest active archive of weather data. The Integrated Surface Database (ISD) consists of global hourly and synoptic observations compiled from numerous sources. Currently there are over 11,000 stations active and updated daily in the database [23]. Weather Source provides historical and real-time digital weather information for tens of thousands of locations across the US and around the world. Weather Analytics [7] provides site-specific TMY and AMY weather files based on the last 30 years of hourly data. The files combine hourly weather station observations and the new NOAA reanalysis data sets. Meteonorm is a weather data generation tool. It integrates a climate database, a spatial interpolation tool and a stochastic weather generator. The typical

Table 2Commercial reference buildings.

Building type	Subtype
Offices	Small office; medium office; large office
Retails	Stand-alone retail; strip mall
Schools	Primary school; secondary school
Hospitals	Outpatient healthcare; hospital
Hotels	Small hotel; large hotel
Restaurants	Quick service restaurant; full service restaurant
Apartments	Mid-rise apartment; high-rise apartment
Others	Warehouse (non-refrigerated)

years with hourly or 1-min time resolution can be calculated for any site [24].

In this study, the weather data for 17 climate zones, including the 30-year AMY weather files covering 1980–2009 from Weather Analytics and the TMY3 weather data, were used in the simulations to investigate the weather impact on building performance. Table 1 lists the climate type, criteria, and representative cities for the 17 climates – major US cities except Riyadh in Saudi Arabia and Vancouver in Canada.

2.3. Prototype buildings

To calculate the impact of ASHRAE Standard 90.1, researchers at Pacific Northwest National Laboratory (PNNL) created a suite of 16

prototype buildings [25] covering 80% of the commercial building floor area in the United States for new construction. These prototype buildings were derived from the US Department of Energy (USDOE) [26] but with substantial modifications based on extensive inputs from ASHRAE 90.1 Standing Standards Project Committee members and other building industry experts. The prototype models include the 16 building types in 17 climate locations for three editions of ASHRAE Standard 90.1 (90.1-2004, 90.1-2007 and 90.1-2010). Table 2 summarizes the building types. The EnergyPlus models of these buildings are available; including Energy-Plus model input files (.idf) and output files (.html). The description of the building, HVAC systems, internal loads, operating schedules, and other key model inputs are summarized in scorecard spreadsheet files that are also available from the web site. The detailed methodology and modeling strategy used to develop these prototype models as well as the energy and cost saving analysis is presented in [22].

From these prototype buildings, the three types of office buildings with different sizes, small, medium and large, were chosen for this study. Office buildings represent the most typical commercial buildings in the United States in terms of buildings numbers and total floor area [20]. The large-size office building is served by a central built-up variable air volume (VAV) system with a central plant. The medium office has packaged VAV systems, and the small office has packaged single zone systems. The key features of these office buildings are summarized in Table 3. The EnergyPlus models

Table 3

Summary of key features of the three types of office buildings.

	Large-size office	Medium-size office	Small-size office
Total floor area (m ²)	46,320	4980	510
Number of stories	12	3	1
% Perimeter zone area	30%	40%	70%
Envelope			
Window-wall-ratio (WWR)	40%	33%	24.4% for South and 19.8% for the other three orientations
Walls, roofs, floors: U-factor	ASHRAE 90.1 Requirements, nonresiden	tial; walls, above-grade, steel-framed; ro	ofs, insulation entirely above deck
Windows: U-factor and SHGC	ASHRAE 90.1 requirements nonresidential	ASHRAE 90.1 requirements nonresidential; vertical glazing, 31.1–	ASHRAE 90.1 requirements nonresidential; vertical glazing, 20–
		40%, 0 11/20	50%, 0 lixed
HVAC systems	Control I will an MAN motore	De des es d MAM essets es e	De des esta de la companya contenera
System type	Central Dulit-up VAV systems	Packaged VAV systems	Packaged single zone systems
Heating source	Gas Dollel	Gas Iulliace	furnace as back up
Cooling source	Water-cooled centrifugal chillers	Air-cooled direct expansion	Air-source heat numn
Air distribution and terminal units	VAV terminal box with hot-water	VAV terminal box with hot-water	No terminal unit
	reheat coil, minimum damper position	reheat coil, minimum damper position	
	set at 30%	set at 30%	
Thermostat setpoint	24 °C Cooling/21 °C Heating	24 °C Cooling/21 °C Heating	24 °C Cooling/21 °C Heating
Air-side economizer	Applicable based on 90.1	Applicable based on 90.1	None
Internal loads			
Average lighting power density (W/m^2)	90.1-2004: 10.76	90.1-2004: 10.76	90.1-2004: 10.76
	90.1-2010: 8.99	90.1-2010: 8.87	90.1-2010: 9.15
Average plug-load power density (W/m ²)	7.8	8.07	6.78
Average occupant density (m ² /person)	18.6	18.6	16.6
Operating schedules			
Lighting, plug-loads, and occupants	Lighting Plug Occupancy	Lighting Plug Occupancy	Lighting Plug Occupancy
	1	1 1111 1111	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
	P 0.8	g 0.8	g 0.8
	at 0.6	M 0.6	6
	F 0.4		F 0.4
	ξ ₀₂ δ	⁵ Ω ^ŏ	Б _{ар}
	1 3 5 7 9 11 13 15 17 19 21 23	1 3 5 7 9 11 13 15 17 19 21 23	1 3 5 7 9 11 13 15 17 19 21 23
	Weekday	Weekday	Weekday
Misc.			

Exterior lighting peak power (W)

90.1-2004: 62787 90.1-2010: 43305 90.1-2004: 14385 90.1-2010: 7476

90.1-2004: 1634 90.1-2010: 896 for the three office buildings in 17 climates based on ASHRAE Standard 90.1-2004 and 90.1-2010 were downloaded and converted for use with EnergyPlus version 7.1. The 90.1-2010 models represent high energy-efficiency designs, with better insulation and windows, more efficient lighting and HVAC systems, exceeding the performance of the 90.1-2004 models by approximately a 30% reduction in site energy use.

2.4. Simulation engine

EnergyPlus [27] version 7.1, released in June 2012, was used to perform the building simulations. EnergyPlus is developed by USDOE as a new generation building energy modeling program that builds upon the most popular features and capabilities of BLAST [28] and DOE-2 [29]. EnergyPlus has innovative simulation capabilities including sub-hourly time steps, an integrated solver for system models with a zone heat balance model, and user definable and configurable HVAC systems and components. It calculates space temperature, occupant thermal comfort, cooling and heating loads, HVAC equipment sizes, energy consumption, utility cost, air emissions, water usage, renewable energy, etc. EnergyPlus is a stand-alone simulation program without a 'user friendly' graphical interface. It reads input and writes output as text files. Since the first release in April 2001, EnergyPlus has been evolving with new and enhanced modeling features and improved usability. EnergyPlus has been validated through three types of tests, including analytical tests, comparative tests and empirical tests.

The EnergyPlus weather file, an epw file, contains 29 weather variables at 1-h intervals (but can be sub-hourly), among which nine important variables were used in the simulations. These key variables can be sorted into four groups: (1) outdoor air conditions: dry-bulb temperature, dew-point temperature, relative humidity, and atmospheric pressure; (2) solar radiation: direct normal solar radiation and diffuse horizontal solar radiation; (3) sky radiation: horizontal infrared radiation; and (4) wind conditions: wind direction and wind speed. Another important weather variable contained in the epw weather file and used by EnergyPlus is the monthly ground temperature at various soil depth levels. EnergyPlus is usually run with a time step of 10 or 15 min, and the hourly weather variables are interpolated to the half-hour intervals.

3. Results and discussion

3.1. Variations of weather data

Variations of weather data and climate zone classification for each of the 17 cities based on the annual HDD18 (Heating Degree Days with base temperature of 18 °C) and CDD10 (Cooling Degree Days with base temperature of 10 °C) of the AMY data from 1980 to 2009 are illustrated in Fig. 2. The climate zones displayed in Fig. 2 correspond to the criteria listed in Table 1. It can be seen that most cities do not belong to only one climate zone. For the 30-year period, the climates of some cities vary across two zones and some even across three or more zones. For example, Fairbanks exhibits climatic conditions indicative of the very cold Climate Zone 7 and the subarctic Climate Zone 8, while Helena shows conditions typical of five climate zones: the cool-humid 5A, the cool-dry 5B, the cool-marine 5C, the cold-humid 6A, and the cold-dry 6B. The spread of climate zones for a city based on 30-year AMY weather data is a good indicator of weather change year-over-year, which cannot be represented by a single-year TMY3 weather data file. Therefore, running simulations using multi-decade AMY weather data is necessary to evaluate fully the effect of weather on the energy performance of buildings.

The variation in annual average global horizontal solar radiation for the 17 cities from 1980 to 2009 is listed in Table 4. In general, the highest and lowest levels of annual average global horizontal solar radiation occur in the hotter and colder climates respectively. For example, Riyadh has the highest value of 6588 Wh/ m^2 in 2001, while Fairbanks has the lowest value of 2473 Wh/m² in 1995. Table 4 also shows the maximum variations, defined as the maximum of the annual difference between the highest and the lowest values of all cities across the 30-year period. Among the 17 cities, Chicago has the largest variation of 652 Wh/m², while Boise has the smallest variation of 360 Wh/m². The values listed in the fifth and sixth columns represent the average global horizontal solar radiation over the 30 years for the AMY data and TMY3 data respectively. The values listed in the last two columns are the absolute and relative differences between the TMY3 values and the average values. The largest difference between TMY3 and the average AMY is 809 Wh/m² which occurs in Miami, a hot climate. However, compared with the cities in hotter and colder climates, cities in mixed climates tend to have greater differences. There is a noted trend that the AMY data have higher global



Fig. 2. Variations of climate zone based on annual HDD and CDD for 17 cities using AMY weather data from year 1980 to 2009.

City	Annual average global horizontal solar radiation (Wh/m²), year		Average AMYs	e TMY3 Variation Variat (Highest – Lowest) (TMY)		Variation (TMY3 – Average)	Variation Variation% (TMY3 – Average) (TMY3 – Average)/ Average	
	Highest	Medium	Lowest					
Miami	5825,	5614,	5444,	5612	4803	380	-809	-14.4
	1986	1991	1992					
Riyadh	6588,	6329,	5977,	6318	6114	611	-204	-3.2
	2001	1983	1982	4750	4450	69.4	201	<u>.</u>
Houston	5099,	4765,	4474,	4750	4459	624	-291	-6.1
	1999	1992	1982					
Phoenix	6069,	5868,	5531,	5832	5738	538	-94	-1.6
	2002	1980	1983					
Memphis	4799,	4560,	4230,	4564	4493	570	-71	-1.6
	1999	1996	1991					
EI Paso	6072,	5749,	5519,	5758	5657	554	-101	-1.8
	2003	1997	1986					
San	5520,	5352,	4952,	5322	4703	568	-619	-11.6
Francisco	1988	1981	1998					
Baltimore	4435,	4240,	3918,	4223	4078	517	-145	-3.4
	2006	1987	2003					
Albuquerque	6054,	5906,	5635,	5881	5426	419	-455	-7.7
	2003	2009	1983					
Salem	4110,	3865,	3692,	3881	3701	418	-180	-4.6
	1987	1995	1998					
Chicago	4484,	4099,	3832,	4100	3854	652	-246	-6.0
	1988	2008	1993					
Boise	5106.	4927.	4746.	4926	4429	360	-497	-10.1
20120	2002	1990	1982	1020	1120	500	107	1011
Vancouver	3946.	3682.	3361.	3674	3369	585	-305	-8.3
	1985	1998	2007					
Burlington	3863	3715	3465	3699	3675	398	-24	-0.6
Samigeon	1995	2002	2000	2000	3075			5.0
Helena	4598	4367	4082	4377	3997	517	-380	-87
iiciciia	2001	1981	1998	1.11	5557	517	500	0.7
Duluth	4060	3746	2525	3744	3678	544	66	1.8
Dalutti	1009,	1000	1003	5/44	2010	JTT	-00	-1.0
Fairbanko	2019	1999	1995	2000	2501	545	277	0.7
FallDallKS	1007	∠000, 1009	2475,	2000	2591	J4J	-211	-3.1
	1987	1998	1992					

 Table 4

 Statistics of the annual average global horizontal solar radiation of the 17 cities from year 1980 to 2009.

Table 5

Statistics of the annual average dry-bulb temperature of the 17 cities from year 1980 to 2009.

City	Annual average dry-bulb temperature (°C), year			Average AMYs	TMY3	Variation (Highest – Lowest)	Variation (TMY3 – Average)
	Highest	Medium	Lowest				
Miami	25.3, 1998	24.8, 2003	23.8, 1984	24.7	24.5	1.5	-0.2
Riyadh	27.8, 1999	26.7, 1981	25.0, 1992	26.6	26.2	2.8	-0.4
Houston	21.4, 2006	20.6, 2003	19.0, 1983	20.5	20.4	2.4	-0.1
Phoenix	24.8, 1989	23.9, 2000	22.5, 1998	23.9	23.8	2.3	-0.1
Memphis	18.5, 2007	17.1, 2002	16.2, 1997	17.2	17	2.3	-0.2
EI Paso	19.8, 1994	18.5, 2008	16.7, 1987	18.3	18	3.1	-0.3
San Francisco	14.7, 1997	13.8, 2009	12.8, 1982	13.8	13.8	1.9	0
Baltimore	14.4, 1990	13.2, 2005	12.2, 2003	13.2	13.2	2.2	0
Albuquerque	15.0, 2003	14.1, 2008	13.0, 1984	14.0	13.7	2.0	-0.3
Salem	12.9, 1992	11.6, 2002	10.0, 1985	11.6	11.7	2.9	0.1
Chicago	12.1, 1998	10.1, 2000	8.7, 1985	10.0	10	3.4	0
Boise	12.7, 2003	11.3, 2005	8.1, 1985	11.1	11.2	4.6	0.1
Vancouver	11.6, 2004	10.5, 2002	9.1, 1985	10.5	9.7	2.5	-0.8
Burlington	9.2, 1998	7.8, 2007	7.0, 1980	7.9	7.9	2.2	0
Helena	9.1, 2007	7.4, 2005	4.8, 1996	7.1	7.2	4.3	0.1
Duluth	6.3, 1998	4.3, 2000	2.6, 1996	4.3	4	3.7	-0.3
Fairbanks	0.3, 1981	-1.8, 2001	-4.4, 1999	-2.0	-1.4	4.7	0.6

horizontal solar radiation than the TMY3 data, which can lead to the AMYs overestimating the cooling energy use and underestimating the heating energy use when compared to the TMY3s. Further discussion is provided in Section 3.7.

Table 5 shows the variations in annual average dry-bulb temperature of the 17 cities from 1980 to 2009. The variations are more significant for cold climates. For example Fairbanks, Helena and Duluth all have variations greater than 3.7 °C. In general, the differences between the TMY3 values and the average AMY are small, except the TMY3 values have a higher average temperature by 0.6 °C for Fairbanks and a lower temperature by 0.8 °C for Vancouver.

In summary, the variation in weather data year-over-year is significant, especially for cold climates. Such variations should not be



Fig. 3. Variations of percentage changes of HVAC source EUI between AMY and TMY3: (a) large office, 90.1-2004 models; (b) large office, 90.1-2010 models; (c) medium office, 90.1-2004 models; (d) medium office, 90.1-2010 models; (e) small office, 90.1-2004 models; (f) small office, 90.1-2010 models. The red bars represent the variations across the 30-year while the green bars excluding the six percentage changes from the top three and the bottom three extreme weather years. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ignored and cannot be represented by single-year weather data – either a historical year or a synthetic year such as TMY.

3.2. Weather impact on HVAC source energy use for individual cities

HVAC energy use is directly affected by weather, because the cooling and heating loads of buildings are dependent upon weather conditions such as outdoor air temperature and humidity, wind speed, and solar radiation. The percentage variation of HVAC

source energy use intensity (EUI, kWh/m²) for the three types of office buildings with two design efficiency levels in the 17 cities are shown in Fig. 3. The simulation results from using the TMY3 weather data are used as the baseline and are represented as 0% in these figures. The red bars represent the variation of the percentage changes across the 30-year period (1980–2009). The green bars show the same results but excluding the top three largest and the bottom three smallest values to filter out the extreme AMY cases. The left side bars with negative values indicate TMY3 results

340

are over-estimating the AMY results while the right side bars with positive values indicate TMY3 results are under-estimating the AMY results. The cities on the vertical axis of the figures from the top to the bottom are arranged by climate zone from the very hot and humid climate zone 1A to the subarctic climate zone 8.

In general, the AMY results show large differences when compared to results using the TMY3 weather data. The TMY3 results can over-estimate AMY results as much as 18% and under-predict as much as 37%. Three-dimensional comparisons are made to analyze the relative weather impact by climate zone, building type, and building design efficiency. First, it can be seen that most large changes occur in colder climates, regardless of the building type (large-, medium-, or small-size office) or building design efficiency level (low, 90.1-2004, or high, 90.1-2010). Usually the largest under-estimates occur in Boise, followed by Helena and then San Francisco, while the largest over-estimates occur in Fairbanks, followed by Chicago and then Duluth. Secondly, the larger changes occur for the medium-size office building, followed by the largesize and then the small-size building. The medium office building has a larger perimeter area than the large office, and has air-side economizers, while the small office does not. Thirdly, the larger changes occur for the large and medium offices with the high-efficiency design level (90.1-2010) than the low-efficiency design level (90.1-2004). The opposite is true for the small office – the low-efficiency design level shows larger changes. Fourthly, the differences between the red and the green bars for each case are compared. The largest differences occur in Boise regardless of building type and building efficiency design level, followed by Helena, Fairbanks, and Miami. In general, the differences in the hotter and colder climates are larger than those in the mixed climates. Finally, comparing the HVAC source EUI between the average of the 30-year AMYs and the TMY3 for the large office at both efficiency design levels in Tables 6 and 7, it can be seen that the TMY3 results are usually lower than the AMY results, occurring in 13 out of the 17 cities, and by as much as 9–9.2% in Riyadh, 5.6–8.7% in Boise, and 5.2–7.7% in San Francisco. Similar trends can be observed for the medium and small offices.

As an example, detailed variations of the HVAC source EUI of the large office in Chicago with low and high building efficiency levels from 1980 to 2009 are illustrated in Fig. 4. The TMY3 results, the average of the AMY results, as well as the average results plus and minus one and two standard deviations are plotted on the same figures. The TMY3 results are fairly close to those of the average AMY results, within the range of +2.6% and one standard deviation. Except for 1992, all AMY results fall within one standard deviation. The variation, in percentage changes, between the maximum and minimum AMY results is large, 22.6% for the 90.1-2004 office and 28% for the 90.1-2010 office.

In summary, the weather impacts on the HVAC source energy use are significant, especially for the medium-size office building and for all office buildings in cold climates. The impacts are the least for the small-size office among the three office types. The medium-size office buildings have air-side economizers, as required by ASHRAE standard 90.1 in appropriate climates, and more window area than the small offices, but have less window area and more perimeter zone area than the large offices. This makes the medium offices more sensitive to weather variation than the other two.

Weather impacts on buildings are about the same across the two efficiency design levels. Meanwhile, large differences between the simulated results using TMY3 weather data and the AMY weather data are observed across the 30-year period. The TMY3

Table 6

City	HVAC source EUI (kWh/m ²), year		Average AMYs	TMY3	Variation (Highest – Lowest)	Variation% (TMY3 – Average)/		
	Highest	Medium	Lowest					Average
Miami	250.8, 1998	229.3, 1999	206.1, 1984	228.9	227.6	44.7	-1.4	-0.6
Riyadh	217.4, 1998	197.9, 1980	181.7, 1992	200.1	182.1	35.7	-18.1	-9
Houston	206.7, 1980	193.6, 1986	178.3, 1984	193.8	189.2	28.4	-4.7	-2.4
Phoenix	205.2, 1984	196.5, 2008	185.3, 2004	195.9	189.8	19.9	-6.1	-3.1
Memphis	165.3, 1985	151.4, 1996	140.5, 1992	152.6	148.8	24.9	-3.8	-2.5
EI Paso	108.2, 1981	103.1,	96.5, 2004	102.5	97.8	11.7	-4.7	-4.6
San Francisco	74.9, 1997	65.9, 1998	60.9, 1999	66.9	63.5	13.9	-3.4	-5.2
Baltimore	144.9, 1994	134.9, 2004	125.1, 1984	133.6	136.5	19.9	2.8	2.1
Albuquerque	102,	96.8, 1981	91.5, 1986	96.8	93.1	10.5	-3.7	-3.8
Salem	83.1,	74.7,	71.4,	75.1	75.1	11.7	-0.1	-0.1
Chicago	138.2,	128,	112.7,	127.6	130.9	25.5	3.3	2.6
Boise	111.3,	92.8, 1982	83.7,	93.2	87.9	27.6	-5.2	-5.6
Vancouver	74.9,	67.1,	61.1, 1983	66.8	67.5	13.8	0.6	0.9
Burlington	133.3,	118.9,	108.2,	120.1	118.4	25.1	-1.6	-1.4
Helena	116.6,	99.5, 1986	88.7,	100.1	95.5	27.9	-4.6	-4.6
Duluth	146.2,	128.6,	117.9,	130.7	133.1	28.2	2.5	1.9
Fairbanks	180.1, 1999	163.6, 1997	135.8, 1981	161.3	157.7	44.2	-3.6	-2.2
		1007						

Table 7
Statistics of the HVAC source EUI of the large office, 90.1-2010 during the 30-year period.

City	HVAC source EUI (kWh/m ²), year			Average AMYs	TMY3	Variation (Highest – Lowest)	Variation (TMY3 – Average)	Variation%
	Highest	Medium	Lowest					(TMY3 – Average) /Average
Miami	167.2, 1998	151.9, 1991	136.2, 1984	151.2	151.4	31.1	0.2	0.2
Riyadh	164.1, 1998	151.2, 1980	137.4, 1992	152	138	26.7	-14	-9.2
Houston	122.2, 1998	114.2, 2003	106.1, 1984	114.4	111.3	16.1	-3.1	-2.7
Phoenix	129, 1981	122.9, 2009	116.3, 1982	122.9	119.6	12.7	-3.3	-2.7
Memphis	99.5, 1985	92, 1991	85.1, 1992	92.5	90	14.4	-2.5	-2.7
EI Paso	79.2, 1981	75.8, 1990	71.3, 2004	75.5	71.7	7.9	-3.8	-5
San Francisco	45.5, 1997	38.2, 2008	35.3, 1999	39	36	11.2	-2.9	-7.7
Baltimore	84.1, 1994	76, 1985	69.7, 1984	76.1	77.3	14.3	1.2	1.6
Albuquerque	74.9, 2007	71.1, 1981	66.9, 1986	71.6	66.9	7.9	-4.6	-6.4
Salem	53.7, 1990	48.4, 2002	45.3, 1980	48.7	48	8.3	-0.7	-1.5
Chicago	88.7, 1985	80.8, 1986	69.2, 1992	80.9	83	19.5	2.1	2.6
Boise	75.4, 1985	62.4, 1991	55.3, 1981	62.5	57.1	20.1	-5.4	-8.7
Vancouver	47.8, 1998	42.1, 2008	38.2, 2001	42.3	39.9	9.6	-2.4	-5.7
Burlington	85.5, 1989	74.9, 1983	66.9, 2006	75.7	74.5	18.6	-1.3	-1.7
Helena	78.5, 1985	63.7, 1980	55.8, 1999	64.8	60.1	22.7	-4.4	-7.1
Duluth	93.9, 1989	79.6, 2005	70.6, 1992	81.7	83.6	23.3	1.8	2.2
Fairbanks	134.2, 1999	116.3, 1988	91.8, 1981	115.9	111.7	42.4	-4.2	-3.7



Fig. 4. Variations of HVAC source energy of the large office buildings in Chicago from year 1980 to 2009.

results are lower than the AMYs mainly due to the AMYs having higher solar irradiance. Further discussion is provided in Section 3.7.

3.3. Weather impact on the building total source energy use for individual cities

Similar results as shown in Fig. 3 are shown in Fig. 5, but for the building total source energy use intensity (EUI, kWh/m^2). The variation of the building total source EUI are about one-third of those of the HVAC source EUI, because weather changes only affect the HVAC source energy use. The percentage changes of the building total source energy, although much smaller, represent a significant amount of the absolute differences in the building total source energy use.

Similar but slightly different patterns are observed for the building total source EUI. In general, the AMY results show noticeable differences from those from the TMY3. The TMY3 results overestimate the AMY results by as much as 7.8% and under-estimate by as much as 9.7%. First, it can be seen that most large changes occur in colder climates, regardless of the building type or building efficiency design level. Usually the largest under-estimates occur in four climates: Riyadh, Boise, Helena and Fairbanks, while the largest over-estimates occur in four climates: Miami, Chicago, Duluth and Fairbanks. Secondly, the larger changes occur for the medium-size office, followed by the large-size and then the small-size. Thirdly, the slightly larger changes occur for the large and medium offices with the high efficiency design level than the low efficiency design level. The opposite is true for the small office – the low efficiency design level shows larger changes. Fourthly, the



Fig. 5. Variations of percentage changes of total building source EUI: (a) large office, 90.1-2004 models; (b) large office, 90.1-2010 models; (c) medium office, 90.1-2004 models; (d) medium office, 90.1-2010 models; (e) small office, 90.1-2004 models; (f) small office, 90.1-2010 models. The red bars represent the variations across the 30-year while the green bars excluding the six percentage changes from the top three and the bottom three extreme weather years. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

differences between the red and the green bars for each case are compared. The largest differences occur in five climates: Miami, Chicago, Boise, Helena, and Fairbanks. This implies that these climates tend to have more severe weather impacts. Finally, comparing the building total source energy use between the TMY3 weather data and the average of the 30-year AMY weather data, for the large office at both efficiency design levels in Tables 8 and 9, it can be seen that the TMY3 results are usually lower than the AMY results, occurring in 13 out of the 17 cities; but except for Riyadh, the under-estimates are less than 2% for all other climates. 3.4. Weather impact on the HVAC and building total source energy use aggregated for the US office building stock

To analyze the variation in the HVAC and building total source energy for all office buildings in the US, the source energy use are aggregated across the 15 US cities using weighting factors based on the volume of new construction in each of the 15 cities [22]. The percentage changes at the national level are then calculated and shown in Fig. 6.

From Fig. 6, the simulated HVAC source energy use using the TMY3 data can over-estimate and under-estimate the AMY results

City	Total bui (kWh/m ²	lding sourc ²), year	e EUI	Average AMYs	TMY3	Variation (Highest – Lowest)	Variation (TMY3 – Average)	Variation% (TMY3 – Average)/
	Highest	Medium	Lowest					Average
Miami	533, 1998	511.5, 1999	488.3, 1984	511.2	509.9	44.7	-1.4	-0.3
Riyadh	499.5, 1998	479.9, 1980	463.8, 1992	482.2	464.1	35.7	-18.1	-3.7
Houston	489.3, 1980	476.2, 1986	460.9, 1984	476.4	471.7	28.4	-4.7	-1
Phoenix	487.6, 1984	478.9,	467.7, 2004	478.3	472.1	19.9	-6.1	-1.3
Memphis	448.2, 1985	434.3,	423.3,	435.5	431.7	24.9	-3.8	-0.9
EI Paso	391, 1981	385.9, 1982	379.3,	385.3	380.6	11.7	-4.7	-1.2
San Francisco	358.1,	349.2,	344.2,	350.2	346.7	13.9	-3.4	-1
Baltimore	428.2,	418.1,	408.3,	416.9	419.7	19.9	2.8	0.7
Albuquerque	385.2,	380,	374.7,	379.9	376.3	10.5	-3.7	-1
Salem	2007 366.5,	1981 358.2,	1986 354.8,	358.5	358.4	11.7	-0.1	0
Chicago	1990 421.6,	1988 411.5,	1981 396.2,	411.1	414.3	25.5	3.3	0.8
Boise	1983 394.7,	1986 376.3,	1992 367.1,	376.6	371.4	27.6	-5.2	-1.4
Vancouver	1985 358.4,	1982 350.5,	1995 344.6,	350.3	350.9	13.8	0.6	0.2
Burlington	1990 417,	1989 402.6,	1983 391.9,	403.7	402.1	25.1	-1.6	-0.4
Helena	1989 400.4,	2004 383.2,	372.5,	383.8	379.2	27.9	-4.6	-1.2
Duluth	1985 430.2,	1986 412.7,	1999 402,	414.7	417.1	28.2	2.5	0.6
Fairbanks	1989 464.3, 1999	2005 447.9, 1997	1992 420.2, 1981	445.7	442.1	44.2	-3.6	-0.8

 Table 8

 Statistics of the total building total source EUI of the large office, 90.1-2004 during the 30-year period.

by 4.8% and 6.1% respectively for the large office, by 4.7% and 7.6% for the medium office, and by 2.5% and 4.8% for the small office. The corresponding percentage changes for the building total source energy use are 1.4% and 1.7%, 1.7% and 2.7%, and 0.8% and 1.7%. In general, the weather impacts are about the same for buildings with the two efficiency design levels, with slightly larger impacts for the low-efficiency buildings. The largest impacts are for the medium-size office followed by the large and then the small office.

Compared with the variations shown in Figs. 3 and 5, the variations in Fig. 6 are much smaller. This implies the weather impacts across different climates are not uniform and tend to cancel out each other. For example, during a particular year, the TMY3 results may over-estimate the AMY results for some climates but underestimate for others, so the overall TMY3 results at the national level are not so different from the AMY results. However, this should not overshadow the large discrepancies between the TMY3 results and the AMY results for individual climates, because energy efficiency technologies are evaluated and applied locally, and energy policy is made by local jurisdictions.

3.5. Weather impact on the peak electricity demand of buildings

The variations of the percentage changes of the building peak electricity demand are displayed in Fig. 7. The peak demands of the medium office using the TMY3 weather data can under-estimate that from the AMY data by up to 32.4%, and over-estimate by up to 21%. Unlike the variation in the HVAC source energy use mentioned above, there is no clear correlation between the change in peak demand and the climate/city. Except for the medium office, the mixed climates show larger percentage differences. The varia-

tions for the medium office, as shown in Fig. 7c and d, are much larger than those for the large and small offices.

Additionally, the percentage changes for the small office are mostly within ±6% except for a few cases as shown in Fig. 7e and f. For a particular city, if only one green bar can be seen, it is because the red bar is almost the same as the green bar but overlapped by the red bar, and thus cannot be seen. This implies that for the small office building in this city, the peak demand is not so sensitive to extreme weather conditions (the top three and bottom three years). On the other hand, if only one red bar can be seen, it is because the green bar is too small to be seen. This implies that the peak demand is sensitive to extreme weather conditions. When the top three and the bottom three years are eliminated, peak demands from the remaining 24-year AMY data and the TMY3 data are very close or equal, thus the differences cannot be seen.

As an example, detailed variations of the simulated peak demand of the large office in Chicago with low and high efficiency levels from 1980 to 2009 are illustrated in Fig. 8. The TMY3 results, the average of the AMY results, as well as the average results plus and minus one and two standard deviations are plotted on the same figures. The TMY3 result is higher than the average AMY result by 1.1% (within one standard deviation) for the 90.1-2004 office, but lower by 6% (outside two standard deviations) for the 90.1-2010 office. For the 90.1-2004 office, the variation of peak demand is relatively small except for 1991, 2004, and 2008 which has lower peak demand by as much as 7.7% compared to the average value. For the 90.1-2010 office, the variation of peak demand from individual AMY results is more significant, up to 13.4% between the minimum and maximum values.

In summary, the weather impact on the peak electricity demand is significant, even greater than the impact on building

City	Total bui (kWh/m ²	lding sourc ²), year	e EUI	Average AMYs	TMY3	Variation (Highest – Lowest)	Variation (TMY3 – Average)	Variation% (TMY3 – Average)/
	Highest	Medium	Lowest					Average
Miami	401.1, 1998	385.8, 1991	369.9, 1984	385	384.9	31.1	-0.1	0
Riyadh	397.9, 1998	385, 1980	371.2, 1992	385.8	371.6	26.6	-14.2	-3.7
Houston	357.6, 1998	349.6, 2003	341.2, 1984	349.5	345.8	16.4	-3.7	-1.1
Phoenix	363.3, 1981	357.3, 2009	350.6, 1982	357.2	354	12.7	-3.2	-0.9
Memphis	333.9, 1985	326.4, 1983	319.4, 1992	326.9	323.9	14.6	-3.1	-0.9
EI Paso	312.7, 1981	309.3, 2005	304.7, 2004	308.9	305.2	8	-3.7	-1.2
San Francisco	279.5, 1997	272.6, 1995	268.5, 1999	273.2	270.1	11	-3.1	-1.1
Baltimore	318.3, 1994	310.1, 1985	303.8, 1984	310.2	310.9	14.5	0.7	0.2
Albuquerque	308.1,	304.2,	300.1, 1986	304.7	300.3	7.9	-4.3	-1.4
Salem	288.6,	293.2, 1988	280,	283.5	282.2	8.5	-1.3	-0.5
Chicago	323.1,	315.2, 1986	303.5,	315.3	317.1	19.6	1.8	0.6
Boise	309.1, 1985	296.2,	289.2,	296.3	291.1	19.9	-5.3	-1.8
Vancouver	282.9,	277.3,	273.4,	277.4	275.3	9.5	-2.1	-0.8
Burlington	320.3, 1989	309.8, 1983	302,	310.6	308.9	18.3	-1.6	-0.5
Helena	312.7, 1985	298.1,	290.1,	299	294.5	22.6	-4.5	-1.5
Duluth	328.8,	314.8,	305.7,	316.9	318.3	23.1	1.5	0.5
Fairbanks	371.6, 1999	353.8, 1988	329.4, 1981	353.5	349.3	42.2	-4.2	-1.2

Table 9Statistics of the total building source EUI of the large office, 90.1-2010 during the 30-year period.



Fig. 6. Variations of percentage changes of HVAC and total source EUIs of the three types of office buildings with low (90.1-2004 standard) and high (90.1-2010 standard) energy efficiency levels: (a) changes in HVAC source EUI and (b) changes in total source EUI.



Fig. 7. Variations of percentage changes of peak electricity demand: (a) large office, 90.1-2004 models; (b) large office, 90.1-2010 models; (c) medium office, 90.1-2004 models; (d) medium office, 90.1-2010 models; (e) small office, 90.1-2004 models; (f) small office, 90.1-2010 models. The red bars represent the variations across the 30-year while the green bars excluding the six percentage changes from the top three and the bottom three extreme weather years. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

energy use. The simulated peak demands from TMY3 can significantly under- or over-estimate those from the AMY. It is necessary to run simulations using multi-decade of AMY weather data to assess accurately demand response strategies.

3.6. Weather impact on peak electricity demand reduction and energy savings of energy conservation measures

The peak demand reduction (in%) and the HVAC and building total source energy savings (in%) are calculated by comparing the

peak demand and source energy use of the building with the high energy efficiency level, to those of the same building with the low energy efficiency level, using the TMY3 and the 30-year AMY weather data for the three building types across the 17 climates. The results are shown in Fig. 9, where the green¹ bars represent the variation in the demand reduction and source energy savings, using the 30-year AMY weather data. The red marks represent the

346

 $^{^{1}\,}$ For interpretation of color in Fig. 9, the reader is referred to the web version of this article.



Fig. 8. Variations of peak electricity demand of the large office buildings in Chicago from year 1980 to 2009.

corresponding results using the TMY3 weather data. A few key points can be seen from the results in Fig. 9:

- Weather impact on peak demand reduction and HVAC source energy savings are large. There are no consistent patterns across the building type or climate.
- Generally the weather impact on the peak demand reduction is much greater than on the HVAC source energy savings.
- For HVAC source energy savings, larger weather impacts occur for the mixed to cold climates, from San Francisco to Fairbanks. The savings based on TMY3 weather files are usually within the ranges of savings based on the AMY weather files, except for over-estimates in San Francisco, Albuquerque, Boise, Vancouver, and Helena, where the red marks are usually at the very right end or outside of the green bars.
- The peak demand reduction can vary significantly year-over-year for most climates. The differences in demand reduction can be as high as 15% for Chicago and Fairbanks across the 30-year period for the large office, as shown in Fig. 9a.
- Generally the peak demand reductions based on the TMY3 data are within the ranges of reductions based on the AMY data, but a few cases show the TMY3 results (the red marks) are at the high or low end of, or even outside the AMY results (the green bars). Furthermore, some climates even demonstrate opposing weather impacts. For example, in Phoenix, the TMY3 demand reduction is greater than that from the AMY data for the large office, but less for the small office. El Paso shows the totally opposite situation as Phoenix.
- To assess accurately the peak demand reduction and energy savings of ECMs, it is necessary and important to run simulations using multi-decade AMY weather data in comparative studies of energy conservation measures. Results from TMY3 data can sometimes significantly over- or under-estimate the actual energy and cost savings.

It should be noted that the calculated peak demand reduction and source energy savings come from a combination of energy efficiency improvements from ASHRAE standard 90.1-2004 to 90.1-2010. Whether similar trends apply to an individual energy efficiency improvement, such as better wall or roof insulation, better windows, high efficiency lighting systems, or high efficiency HVAC systems, is an open question worth further studies.

3.7. Discrepancies of weather data from different sources and different time periods

Radhi [30] studied the impact of weather data from two different periods, 1961–1990 and 1961–2005, on the simulated electricity use of a low-rise and a high-rise commercial building in Bahrain. Significant variations in simulated energy use from the two different weather periods were found and weather data covering more recent periods were recommended to be used for better prediction of actual energy use in buildings. Bhandari and Shrestha [19] studied the quality of weather data from two different sources by comparing them to actual measured weather data, and the associated impact on building cooling and heating loads and energy consumption for a single year at a specific US location.

The AMY weather data from Weather Analytics and the TMY3 from NREL were used in the current study, although they are from different sources and cover slightly different time periods. The AMYs cover 1980–2009, about 4 years ahead of the TMY3s which cover 1976–2005. Two constraints determined the choice of the AMYs and TMY3s: (1) both data sources are reliable and available to the public [3,7]; (2) Weather Analytics does not provide TMY3 (based on same selection criteria as the NREL TMY3) weather files created from their 30-year AMYs, and the AMYs used to create NREL TMY3 weather files, although available to the public at http://www.rredc.nrel.gov/solar/old_data/nsrdb/1991-2010/



Fig. 9. Variations of percentage reduction of peak electricity demand, and percentage savings of HVAC source energy and total source energy of the 90.1-2010 models over the 90.1-2004 models: (a-c) large office; (d-f) medium office; (g-i) small office.

NCDCStationData/, are not in EnergyPlus weather data epw format and thus need data mapping and conversion.

The temperature data from both sources tend to be more consistent than the solar radiation data, as seen from Table 4 which shows that the TMY3s have lower global horizontal solar radiation than the average of the AMYs across all the 17 climates. Although both sources used similar algorithms, either the original or the enhanced Perez model [31-33] to calculate solar radiation, Weather Analytics data sets lack high quality aerosol data which can lead to a high bias of modeled solar radiation under certain cloudy/high humidity conditions. This explains that, in Table 4, Miami (a humid climate) and San Francisco (with frequent morning fog) have the greatest deviations in solar radiation between the average AMYs and the TMY3. Another source of discrepancies in the solar data is the NREL TMY3s do not include data for certain calendar years due to eruptions of the volcanoes El Chichón and Mount Pinatubo (1982-1984 and 1992-1994, respectively) that decreased solar radiation in the US [3]. This explains that, in Tables 4 and 8 out of the 15 US cities have the lowest solar radiation in those years across the 30-year period.

To quantify what portion of the overestimate of HVAC source energy by the AMYs in Tables 6 and 7 is attributable to the high bias of solar radiation, there is a need to study the correlation between the key weather variables and the simulated building performance. Apadula et al. [34] studied the effect of the meteorological variability on the national monthly electricity demand in Italy. A multiple linear regression model based on calendar and four weather variables, including air temperature, wind speed, relative humidity and cloud cover, is developed to study the relationships between meteorological variables and electricity demand as well as to predict the monthly electricity demand up to 1 month ahead. The model demonstrated an accuracy of better than 1% over the data covering the period 1994–2009. Lam et al. [35] used principal component analysis to study prevailing weather conditions in subtropical Hong Kong. Regression models were developed to correlate the simulated monthly building cooling loads and total energy use, for a generic office building, with a developed climatic index Z, which is a function of the dry-bulb temperature, wet-bulb temperature and global solar radiation. The regression models showed an accuracy of 1% for annual and 4% for monthly simulated energy use over the period 1979–2008.

In the current study, a regression model is derived to calculate the HVAC source energy EUI based on the annual cooling degree days (CDD10), annual heating degree days (HDD18), and the annual average daily global horizontal solar radiation (GHSR):

HVAC Source Energy EUI = $c_0 + c_1 \times \text{CDD10} + c_2 \times \text{HDD18} + c_3 \times \text{GHSR}$

where c_0 to c_3 are regression coefficients.

Table 10 lists the regression results for the large office buildings compliant with ASHRAE Standard 90.1-2004, when the above regression was applied to the 30-year AMYs in the four climates, Miami, San Francisco, Boise, and Fairbanks. The results show that there are more significant discrepancies in solar radiation between the average AMYs and the TMY3s (Table 4). The linear regressions

348

 Table 10

 Regression of HVAC source energy for the 90.1-2004 Large Office during the 30-year period.

City	<i>C</i> ₀	<i>c</i> ₁	<i>c</i> ₂	C ₃	R^2
Miami	-69.19	0.05367	0.02736	0.0101	0.84
San Francisco	6.57	0.03674	0.01388	-0.01795	0.95
Boise	13.15	0.02675	0.01932	-0.02778	0.86
Fairbanks	-40.46	0.05493	0.02366	-0.00532	0.92

are reasonable with R-squared between 0.84 and 0.95. The variations of CDD10, HDD18, and GHSR in the AMYs directly contribute to the variations of the simulated HVAC source energy. AMYs with higher CDD10 and HDD18 will lead to higher HVAC source energy use. Except for the cooling dominated climate of Miami, the other three climates show that higher solar radiation leads to lower HVAC source energy use. The impact of solar radiation on building performance depends on climate – lower or higher solar radiation does not necessarily always dominate.

The regression coefficient c_3 represents the sensitivity of the HVAC Source Energy EUI to the annual average daily global horizontal solar radiation, assuming the indirect impact of solar radiation on ambient air temperature is considered separately in the sensitivity of CDD10 and HDD18. Based on the regression models, the lower solar radiation of the TMY3s in Miami (by 14.4%), San Francisco (11.6%), Boise (10.1%), and Fairbanks (9.7%) would contribute to the underestimate (for Miami) or overestimate (for the other three climates) of HVAC Source Energy EUI of the TMY3s by 3.6%, 16.6%, 14.8%, and 0.9% respectively. The percentages for San Francisco and Boise are much higher mainly due to their much lower HVAC source energy EUI compared to those of Miami and Fairbanks. In conclusion, the discrepancy in solar radiation between different weather data sources can have a significant impact on differences in the simulated HVAC source energy. High quality solar radiation data is key to improving the accuracy of simulated building performance.

It should be noted that the regression model is used to appropriately estimate the effect of the high bias solar data, it is not recommended to replace whole building dynamic simulation for calculating the HVAC source energy.

4. Conclusions

Nowadays with the availability of long-term AMY weather data and sufficient computational power of personal computers, it is feasible and necessary to run simulations with AMY weather data covering multiple decades to fully assess the impact of weather on the long-term performance of buildings, and to evaluate the energy savings potential of energy conservation measures for new and existing buildings from a life cycle perspective. Main findings from this study are: (1) annual weather variation has a greater impact on the peak electricity demand than on the energy use in buildings; (2) simulated building energy use using the TMY3 weather data is not necessarily representative of the average energy use using the AMY data, across the 30-year period. The TMY3 results can be significantly higher or lower than those from the AMY data; (3) the weather impact is greater for buildings in cold climates; (4) the weather has the greatest impact on the medium-size office building, followed by the large office and then the small office; and (5) simulated energy savings and peak demand reduction by energy conservation measures using the TMY3 weather data can be significantly lower or higher when compared to the results using the AMY data. These findings can support energy policy making, energy code development, building technologies evaluation, and utility incentive programs planning.

Future work will continue to investigate the weather impact for other building types, and aggregate the impact across the entire US building stock. If more AMY weather data, for example 50– 100 years, is available, methods will be developed to define and select various TMY weather data representing different conditions. For example, cool vs. warm years, dry vs. wet years, cloudy vs. sunny years, for various applications including HVAC design, demand response for smart grids, and solar renewable energy systems.

Acknowledgements

This work was supported by the US Department of Energy under the US–China Clean Energy Research Center on Building Energy Efficiency. It is also part of our research activities for the IEA ECBCS Annex 53: Total Energy Use in Buildings – Evaluation and Analysis Methods. This work was co-sponsored by the Bureau of Energy, Ministry of Economic Affairs, Taiwan, ROC.

References

- [1] IEA ECBCS Annex 53: total energy use in buildings evaluation and analysis methods.
- [2] Ai-Mofeez IA, Numan MY, Alshaibani KA, Ai-Maziad FA. Review of typical vs. synthesized energy modeling weather files. J Renew Sustain Energy 2012;4(1):012702.
- [3] Wilcox S, Marion W. Users manual for TMY3 data sets. Technical report. NREL/ TP-581-43456; April, 2008.
- [4] Hong TZ, Chou SK, Bong TY. A design day for building load and energy estimation. Build Environ 1999;34(4):469–77.
- [5] Hong TZ, Jiang Y. Stochastic weather model for building HVAC systems. Build Environ 1995;30(4):521–32.
- [6] Jiang Y, Hong TZ. Stochastic analysis of building thermal processed. Build Environ 1993;28(4):509–18.
- [7] Keller JL, Khuen CA. A new climate & hourly data delivery system providing global support for precision modeling and control. SimBuild 2012.
- [8] Freeman T. Evaluation of the typical meteorological years for solar heating and cooling system studies. Technical report SERI/TR-8150-1. Solar Energy Research Institute; 1979.
- [9] Crawley DB. Which weather data should you use for energy simulations of commercial buildings? ASHRAE Trans 1998;104(2):498–515.
- [10] Barnaby CS, Crawley DB. Weather data for building performance simulation. Building performance simulation for design and operation. Spon Press; 2011. p. 37–55.
- [11] Chow TT, Chan ALS, Fong KF, Lin Z. Some perceptions on typical weather yearfrom the observations of Hong Kong and Macau. Sol Energy 2006;80:459–67.
- [12] Crawley DB. Estimating the impacts of climate change and urbanization on building performance. J Build Perform Simul 2008;1(2):91–115.
- [13] Long N. Real-time weather data access guide. User's guide, NREL/BR-550-34303; March, 2006.
- [14] Xu P, Huang YJ, Miller N, Schlegel N. Effects of global climate change on building energy consumption and its implications on building energy codes and policy in California. California Energy Commission, CEC-2008-006; September, 2008.
- [15] Lam JC. Climatic influences on the energy performance of air-conditioned buildings. Energy Convers Manage 1999;40:39–49.
- [16] Yang L, Lam JC, Liu J, Tsang CL. Building energy simulation using multi-years and typical meteorological years in different climates. Energy Convers Manage 2008;49:1123–34.
- [17] Wan KW, Li HW, Liu D, Lam JC. Future trends of building heating and cooling loads and energy consumption in different climates. Build Environ 2011;46:223–34.
- [18] Wan KW, Li HW, Pan W, Lam JC. Impact of climate change on building energy use in different climate zones and mitigation and adaptation implications. Appl Energy 2012;97:274–82.
- [19] Bhandari M, Shrestha S, New J. Evaluation of weather datasets for building energy simulation. Energy Build 2012;49:109–18.
- [20] US Energy Information Administration. 2003 Commercial buildings energy consumption survey; 2012. http://www.eia.gov/emeu/cbecs/.
- [21] ANSI/ASHRAE/IES. ASHRAE standard 90.1-2010: energy standard for buildings except low-rise residential buildings.
- [22] Thornton BA, Rosenberg MI, Richman EE, Wang W, Xie Y, Zhang J, et al. Achieving the 30% goal: energy and cost savings analysis of ASHRAE standard 90.1-2010. PNNL-20405; May, 2011.
- [23] NOAA Satellite and Information Service, National Climatic Data Center; 2012. http://www.ncdc.noaa.gov/oa/climate/isd/index.php/.
- [24] Remund J, Muller SC, Schilter C, Rihm B. The use of Meteonorm weather generator for climate change studies. In: EMS annual meeting: EMS2010-417; 2010. p. 7.
- [25] U.S. Department of Energy. Commercial prototype building models; 2012. http://www.energycodes.gov/development/commercial/90.1_models.
- [26] USDOE. Commercial reference buildings; 2012. <http://www1.eere. energy.gov/buildings/commercial/ref_buildings.html>.

- [27] US Department of Energy. EnergyPlus; 2012. http://apps1.eere.energy.gov/buildings/energyplus/.
- [28] Hittle D. BLAST the building loads analysis and system thermodynamics program. Technical report. Construction Engineering Research Laboratory, University of Illinois; 1977.
- [29] LBNL, DOE-2; 2012. <http://www.gundog.lbl.gov/dirsoft/d2whatis.html>.
- [30] Radhi H. A comparison of the accuracy of building energy analysis in Bahrain using data from different weather periods. Renew Energy 2009;34:869–75.
- [31] Perez R, Stewart R, Arbogast C, Seals R, Scott J. An anisotropic hourly diffuse radiation model for sloping surfaces: description, performance validation, site dependency evaluation. Sol Energy 1986;36:481–97.
- [32] Perez R, Ineichen P, Seals R, Michalsky J, Stewart R. Modeling daylight availability and irradiance components from direct and global Irradiance. Sol Energy 1990;44:271–89.
- [33] Perez R, Ineichen P, Maxwell EL, Seals R, Zelenka A. Dynamic global to direct irradiance conversion models. ASHRAE Trans 1992;98:354–69.
- [34] Apadula F, Bassini A, Elli A, Scapin S. Relationships between meteorological variables and monthly electricity demand. Appl Energy 2012;98:346–56.
- [35] Lam JC, Wan K, Lam T, Wong SL. An analysis of future building energy use in subtropical Hong Kong. Energy 2010;35:1482–90.

Applied Energy 111 (2013) 515-528

Contents lists available at SciVerse ScienceDirect

Applied Energy

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

On variations of space-heating energy use in office buildings

Hung-Wen Lin^a, Tianzhen Hong^{b,*}

^a Intelligent Energy-Saving System Division, Green Energy and Environment Research Laboratories, Industrial Technology Research Institute, Hsinchu 31040, Taiwan, ROC ^b Environmental Energy Technologies Division, Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA 94720, USA

HIGHLIGHTS

• Space heating is the largest energy end use in the U.S. building sector.

• A key design and operational parameters have the most influence on space heating.

• Simulated results were benchmarked against actual results to analyze discrepancies.

• Yearly weather changes have significant impact on space heating energy use.

• Findings enable stakeholders to make better decisions on energy efficiency.

ARTICLE INFO

Article history: Received 21 November 2012 Received in revised form 4 March 2013 Accepted 15 May 2013

Keywords: Building simulation Design and operation EnergyPlus Office buildings Performance benchmarking Space heating

ABSTRACT

Space heating is the largest energy end use, consuming more than seven quintillion joules of site energy annually in the U.S. building sector. A few recent studies showed discrepancies in simulated space-heating energy use among different building energy modeling programs, and the simulated results are suspected to be underpredicting reality. While various uncertainties are associated with building simulations, especially when simulations are performed by different modelers using different simulation programs for buildings with different configurations, it is crucial to identify and evaluate key driving factors to space-heating energy use in order to support the design and operation of low-energy buildings. In this study, 10 design and operation parameters for space-heating systems of two prototypical office buildings in each of three U.S. heating climates are identified and evaluated, using building simulations with EnergyPlus, to determine the most influential parameters and their impacts on variations of spaceheating energy use. The influence of annual weather change on space-heating energy is also investigated using 30-year actual weather data. The simulated space-heating energy use is further benchmarked against those from similar actual office buildings in two U.S. commercial-building databases to better understand the discrepancies between simulated and actual energy use. In summary, variations of both the simulated and actual space-heating energy use of office buildings in all three heating climates can be very large. However these variations are mostly driven by a few influential parameters related to building design and operation. The findings provide insights for building designers, owners, operators, and energy policy makers to make better decisions on energy-efficiency technologies to reduce space-heating energy use for both new and existing buildings.

© 2013 Elsevier Ltd. All rights reserved.

1. Introduction

According to the 2010 United States Department of Energy (US-DOE) Building Energy Databook [1], space heating is the largest end use in the U.S. building sector. Space heating consumes about 5.2 and 2.3 quintillion joules of annual site energy for residential and commercial buildings, respectively. The U.S. Energy Information Administration (EIA) 2003 Commercial Buildings Energy Consumption Survey (CBECS) [2] indicates that office buildings are the most common building type, comprising the largest floor area and con-

suming the most energy in the commercial building sector. In office buildings, space heating consumes about one-third of total site energy, according to the CBECS. It is therefore crucial to study the space-heating energy use of such buildings in order to reduce their energy use and carbon emissions.

The growth in energy use allocated to the commercial buildings sector averaged 2.8% annually from 1950 to 2006 [3]. In the past decade, energy-saving technology improvements in office buildings have received a lot of attention [3–9]. Andrew and Krogmann [8] investigated issues affecting the adoption of energy-efficient heating technology in U.S. office buildings. The factors he studied included energy price, building location, floor area, rental, building vintage, window area, and office equipment. In his study, the mul-







^{*} Corresponding author. Tel.: +1 510 4867082; fax: +1 510 4864089. *E-mail address*: thong@LBL.gov (T. Hong).

^{0306-2619/\$ -} see front matter @ 2013 Elsevier Ltd. All rights reserved. http://dx.doi.org/10.1016/j.apenergy.2013.05.040

tinomial logistic analysis of these factors employed spreadsheet manipulations and statistical calculations. Liu et al. [9] describe a mathematical modeling framework for energy systems to improve energy efficiency and environmental performance of commercial buildings, with the goal of achieving optimal energy designs. However, a systematic integration approach for truly achieving optimal energy-systems design in commercial buildings is still lacking. Recently, more new building designs aim to green buildings or zero net energy buildings, emphasizing the importance of energy-efficiency technologies and system designs, building operation and maintenance, and occupant behavior. Good operational practice and high building design efficiency could lower the energy use of space heating [10,11]. Santin [12] looked at the relationship between user behavior and space-heating energy consumption, and concluded that behavior patterns could be used in space-heating energy calculations, and usage profiles with different behaviors could be discerned.

Pan et al. [13] simulated effects of external wall insulation thickness on annual cooling and heating energy uses of an office building in three Chinese climates. It was found that, for heating dominant climate like Beijing, more insulation reduced the combined annual cooling and heating energy uses of perimeter offices facing all four cardinal orientations. More insulation reduces annual energy uses of offices facing North, East, and West, but not necessarily for the south facing office. For cooling dominant climate like Guangzhou more insulation did not reduce annual energy use at all. Yang et al. [14] surveyed envelope designs of existing office buildings in five major Chinese climates, and found the overall thermal transfer value of envelope was much higher than the current local energy code and almost double the ASHRAE Standard 90.1-2001. More insulation of exterior walls and roofs was recommended to reduce heating energy use for buildings in cold climate. Dovjak et al. [15] studied problem of High Heating energy use in Slovenian buildings with exergy and energy analysis. Their energy analyses showed that less thermal insulation contributed the most to the highest heating energy demand especially in colder climate. The results from exergy analysis drew similar conclusions – insulation has much bigger effect than effect of boiler efficiency. However, the most effective solution is to improve building envelope together with boiler efficiency. Yildiz and Gungor [16] presented energy and exergy analyses for the whole process of space heating in buildings in Turkey climates using simplified steady state heating load and energy calculations. Three heating systems, liquid natural gas (LNG) fired conventional boiler, LNG condensing boiler, and air-to-air heat pump, were compared from the power plant through the building envelope using exergy analysis. Eskin and Turkmen [17] studied the interactions between different conditions, control strategies and heating/cooling loads in office buildings in the four major climatic zones in Turkey using building energy simulation. Calibrated energy models were used to examine energy conservation opportunities on annual cooling, heating and total building load at four major cities. The effect of the parameters like the climatic conditions, insulation and thermal mass, aspect ratio, color of external surfaces, shading, window systems including window area and glazing system, ventilation rates and different outdoor air control strategies on annual building energy requirements is examined and the results are presented for each city.

The lack of knowledge about the factors that determine total building energy use is a significant barrier to achieving substantial building energy efficiency. Recently, a few studies [18,19] using simulations to calculate building performance showed relatively low space-heating energy use compared with rules-of-thumb and large discrepancies in space-heating energy use between different simulation programs, which raised concerns of whether simulation can be used to predict space-heating energy use. While various uncertainties are associated with building simulations, especially when simulations are performed by different modelers using different simulation programs for buildings with different configurations, it is crucial to identify and evaluate key driving factors to space-heating energy use to support the design and operation of low-energy buildings. These key driving factors can be categorized into six groups: climate conditions, building envelope, space-heating systems, building operation and maintenance, occupant behavior, and indoor environmental conditions.

The New Buildings Institute recently published a simulation study on total site energy use in midsize office buildings [20] to look at key driving factors of building energy use. Twenty-eight building characteristics were identified and grouped into design assets, operation practice, and tenant behaviors. Three systems and equipment-operation practices with respect to building energy use were identified by using different performance values for each characteristic parameter. Simulation results showed the key factors that affect total site energy use in midsize office buildings in 16 U.S. climates. Total site energy is a simple sum of electricity use and gas use - one unit of electricity is valued the same as one equal unit of natural gas; no generation or transmission or distribution loss is considered. As the total energy use of a building includes all end uses such as lighting, space heating, space cooling, service water heating, and plug-loads, the key driving factors of a building's total energy use would be very different from those of a specific end use like space heating. The use of source or primary energy would be a better indicator of building energy performance.

The objective of the current study is to identify, understand, and quantify important building design and operation parameters that can have significant impacts on space-heating energy use in office buildings, with different characteristics located in different heating climates, by computer simulations with EnergyPlus. The impact of weather data on space-heating energy use is also investigated by running simulations with multiple decades of historical weather data. The simulated results are further benchmarked with the space-heating energy use of comparable office buildings selected from the two well-known U.S. commercial building databases to investigate discrepancies between simulated and actual heating energy use.

It is not the intent of this paper, although the analysis and simulation method can apply, to analyze the total energy use of buildings; therefore, this study's results and findings should not be directly applied to the whole-building energy use, which includes other end uses. The heating systems discussed in this article are stand-alone systems powered by natural-gas hot-water boilers or electric resistance; they are not part of the district heating systems that are popular in Northern Europe countries and Northern China [21].

This study is part of a bigger effort to study key driving factors of energy performance of buildings under the International Energy Agency (IEA) Energy Conservation in Buildings & Community Systems (ECBCS) Annex 53 Total Energy Use in Buildings: Analysis & Evaluation Methods.

The first section of the paper describes analysis methodology, and the second section provides details of the selected building design and operation parameters, together with definitions of simulation runs. The third section presents and discusses the results. The conclusion section summarizes key findings and potential future research.

2. Analysis methodology

Building simulations and benchmarking with building energy consumption databases are the two methods we used to study the space-heating energy use in office buildings. Two office buildings with different sizes and design configurations – the high-rise large office and the single-story small office – are studied. To look at the influence of climate, three typical climate zones that require significant space heating are studied. Based on design and operation practice, a few key parameters for the large- and small-size office buildings are identified and their impacts on space-heating energy use are evaluated by energy simulations. The simulated space-heating energy uses are benchmarked with two U.S. commercial building databases of measured whole-building energy use. Furthermore, 30 years of actual meteorological weather data, from 1980 to 2009, are used in the simulations to study the impact of weather changes year-over-year on space-heating energy use.

As defined in this study, space-heating energy use is the site's energy in the form of natural gas consumed by boilers in the large office building or furnaces in the small office building; it does not include the electricity use of the hot-water pump for the large office building, or the fans of the air-handling units for both office buildings during heating operations. For the large office building, the space-heating energy use includes hot-water energy consumed by the reheat coils in the zone terminal units (i.e., variable air volume [VAV] boxes) and the central heating coils located in the air-handling units. For benchmarking purpose, the space-heating energy is also presented in energy use intensity (EUI), defined as annual site energy in MJ (mega joules) of space heating per building total floor area in m².

2.1. Characteristics of the large- and small-size office buildings

The large- and small-size office buildings were selected from the USDOE commercial reference buildings (CRBs) [22], which comply with the American Society of Heating, Refrigeration, and Air-conditioning Engineers (ASHRAE) Standard 90.1-2004 [23]. As Standard 90.1-2004 has different efficiency requirements for buildings located in different climate zones, the efficiency levels of both office buildings, including envelope insulation, window types, and HVAC systems, depend on the building's location or climate zone. The internal loads, including interior lighting power and plug loads, occupant density, and operation schedules, stay the same across all climates.

2.1.1. The large-size office building

The large office building has 12 stories and a basement, with a total floor area of 46,320 m². The building has a rectangular shape with the long axis along the east-west and an aspect ratio of 1.5. Each floor has four perimeter zones and one core zone with about 30% and 70% of the total floor area, respectively. The window-wall ratio (WWR) is about 40%, excluding the basement wall area. The roofs are flat with insulation above deck. The building has central built-up VAV systems with hot-water zone reheat. The VAV boxes have reverse acting dampers with a maximum supply air temperature of 35 °C. The reverse acting damper in a VAV box can open wider to meet zone heating loads, which differentiates it from a normal acting damper that stays at a fixed minimum position during heating operations. The supply air temperature leaving the cooling coils is set to 12.8 °C during cooling mode. There is no heat recovery between outdoor air and exhaust air. There is no humidifier. The central plant has two water-cooled chillers and a hotwater gas-fired boiler. Fig. 1a illustrates the 3-D and plan views of the building.

2.1.2. The small-size office building

The small office building has only one floor with an area of 511 m^2 . The building has a rectangular shape with the long axis along the east–west and an aspect ratio of 1.5. Four perimeter zones and the core zone have about 70% and 30% of the total floor area, respectively; the perimeter–core ratio is the opposite of that of the large office building. The WWR is about 20%. The building has an attic, as shown in Fig. 1b. Each of the five zones is served by a packaged single-zone system: a constant-volume HVAC sys-



(a) The 3-D and plan views of the large-size office building.



(b) The 3-D and plan views of the small-size office building.

Fig. 1. The large- and small-size office buildings from the USDOE commercial reference buildings. (a) The 3-D and plan views of the large-size office building. (b) The 3-D and plan views of the small-size office building.

Table 1Characteristics of selected cities and climate zones.

City	ASHRAE climate zone	CBECS census region	HDD18	CDD10
Chicago	Cool-Humid, 5A	West North Central, Midwest	6176	3251
Minneapolis	Cold-Humid, 6A	East North Central, Midwest	7981	2680
Fairbanks	Subarctic, 8	West Pacific	13,940	1040

tem with heating from a gas furnace and cooling from a directexpansion (DX) unitary system.

2.2. Climate zones

Three climates – Chicago, Minneapolis, and Fairbanks – were selected in this study to represent typical climates that require significant space heating in the United States. Based on the climate zones used in the ASHRAE Standard 90.1-2010 [24], Chicago belongs to the cool and humid zone 5A, Minneapolis belongs to the cold and humid zone 6A, and Fairbanks belongs to the subarctic zone 8. Table 1 lists the climate zone information for the three cities. In the table, HDD18 is the heating degree days with a base temperature of 18 °C, and CDD10 is the cooling degree days with a base temperature of 10 °C.

2.3. Weather data

The typical meteorological year, third generation (TMY3) [25,26], weather data of the three cities, available at the EnergyPlus web site, were used in the simulations. The TMY3s are data sets of hourly values of solar radiation and meteorological elements for a one-year period of 12 representative months compiled from 1976 to 2005. They are intended to be used for computer simulations of solar energy conversion systems and building systems to facilitate performance comparisons of different system types, configurations, and locations in the United States. Because they represent typical rather than extreme conditions, they are not suited for designing systems to meet the worst-case conditions occurring at a location.

Historical weather data, generated from actual weather measurements and observations from 1980 to 2009 for Chicago and Fairbanks, are used in the simulations to study the impact of weather on space-heating energy use for both office buildings. Such weather data were not available for Minneapolis during the study, so similar analysis is not done for Minneapolis.

2.4. Simulation engine

The EnergyPlus version 7.2, released in October 2012, was used for the study's building simulations. USDOE developed it as a newgeneration building energy simulation program that builds on the most popular features and capabilities of the Building Loads Analysis and System Thermodynamics (BLAST) and DOE-2. EnergyPlus has innovative simulation capabilities, including time steps of less than an hour, and modular systems simulation modules that are integrated with a zone heat balance simulation. It calculates space temperature, occupant thermal comfort, cooling and heating loads, HVAC equipment sizes, energy consumption, utility cost, air emissions, water usage, renewable energy, etc. EnergyPlus is a standalone simulation program without a "user friendly" graphical interface. It reads input and writes output as text files. Since the first release in April 2001, EnergyPlus has evolved to provide new and enhanced modeling features and improved usability.

EnergyPlus has been validated through three types of tests [27]:

- (1) Analytical tests compare EnergyPlus simulation results with analytical mathematical solutions for simple buildings:
- HVAC tests, based on ASHRAE Research Project 865.
- Building fabric tests, based on ASHRAE Research Project 1052.
 (2) Comparative tests compare EnergyPlus simulation results with those of other simulation engines such as DOE-2, ESP, and Transient System Simulation Tool (TRNSYS):
- ANSI/ASHRAE Standard 140-2007.
- IEA Solar Heating and Cooling Programme (IEA SHC) BESTest (Building Energy Simulation Test) methods not yet in Standard 140.
- EnergyPlus HVAC component comparative tests.
- EnergyPlus Global Heat Balance tests.
- (3) Empirical tests compare EnergyPlus simulation results with measurements of actual buildings. Although some applications compare and calibrate EnergyPlus simulation results with measured energy and performance of buildings, much more needs to be done with this type of test for actual buildings of various complexities of design and operations.

2.5. Building databases

The simulation results are benchmarked with two databases of commercial buildings in the United States: the 2003 CBECS and the USDOE high-performance buildings (HPBs) database [28]. The CBECS is a national survey that collects information on energy consumption and expenditures of U.S. commercial buildings. In this database, commercial buildings include all those in which at least half of the floor area is used for a purpose that is not residential or industrial; they include building types that might not traditionally be considered "commercial," such as schools, correctional institutions, and buildings used for religious worship. The HPB database has more than 100 commercial buildings (mostly in the United States) that were built recently and have low energy consumption. The database has detailed building descriptions and either measured or simulated energy-consumption data. The space-heating energy use from the HPB database was mostly calculated from calibrated energy models.

For the CBECS, building location is grouped into four U.S. Census regions that are subdivided into nine divisions. The four regions are the West, Midwest, Northeast, and South regions. Fairbanks belongs to the Pacific division of the West region; Chicago to the West North Central division of the Midwest region; and Minneapolis to the East North Central division of the Midwest region.

A few buildings were selected from the two databases in order to match the simulated buildings as much as possible according to the criteria: (1) building type (office), (2) building size (large or small), (3) vintage, and (4) location.

3. Building design and operation parameters

Based on office-building design and operation practice, 10 parameters with potentially significant impacts on space-heating energy use were selected for the study. The parameters were sorted into two groups – design and operation – as shown in Table 2, based on whether a parameter is mostly determined during building design or operation. The classification for design and operation parameters for space-heating energy use is listed in Table 2. The selected parameters include envelope insulation, window area, window type, internal loads, infiltration (rate and schedule), space-heating temperature setpoint, heating setback during unoccupied hours, terminal VAV box minimal damper position, and boiler/furnace efficiency. For each parameter, the reference value is set in the basecase models, which are based on ASHRAE Standard 90.1-2004; a better and a worse performance value are then determined based

Table 2Selected design and operation parameters for space heating.

Design parameters	Operation parameters
Window type Boiler/furnace efficiency Internal loads (lighting and plug- loads)	Air infiltration rate Air infiltration schedule Space-heating thermostat setting
Envelope insulation Window area (window-wall-ratio)	Heating setback control VAV box minimum damper position setting

on building design or operation practice, applicable building-energy standards, and available measurement or analysis reports. The selection and determination of these parameters are from the perspectives of practical building design and operations. This differentiates the current study from sensitivity analyses that do not use or require a high fidelity of parameters, as the sensitivity is calculated as a ratio between the change in outputs and the change in inputs.

3.1. Design parameters

3.1.1. Internal loads

Internal loads include heat gains from interior lighting, plugloads, and occupants. Internal loads reduce space-heating loads. For the basecase, interior lighting power density (LPD) is set to 10.76 W/m², based on ASHRAE Standard 90.1-2004. The plug-load (receptacle) equipment power density (EPD) is set to 10.76 W/m^2 . based on the CRBs. For the High Internal Loads case, the LPD and EPD are set 50% higher than the basecase, while for the Low Internal Loads case, they are set 50% lower. The LPD of the High Internal Loads case is set to 16.14 W/m^2 , which is based on the prescriptive requirement of interior lighting for the whole building in ASHRAE Standard 90.1-1989 [29]. The 50% lower LPD is based on the stateof-the-art lighting technologies for office buildings. The 50% lower EPD references Fisher's study [30], which shows plug-load energy use could be reduced over 50% by using energy-efficient appliances, installing an energy-management system, and most important, educating and training occupants on how to save energy.

3.1.2. Envelope insulation

Better insulation of a building envelope reduces space-heating loads. For the basecases, the insulation levels of the wall and roof constructions are based on ASHRAE Standard 90.1-2004. For the More Envelope Insulation cases, the insulation levels are based on ASHRAE Standard 90.1-2010. For the Less Envelope Insulation

Table	3
-------	---

Parameters for three building types.

Vintage	Roof construction U-factor (W/m ² K) (Large/small office)	Wall construction <i>U</i> -factor (W/m ² K) (Large/small office)
Less Insulation (USDOE CRBs, Pre-1980)	IEAD/IEAD [*] 5A, 0.358/0.358 6A, 0.358/0.358 8, 0.273/0.273	Steel/mass 5A, 0.698/0.505 6A, 0.591/0.477 8, 0.454/0.363
Basecase (ASHRAE 90.1-2004)	IEAD/attic 5A, 0.358/0.193 6A, 0.358/0.153 8, 0.273/0.153	Mass/mass 5A, 0.698/0.698 6A, 0.591/0.591 8, 0.454/0.454
More Insulation (ASHRAE 90.1- 2010)	IEAD/attic 5A, 0.273/0.153 6A, 0.273/0.153 8, 0.273/0.119	Mass/mass 5A, 0.511/0.511 6A, 0.454/0.454 8, 0.403/0.403

^{*} IEAD: insulation entirely above deck.

cases, the insulation levels are set according to the pre-1980 offices from the CRBs. Table 3 lists a few key parameters of the office buildings constructed at three different ages.

3.1.3. Window area

With more windows, space-heating loads tend to increase for most climates that require heating because windows usually contribute more heat loss than walls, even taking into account windows' solar-heat gains. For the basecases, the large office building has a WWR of 40%, while the small office building has a WWR of 20%. The High WWR cases double the window area: The large office building has a WWR of 68% (cannot reach 80% due to the assumption of no windows on the plenum walls), while the small office building has a WWR of 40%. The Low WWR cases reduce window area by 50% from the basecases: The large office building has a WWR of 20%, while the small office building has a WWR of 10%.

3.1.4. Window type

Windows with lower U-factor and higher solar heat gain coefficient (SHGC) reduce space-heating loads. The U-factor is the heat transfer rate through the window per unit area and per unit temperature difference. The SHGC represents the fractional amount of solar energy that strikes the window and ends up warming the indoor environment. Visible transmittance (VT) is the fraction of visible light that comes through the glass. This is influenced by glass selection as well as the amount of the opening taken up by nontransparent components such as the frame. The basecases have double-pane windows. The worst cases use single-pane windows, while the better cases use triple-pane windows. Table 4 summarizes window-type performance for relevant cases at different climate zones.

3.1.5. Boiler and Furnace Efficiency

A higher efficiency of heating equipment reduces space-heating energy use. For the basecases, the large office building has a boiler of 80% efficiency, while the small office building has furnaces of 78% efficiency. The High Boiler/Furnace Efficiency cases, assuming the use of condensing boilers and furnaces, have a boiler of 91% efficiency for the large office building and furnaces of 88% efficiency for the small office building.

3.2. Operation parameters

3.2.1. Air infiltration rate

Air infiltration during heating seasons increases space-heating loads. Parameters of air infiltration include peak infiltration rate and infiltration schedule. According to a report by National Institute of Standards and Technology [31,32], peak infiltration rates measured for typical commercial buildings range from 2.04 to 9.14 L/(s m²), based on 75 Pa of pressure difference and per unit of gross exterior wall area. For EnergyPlus simulations, these infil-

Table 4	
Window	type.

NFRC rated values	U-factor (W/ m ² K)	SHGC	VT
Base case: double-pane window, low-e			
Chicago	3.24	0.385	0.305
Minneapolis	3.24	0.385	0.305
Fairbanks	2.62	0.296	0.212
Single-pane window, clear	5.81	0.822	0.882
Triple-pane window, spectral selective,	0.87	0.285	0.451
clear, low-e			

tration rates are adjusted to the 4 Pa of pressure difference. The basecase infiltration rate is $2.04 \text{ L/(s} \text{ m}^2)$ (equivalent to 0.65 air changes per hour), which is also defined in ASHRAE Standard 90.1-2010. For the High Infiltration Rate case, the 7.61 L/(s m²) (2.44 ach) is used in reference to the proposal to ASHRAE Standard 90.1-2013 for buildings without installation of a continuous air barrier. The High Infiltration Rate is 375% higher than the basecase. The 50% lower infiltration rate is used in the Low Infiltration Rate case for airtight buildings.

The peak air-infiltration rate depends to a great extent on a building's airtightness, especially the opening and closing of windows and doors, which are more related to building operation and occupant activity. Therefore, air-infiltration rate is categorized as an operation rather than a design parameter.

3.2.2. Air infiltration schedule

A schedule is used to describe the variation of air infiltration during occupied and unoccupied hours. For the basecases, air infiltration during occupied hours is assumed to be 25% of the peak infiltration rate. Values of 50% and 100% are used in the Medium and High Infiltration Schedule cases to represent buildings that are not airtight or that have poor air balancing during occupied hours.

3.2.3. Space-heating thermostat setting

A higher space-heating temperature setpoint increases space-heating loads. The basecases set the space-heating temperature for occupied hours to 21 °C, which is typical for office buildings in the United States. The High Heating Setpoint case raises the heating thermostat setting to 23 °C, while the Low Heating Setpoint case lowers it to 18 °C.

3.2.4. Space-heating setback control

Setback control is usually used to lower space-heating thermostats for office buildings during unoccupied hours. The basecases assume a heating setback to 10 °C during unoccupied hours, which may be too aggressive. Hence, two heating-setback cases are considered: One is set back to 15 °C to represent the typical operation of most office buildings, and the other is to have no setback at all to represent the worst-case scenario.

3.2.5. VAV box minimum damper position

The large office building is served by central VAV systems, which use reheat coils at the zone terminal boxes to provide space heating. The terminal boxes have reverse acting dampers, which can open beyond the minimum position during the heating mode to meet zone heating loads. The higher the minimum damper position, the more reheat energy can be consumed. The basecases have the VAV box minimum damper position set to 30%, based on a typical design that meets recent building energy standards [33]; the High Minimum VAV Box Damper Position case sets it to 50%, based on surveys of office buildings [34]; and the Low Minimum VAV Box Damper Position case sets it to 15%, based on proposals to update 2008 California and 2010 ASHRAE building energy-efficiency standards.

4. Simulation runs

Table 5 lists the parametric of the simulation runs for the two office buildings. There are 126 EnergyPlus simulation runs in total, including 22 runs for the large office building and 20 runs for the small office building for each of the three cities. These runs include the basecase, the High and Low Internal Loads cases, the High and Low Infiltration Schedule cases, the High and Low Minimum VAV Box Damper Position

Table 5 Parametric of the simulation runs.										
Description of runs	LPD (W/m ²)	EPD (W/m ²)	WWR (large/small office)	Infiltration rate (m³/s m²)	Infiltration schedule (occupied hours)	Min. VAV box damper position (large office)	Heating setpoint/ setback (°C)	Boiler/furnace efficiency	Envelope construction	Window type
Basecase	10.76	10.76	0.4/0.2	0.000302	0.25	0.3	21/10	78%/80%	90.1-2004	90.1-2004
High internal loads	16.14	16.14	0.4/0.2	0.000302	0.25	0.3	21/10	78%/80%	90.1-2004	90.1-2004
Low internal loads	5.38	5.38	0.4/0.2	0.000302	0.25	0.3	21/10	78%/80%	90.1-2004	90.1-2004
High WWR	10.76	10.76	0.68/0.4	0.000302	0.25	0.3	21/10	78%/80%	90.1-2004	90.1-2004
Low WWR	10.76	10.76	0.1/0.1	0.000302	0.25	0.3	21/10	78%/80%	90.1-2004	90.1-2004
High infiltration rate	10.76	10.76	0.4/0.2	0.001133	0.25	0.3	21/10	78%/80%	90.1-2004	90.1-2004
Low infiltration rate	10.76	10.76	0.4/0.2	0.000189	0.25	0.3	21/10	78%/80%	90.1-2004	90.1-2004
High infiltration schedule	10.76	10.76	0.4/0.2	0.000302	1	0.3	21/10	78%/80%	90.1-2004	90.1-2004
Medium infiltration schedule	10.76	10.76	0.4/0.2	0.000302	0.5	0.3	21/10	78%/80%	90.1-2004	90.1-2004
High minimum VAV box damper position	10.76	10.76	0.4/0.2	0.000302	0.25	0.5	21/10	78%/80%	90.1-2004	90.1-2004
Low minimum VAV box damper position	10.76	10.76	0.4/0.2	0.000302	0.25	0.15	21/10	78%/80%	90.1-2004	90.1-2004
High Heating Setpoint	10.76	10.76	0.4/0.2	0.000302	0.25	0.3	23/10	78%/80%	90.1-2004	90.1-2004
Low Heating Setpoint	10.76	10.76	0.4/0.2	0.000302	0.25	0.3	18/10	78%/80%	90.1-2004	90.1-2004
Single-pane window	10.76	10.76	0.4/0.2	0.000302	0.25	0.3	21/10	78%/80%	90.1-2004	Single
Triple-pane window	10.76	10.76	0.4/0.2	0.000302	0.25	0.3	21/10	78%/80%	90.1-2004	Triple
Thermostat setback to 15 °C	10.76	10.76	0.4/0.2	0.000302	0.25	0.3	21/15	78%/80%	90.1-2004	90.1-2004
Thermostat no setback	10.76	10.76	0.4/0.2	0.000302	0.25	0.3	21/21	78%/80%	90.1-2004	90.1-2004
Less envelope insulation	10.76	10.76	0.4/0.2	0.000302	0.25	0.3	21/10	78%/80%	Pre-1980	90.1-2004
More envelope insulation	10.76	10.76	0.4/0.2	0.000302	0.25	0.3	21/10	78%/80%	90.1-2010	90.1-2004
High boiler/Furnace Efficiency	10.76	10.76	0.4/0.2	0.000302	0.25	0.3	21/10	91%/88%	90.1-2010	90.1-2004
High Heating	5.38	5.38	0.4/0.2	0.001133	1	0.5	23/15	78%/80%	Pre-1980	Single
Low Heating	16.14	16.14	0.4/0.2	0.000189	0.25	0.15	18/10	91%/88%	90.1-2010	Triple

cases for large office only, the High and Low Heating Setpoint cases, the High and Low WWR cases, the Single and Triple Pane Window cases, the More and Less Envelope Insulation cases, and the High Boiler/Furnace Efficiency cases. Each run varies only one parameter from the basecase, except the High Heating case and the Low Heating case, which combine the worse and better values (based on the influence on space-heating energy) of the selected parameters, respectively. In the High Heating and Low Heating cases, the value of the WWR stays the same as that of the basecase for both office buildings. The High Heating and Low Heating cases aim to capture the worst case of buildings that consume the most heating and the best case of buildings that consume the least heating.

In addition to the above-mentioned 126 runs, there are 60 runs using the 30 historical years of weather data for Chicago and Fairbanks.

5. Results and discussions

5.1. Impact of design and operation parameters

Fig. 2 shows the percentages of change in space-heating EUIs calculated by comparing the space-heating EUI from each parametric run to that of the basecase for the large office building in the three climates. Fig. 3 shows similar data for the small office building. Both figures are sorted by the percent changes for the Chicago climate.

Looking at results in Fig. 2 for the large office building, it can be seen that: (1) based on the relative impact of the building operation, the most influencing operation parameters are high minimum VAV box damper position setting, thermostat without setback during unoccupied hours, High Heating Setpoint, and High Infiltration Rate; (2) for the building design efficiency aspect, the most influencing parameters are low and high internal load, window type, and window area; and (3) other parameters, including low air infiltration rate, low minimum VAV box damper position setting, infiltration schedule for the operation aspect, and boiler efficiency and envelope insulation for the building design aspect have less impact on space-heating energy use.

From the operation aspect of the large office building, there are several significant findings:

- The impact of minimum VAV box damper position setting ranges from -12% to 128% for Chicago, -7.5% to 78% for Minneapolis, and -2.5% to 31% for Fairbanks; the Low Minimum VAV Box Damper Position cases show small impact on space-heating energy use. Oversizing the VAV box or setting the minimal damper position too high can result in huge space-heating penalty.
- The cases of Thermostat No Setback during unoccupied hours increase the space-heating EUIs by 50–102% from the basecases for the three climates while the cases of Thermostat Setback to 15 °C during unoccupied hours have increases from 10% to 12%. Thermostat setback is an effective operation strategy to reduce space-heating energy use during unoccupied hours.
- The impact of space-heating setpoint ranges from -44% to 65% for Chicago, -32% to 44% for Minneapolis, and -19% to 22% for Fairbanks. Lowering the heating thermostat setpoint is an easy way to save space-heating energy use during occupied hours.
- The cases of High Infiltration Rate show significant increase in space-heating energy use by 42%, 38.5%, and 38.9% for Chicago, Minneapolis, and Fairbanks, respectively. However, the cases of Low Infiltration Rate have small impact on space-heating energy use in all three climates, which may be because the low infiltration rates are only 50% lower than the basecases while they are 375% higher for the High Infiltration Rate cases.
- From the design-efficiency aspect of the large office building, it can be seen that:
- Triple-pane windows can save space-heating energy by 51%, 43%, and 29% for Chicago, Minneapolis, and Fairbanks, respectively. On the other hand, single-pane windows increase space-heating energy by 46% for Chicago, and 34% for both Minneapolis and Fairbanks. High-performance windows with low U-factors have great potential to reduce space-heating energy use for cold climates.



Fig. 2. Impact of design and operation parameters on space-heating energy use of the large office building.



Fig. 3. Impact of design and operation parameters on space-heating energy use of the small office building.

- Window area also plays an important role. High WWR cases could increase space-heating energy use by 23–38%; on the other hand, low WWR cases could save space heating by 24% to 33%.
- Internal loads can change space heating from -30% to 48%, compared with the basecase in Chicago; -30% to 40% in Minneapolis; and -28% to 30% in Fairbanks. Internal loads from lighting, equipment, and occupants directly reduce space-heating loads.
- Wall insulation has less influence compared with other building-design parameters mainly due to the basecase has good insulation. From the simulated results, the More Envelope Insulation cases used the latest version of the ASHRAE standard published in 2010, however, this high insulation level reduces space-heating energy use by less than 5%.

The relative impacts of the significant parameters on space heating are consistent across the three climates, with Chicago showing the largest impact, followed by Minneapolis and Fairbanks. Fairbanks shows the least impact due to its high space-heating EUI of the basecase compared with the other two climates.

Similarly, the results in Fig. 3 for the small office building reveal that, based on the relative impact for the operation aspect, the most influencing parameters are high and low space-heating setpoint, thermostat without setback during unoccupied hours, high air infiltration rate, and high infiltration schedule. For the building-design efficiency aspect, the most influencing parameters are internal loads, triple-pane windows, and less envelope insulation. All the parameters described above except window type and envelope insulation can be controlled by building occupants or operators. Other parameters, including low WWR, high furnace efficiency, and single-pane windows for the building design parameters; and low infiltration rate and thermostat setback to 15 °C during unoccupied hours for the operation aspect have smaller impact on space-heating energy use. Small office buildings show very similar patterns to the large office buildings – operation parameters have greater impact than design parameters.

From the operation aspect of the small office building, a few key results are:

- The impact of the space-heating setpoint ranges from -61% to 61% for Chicago, -50% to 46% for Minneapolis, and -33% to 26% for Fairbanks. The heating setpoint could be easily controlled by occupants in small office buildings because in packaged single-zone systems, thermostats are usually located in office spaces. Decreasing the heating setpoint by 3 °C could save more than 50% in space-heating energy, while increasing the heating setpoint by 2 °C would consume more than 50% of space-heating energy in cold climates. Fairbank belongs to the subarctic region; it needs more space-heating energy than other climates at the same building design and operation conditions. Thus the percentage changes to space-heating energy use are smaller than other climates by adjusting the same degrees of the heating setpoint.
- Not setting back the heating thermostat during unoccupied hours can increase space heating from 37% to 42% for the three climates.
- Similar to the results of the infiltration rate cases for the large office buildings, a High Infiltration Rate can significantly increase space heating by 41%, 37%, and 30% for Chicago, Minne-apolis, and Fairbanks, respectively. The cases of Low Infiltration Rate in the three cities demonstrate relatively small impact compared with other cases with same reason mentioned above.
- From the large office building design parameters, it can be seen that:
- Internal loads can change the space heating from -40% to 52% for Chicago compared with the basecase, -33% to 39% for Minneapolis, and -21% to 21% for Fairbanks. The variations of space-heating energy use due to changes to internal load are



Fig. 4. Comparison of space-heating energy use among the High Heating cases, the basecases, and the Low Heating cases for the large and small office buildings.

similar to the large office building in each city. Internal loads from lighting, equipment, and occupants directly reduce the needs of space-heating loads.

- The High WWR cases increase the space heating from 12% to 15% in the three climates; on the other hand, the Low WWR cases could save space heating by about 5% to 10%.
- Triple-pane windows can save space heating by 27%, 25%, and 16% for Chicago, Minneapolis, and Fairbanks, respectively.
- In all three climates, less window area and the use of singlepane windows show relatively small influence on space-heating energy use, which can be due to the tradeoff between the window conduction heat losses and solar heat gains.

Fig. 4 benchmarks the space-heating EUI of the High and Low Heating cases against the basecases for both office buildings across the three climates. There are huge differences in heating energy use between the High Heating (the worst) cases and the Low Heating (the best) cases – by factors of about 60, 30, and 15 for both office buildings in Chicago, Minneapolis, and Fairbanks, respectively. The space-heating EUI ranges from 14.3 to 828.5 MJ/m² (3.97–230.1 kWh/m²), 31.0 to 978.3 MJ/m² (8.61–271.8 kWh/m²) and 87.5 to 1315 MJ/m² (24.3–365.3 kWh/m²) for the large office buildings in Chicago, Minneapolis, and Fairbanks, respectively. For the small office buildings, the ranges are 6.5-482 MJ/m² (1.81–133.9 kWh/m²), 19.7–671 MJ/m² (5.47–186.4 kWh/m²), and 93.4–1185 MJ/m² (25.9–329.2 kWh/m²) in Chicago, Minneapolis, and Fairbanks, respectively.

Compared with the basecases, the High Heating cases significantly increase space-heating energy use by a factor of 3–5 for the large office buildings in these climates; while for the small office buildings, the increase in space-heating energy use is by a factor about 3. Similarly, compared with the basecases, the Low Heating cases dramatically decrease space-heating energy use to 1/8, 1/5, and 1/3 for the large office buildings in Chicago, Minneapolis, and Fairbanks, respectively; and to 1/17, 1/9, and 1/4 for the small office buildings.

For the large office building served by VAV systems with zone reheat, potential reheat during the summer cooling season is a waste of energy and thus increases space-heating energy use. Fig. 5 shows monthly space-heating EUIs of the large office building in Chicago. It can be seen that most of the heating is used during winter, especially December and January. A relatively small amount of heating may occur during summer for the large office building, mainly due to heating the basement. There is almost no reheat during summer except for the High Minimum VAV Box Damper Position case and the High Heating case. This agrees with common operational practice that setting the VAV box damper wide open is one of the major causes of high reheat energy during summer.

Based on above analysis, it can be seen that space-heating energy use can be significantly reduced by more efficient building design and even more so by improving the operation of space-heating systems. To improve the accuracy of the prediction of space-heating energy use by simulations, it is crucial to have proper inputs to the most important design and operation parameters as identified in the study.

5.2. Impact of weather data

To look at the impact of weather data on space-heating energy use, a percentage change of space-heating energy use is calculated by comparing the space-heating energy use of a historical year (from 1980 to 2009 for Chicago and Fairbanks) to that of the basecase using the TMY3 weather. Figs. 6 and 7 show that the impact of weather data on space-heating energy use is significant for the large and small office buildings in both Chicago and Fairbanks.

For Chicago, the large office building shows that space-heating energy use varies from -18% to +33%; while the small office building shows variations from -24% to +33%. The results indicate that 1985 was the coolest year and 2006 the warmest year for both office buildings across the 30-year period. Most warm years occurred from 1998 to 2006, while most cool years occurred from 1980 to 1986.

For Fairbanks, the large office building shows that space-heating energy use varies from -20% to +24%; while the small office building shows variations from -17% to +22%. The results indicate that 1999 was the coolest year and 1981 was the warmest year for both office buildings across the 30-year period. Most warm years occurred from 2000 to 2003, while most cool years occurred from 1988 to 1999.

The impact of weather on space-heating energy use is very consistent across both office buildings in the same climate, but is very



Fig. 5. Monthly space-heating energy use of the large office building in Chicago.



Fig. 6. Multiyear space-heating energy use in Chicago.

different across both climates – the coolest and warmest years occurred differently during the period from 1980 to 2009.

It should be noted that space-heating energy use from simulations using TMY3 weather data can underestimate by up to 33% or overestimate by up to 25% compared with using historical weather data. For Fairbanks, simulated results using TMY3 underestimate space-heating energy for most of the years during the 30year period. Comparing the space-heating energy use of the coolest year to the warmest year for Chicago, the increase is 51% and 57% for the large and small office buildings, respectively; while for Fairbanks, the increases are 44% and 39%. Thus it is crucial to run simulations with multiple decades of weather data to fully evaluate the impact of weather on the energy performance of space-heating systems in buildings.



Fig. 7. Multiyear space-heating energy use in Fairbanks.



Fig. 8. Benchmarking simulation results with the building databases for the large office building in Chicago.

5.3. Benchmarking with building databases

To form a clear picture of how space-heating energy use varies in actual buildings, we selected ones from the two databases for Chicago and Minneapolis that were similar to the simulated large and small office buildings in terms of building type or function, size, location, and construction age. Figs. 8–11 show both the simulated and the actual space-heating EUIs. Each horizontal line represents result from a selected building in one of the two databases. The solid lines represent buildings selected from the CBECS database, while the dashed lines representing buildings from the HPB database.

In general, space-heating EUIs vary significantly for the selected buildings from both databases and even more across the two databases. Fig. 8 shows the benchmark results for the large office in Chicago. From CBECS, 10 buildings were found with floor area ranging from 18,580 to 46,450 m², vintage 1990–2003. The space-heating EUIs for these buildings vary from 136.7 to 559.72 MJ/m² (38.0–155.5 kWh/m²). Fig. 9 shows the benchmark results for the small office in Chicago. The selection criteria for the CBECS are set as follows: (1) floor area from 93 to 9290 m², (2) vintage 1990–2003, and (3) location in Chicago. Seven such small office buildings were found from the CBECS with a space-heating EUI from 249 to 1023 MJ/m² (69.2–284.2 kWh/m²). Two small office buildings were found from the HPB database that are near Chicago and have a floor area of 1390 and 3716 m². The two offices have space-heating EUIs of 208.8 and 335.2 MJ/m² (58.0–93.1 kWh/m²).

For Chicago, the simulated results are always much lower than the databases except for the High Heating case. Although the High


Fig. 9. Benchmarking simulation results with the building databases for the small office building in Chicago.



Fig. 10. Benchmarking simulation results with the building databases for the large office building in Minneapolis.

Heating case results overlap with some low-end results from the databases, it is much lower than the high-end results - by more than 20%. This implies that there might be other important parameters that should be considered in simulations; for example, design and operation problems or faults of the space-heating systems.

Minneapolis belongs to the East North Central division of the Midwest region in the CBECS. Fig. 10 shows the benchmark results for the large office building, and Fig. 11 shows the small office

building. In Fig. 10, three buildings, selected based on the criteria of floor area larger than 9290 m² and vintage 1990 and 2003, have space-heating EUIs ranging from 150.7 to 299.3 MJ/m² (41.9-83.1 kWh/ m^2 , by a factor of 2). On the other hand, eight small office buildings were selected based on floor area from 93 to 9290 m² and vintage 1990 to 2003. The space-heating EUI of the eight buildings vary from 122.7 to 845 MJ/m² (34.1-234.7 kWh/m², by a factor of 7). Only one small building was found from the HPB with



Fig. 11. Benchmarking simulation results with the building databases for the small office building in Minneapolis.

floor area of 1104 m^2 . The space-heating EUI of this office is $75.9 \text{ MJ}/\text{m}^2$ (21.1 kWh/m²).

It should be noted that there are uncertainties associated with the two benchmark databases: (1) the space-heating energy uses are not from actual measurements; rather, they are calculated from statistical analysis (CBECS) or energy modeling (HPB); and (2) the floor area used to calculate the EUI might not accurately match the actual floor area of the buildings. Furthermore, the buildings selected from the databases may not exactly match the simulated buildings in terms of floor area, vintage, and location. This contributes to discrepancies between the simulated and benchmarked space-heating energy uses.

6. Conclusions

The simulated space-heating energy use of the small- and largesize office buildings across the three heating climates can vary significantly, depending on details of a few key building design and operation parameters. The most influencing parameters are space-heating temperature setpoint and setback strategies, air infiltration, VAV terminal box damper minimum position settings for the large office, window type, WWR, and internal loads. The relative impacts of these parameters vary with building type and climate.

Compared with the basecase, the High Heating case consumes more than double the space-heating energy, while the Low Heating case consumes less than half for both office buildings in all the three climates.

For the two climates with the 30-year historical weather data, the simulated space-heating energy use for a particular year can vary dramatically, compared with the average results across the 30-year period. For the basecase, the simulated space-heating energy use with the TMY3 weather data can overpredict by 24% and underpredict by 34%, compared with the results with the historical weather data. To understand the long-term impact of weather on space-heating energy use, it is critical and necessary to run simulations with multiple decades of actual weather data, considering the availability and affordability of such data and low extra cost of running such simulations on current PCs with high computing power. Besides, dynamic analyses should be introduced to study the integrated effect of driving factors to space heating energy use.

The actual space-heating energy use for the similar office buildings from the CBECS and HPB databases also vary significantly, with wide ranges that well overlap the variation ranges of the simulated results. Based on the study, simulations do not necessarily always under- or overpredict space-heating energy use. The simulated space-heating energy use depends on building type, configuration, and climate, with a few special key influential building design and operation parameters.

High-efficiency designs and better operation of buildings can reduce space-heating energy use, but the latter plays a more important role. For building designers, paying more attention to the most influential design parameters has significant potential to reduce space-heating energy use for new buildings. For building owners and operators, improving building operations through commissioning and retrofits to control key operation parameters is an effective way to reduce space-heating energy use for existing buildings. Finally, for energy policy makers, enforcing more stringent regulations on these design and operation parameters can significantly reduce space-heating energy use in new and existing buildings.

To lower space heating energy use in office buildings, the following steps are recommended: (1) lower space-heating temperature setpoint while maintaining thermal comfort, (2) use heating thermostat setback during unoccupied hours, (3) reduce air infiltration rate by improving air tightness of the building envelope, (4) decrease the minimum damper position settings of VAV terminal boxes if applicable, and (5) replace with better insulated windows.

This study did not look at other influencing factors of space heating, such as building occupancy level and operational faults of space-heating systems. Building occupancy levels vary case by case, and insufficient data is available for this study. Future research can study the impact of HVAC operational faults on spaceheating energy use. Other potential causes of high space-heating energy in actual buildings might relate to occupants opening windows during heating season, space overheating due to lack of temperature controls, heat losses from air ducts, hot-water piping, and boilers that might not be counted well or at all in energy-modeling programs. Similar analysis can be done for other building types and climates, and to aggregate the impacts at the regional and national levels.

Acknowledgement

This work was supported by the U.S. Department of Energy under the U.S.–China Clean Energy Research Center on Building Energy Efficiency. It was co-sponsored by the Bureau of Energy, Ministry of Economic Affairs, Taiwan, ROC.

References

- [1] United States Department of Energy. 2010 Buildings Energy Data Book; 2011. [2] United States Energy Information Administration. Commercial Buildings
- Energy Consumption Survey. http://www.eia.gov/emeu/cbecs/.
- [3] Energy Information Administration (EIA), United States Department of Energy. Annual Energy Review 2007. Report No. 0384; 2008.
- [4] Pedrini A, Westphal FS, Lamberts R. A methodology for building energy modeling and calibration in warm climates. Build Environ 2002;37:903–12.
- [5] Lam JC. Energy analysis of commercial buildings in subtropical climates. Build Environ 2000;35:19–26.
- [6] Dai X, Wu Y, Di Y, Li Q. Government regulation and associated innovations in building energy-efficiency supervisory systems for large-scale public buildings in a market economy. Energy Policy 2009;37:2073–8.
- [7] Yamaguchi Y, Shimoda Y, Mizuno M. Transition to a sustainable urban energy system from a long-term perspective: case study in a Japanese business district. Energy Build 2007;39:1–12.
- [8] Andrews CJ, Krogmann U. Explaining the adoption of energy-efficient technologies in U.S. commercial buildings. Energy Build 2009;41:287–94.
- [9] Liu P, Pistikopoulos EN, Li Z. An energy systems engineering approach to the optimal design of energy systems in commercial buildings. Energy Policy 2010;38:4224–31.
- [10] Linden AL, Carlsson-Kanyama A, Eriksson B. Efficient and inefficient aspects of residential energy behaviour: what are the policy instruments for change? Energy Policy 2006;34:1918–27.
- [11] Branco G, Lachal B, Gallinelli P, Weber W. Predicted versus observed heat consumption of a low energy multifamily complex in Switzerland based on long-term experimental data. Energy Build 2004;36:543–55.
- [12] Santin OG. Behavioural patterns and user profiles related to energy consumption for heating. Energy Build 2011;43:2662–72.
- [13] Pan D, Chan M, Deng S, Lin Z. The effects of external wall insulation thickness on annual cooling and heating energy uses under different climates. Appl Energy 2012;97:313–8.
- [14] Yang L, Lam JC, Tsang CL. Energy performance of building envelopes in different climate zones in China. Appl Energy 2008;85:800–17.
- [15] Dovjak M, Shukuya M, Olesen BW, Krainer A. Analysis on exergy consumption patterns for space heating in Solvenian buildings. Energy Policy 2010;38:2998–3007.
- [16] Yildiz A, Gungor A. Energy and exergy analyses of space heating in buildings. Appl Energy 2009;86:1939–48.
- [17] Eskin N, Turkmen H. Analysis of annual heating and cooling energy requirements for office buildings in different climates in Turkey. Energy Build 2008;40:763–73.
- [18] Center for the Built Environment, University of California at Berkeley. eQuest vs EnergyPlus comparison, 2011. Personal communication.

- [19] COMFEN development team of the Lawrence Berkeley National Laboratory. CBECS/eQUEST/EnergyPlus Comparison, 2010. Personal communication.
- [20] Heller J, Heater M, Frankel M. Sensitivity analysis: comparing the impact of design, operation, and tenant behavior on building energy performance. Report of the New Building Institute; 2011 July.
- [21] Rezaie B, Rosen AM. District heating and cooling: review of technology and potential enhancements. Appl Energy 2012;93:2–10.
- [22] Field K, Deru M, Studer D. United States Department of Energy commercial reference building models of the national building stock. Fourth National Conference of IBPSA-USA; 2010. p. 85–93.
- [23] Energy standard for buildings except low-rise residential buildings, ANSI/ ASHRAE/IESNA Standard 90.1-2004; 2004.
- [24] Energy standard for buildings except low-rise residential buildings, ANSI/ ASHRAE/IESNA Standard 90.1-2010; 2010.
- [25] Typical Meteorological Year 3 (Internet). United States Department of Energy. http://www1.eere.energy.gov/buildings/commercial_initiative/new_construction.html>.
- [26] Wilcox S, Marion W. User's Manual for TMY3 Data Sets. Report of National Renewable Energy Laboratory (NREL); 2008.
- [27] EnergyPlus Version 7.2 (Internet). United States Department of Energy. http://www.apps1.eere.energy.gov/buildings/energyplus/.
- [28] High performance buildings database (Internet). United States Department of Energy. <http://www.eere.buildinggreen.com/index.cfm>.
- [29] Energy code for commercial and high-rise residential buildings, ANSI/ASHRAE/ IESNA Standard 90.1-1989; 1989.
- [30] Fisher SM, Sultan N, Stromquist RC. Plug load reduction for a net zero energy building, ACEEE summer study on energy efficiency in buildings. California (USA): Pacific Grove; 2006. p. 119–23.
- [31] Emmerich SJ, McDowell T, Anis W. Investigation of the impact of commercial building envelope airtightness on HVAC energy use, Report of National Institute of Standards and Technology, NISTIR-7238; 2005.
- [32] Persily A, Gorfain J. Analysis of ventilation data from the U.S. Environmental Protection Agency building assessment survey and evaluation (BASE) study, Report of National Institute of Standards and Technology, NISTIR 7145; 2008.
- [33] Building energy efficiency standards for residential and nonresidential buildings, California Energy Commission; 2005.
- [34] Advanced variable air volume system design guide, California Energy Commission; 2005.

Glossary

ASHRAE: American Society of Heating, Refrigeration, and Air-conditioning Engineers

BESTest: Building Energy Simulation Test

BLAST: Building Loads Analysis and System Thermodynamics

CBECS: Commercial Buildings Energy Consumption Survey

CDD: cooling degree day

CRB: commercial reference building

DX: direct expansion

EIA: Energy Information Administration

EPD: equipment power density

- EUI: energy use intensity
- HDD: heating degree day
- HPB: high-performance building
- IEA: International Energy Agency
- IEAD: insulation entirely above deck

LPD: lighting power density

MJ: mega joules

NFRC: National Fenestration Rating Council

SHC: Solar Heating and Cooling Programme

SHGC: solar heat gain coefficient

TRNSYS: Transient System Simulation Tool

WWR: window-wall ratio

VAV: variable air volume

VT: visible transmittance

Modeling and Simulation of HVAC Faulty Operations and

Performance Degradation due to Maintenance Issues

Liping Wang^{*}, Tianzhen Hong

Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA 94720, USA

ABSTRACT

Almost half of the total energy used in the U.S. buildings is consumed by heating, ventilation and air conditionings (HVAC) according to EIA statistics. Among various driving factors to energy performance of building, operations and maintenance play a significant role. Many researches have been done to look at design efficiencies and operational controls for improving energy performance of buildings, but very few study the impacts of HVAC systems maintenance. Different practices of HVAC system maintenance can result in substantial differences in building energy use. If a piece of HVAC equipment is not well maintained, its performance will degrade. If sensors used for control purpose are not calibrated, not only building energy usage could be dramatically increased, but also mechanical systems may not be able to satisfy indoor thermal comfort. Properly maintained HVAC systems can operate efficiently, improve occupant comfort, and prolong equipment service life.

In the paper, maintenance practices for HVAC systems are presented based on literature reviews and discussions with HVAC engineers, building operators, facility managers, and commissioning agents. We categorize the maintenance practices into three levels depending on the maintenance effort and coverage: 1) proactive, performance-monitored maintenance; 2) preventive, scheduled maintenance; and 3) reactive, unplanned or no maintenance. A sampled list of maintenance issues, including cooling tower fouling, boiler/chiller fouling, refrigerant over or under charge, temperature sensor offset, outdoor air damper leakage, outdoor air screen blockage, outdoor air damper stuck at fully open position, and dirty filters are investigated in this study using field survey data and detailed simulation models. The energy impacts of both individual maintenance issue and combined scenarios for an office building with central VAV systems and central plant were evaluated by EnergyPlus simulations using three approaches: 1) direct modeling with EnergyPlus, 2) using the energy management system feature of EnergyPlus, and 3) modifying

^{*} Corresponding author email: lwang@lbl.gov

EnergyPlus source code. The results demonstrated the importance of maintenance for HVAC systems on energy performance of buildings.

The research is intended to provide a guideline to help practitioners and building operators to gain the knowledge of maintaining HVAC systems in efficient operations, and prioritize HVAC maintenance work plan. The paper also discusses challenges of modeling building maintenance issues using energy simulation programs.

KEYWORDS

Building energy use, Building simulation, EnergyPlus, Fault modeling, HVAC maintenance

INTRODUCTION

Almost half of the total energy used in the U.S. buildings is consumed by heating, ventilation and air conditioning (HVAC) according to U.S. Energy Information Administration statistics. For too long, high efficiency design and optimum operational controls to improve energy performance of buildings have been the focus, and deficiencies in building operation and maintenance have been neglected. In fact, among various driving factors to energy performance of building, operation and maintenance play a decisive role. HVAC maintenance keeps plant and HVAC equipment in a healthy state in which HVAC system can function properly. This also includes troubleshooting of defective equipment to perform the intended function in a cost efficient manner, thus extending life serving time. Mill (2009) identified a wide diversity of system deficiencies and report frequency of system deficiencies for existing building and new constructions. The study also found that the most common problems were in air-handling and distribution systems for existing buildings.

Different practices of HVAC system maintenance can result in substantial differences in building energy use, maintenance costs, and equipment life. Based on discussions with HVAC engineers, building operators, facility managers, and commissioning agents, and literature review on maintenance standards (ASHRAE 2008, 2012; CIBSE 2008), maintenance practices for HVAC systems can be categorized into three levels depending on the maintenance effort and coverage:

1) proactive maintenance

The performance-monitored maintenance represents the good practice. The system operation problems can be identified and repaired before a failure occurs. It allows the maintenance manager has control over maintenance.

2) preventive, scheduled maintenance

This practice represents the average practice (business as usual). In this practice, maintenance is scheduled over time. For example, a filter in an air handler unit is replaced every 6 months. Preventive maintenance program may take too long to demonstrate results or fail to justify its cost.

3) reactive, unplanned maintenance

This maintenance repairs or replaces equipment only when it fails and investigates system performance issues based on occupants' complaints. It is often practiced by facilities that are significantly understaffed and underfunded.

Table 1 summarizes the three practices of HVAC maintenance and their implications on equipment operating efficiency and energy use, equipment life, short term maintenance cost, and life cycle cost including maintenance cost, energy cost, and equipment replacement or repair cost. The good practice will lead to lowest life cycle cost, while the bad practice seems to save short term maintenance cost, it will result in the highest life cycle cost.

Maintenance Practice	Description	Equipment Efficiency	Operating Energy	Equipment Life	Short-Term Costs	Life Cycle Costs
	Deferred or no maintenance,					
Reactive (Bad)	"run to fail".	Low	High	Short	Low	High
	Scheduled maintenance,					
Preventive	periodic inspection, cleaning,					
(Average)	and adjustment.	Medium	Medium	Medium	Medium	Medium
	Use periodic measurements					
	to detect evidence that					
Predictive	equipment is deteriorating					
(Good)	and to avoid failing.	High	Low	Long	High	Low

 Table 1. Three types of HVAC maintenance practices

Investigating the impacts of HVAC maintenance issues on building performance is a complicated research subject. The research requires not only on a good understanding of common practices on maintenance issues but also modeling techniques to simulate operation deficiencies. Most building energy simulation programs available today have limited capabilities of directly modeling HVAC operational faults or maintenance issues which occur in almost every building. Basarkar *et al.* (2012) implemented four types of equipment faults in a development version of EnergyPlus to simulate common faulty operation in building systems. The purpose of this study, reported here, is to continue previous research on fault modeling, develop modeling and simulation methods for maintenance issues and assess the impacts of common maintenance issues on building performance.

TECHNICAL APPROACH

EnergyPlus is used as the simulation tool in the study for modeling maintenance issues. EnergyPlus, developed by U.S. Department of Energy, is an open-source whole-building energy simulation program built upon sub-hourly zone heat balance and integrated solutions of building loads, HVAC systems, and central plant equipment. Three different approaches using EnergyPlus, in order of difficulty, are used to model HVAC maintenance issues:

1) Direct modeling with EnergyPlus (Direct Modeling)

Maintenance issues are directly modeled using existing inputs (either design input parameters or performance curves) in the current version of EnergyPlus. This modeling approach can be applied to such maintenance issues as supply air sensor offset, zone thermostat offset and outdoor air damper leakage. This approach is also applied to model simplified maintenance issues such as chiller or boiler fouling by introducing a degradation factor to the chiller or boiler efficiency inputs to the EnergyPlus models. The advantage of this approach is easy implementation.

2) Using the energy management system (EMS) in EnergyPlus

EMS is an advanced feature of EnergyPlus and designed for users to develop customized high-level, supervisory control routines to override specified aspects of EnergyPlus modeling in the EMS program. The EMS feature in EnergyPlus is flexible to allow users to simulate equipment operating with some maintenance issues by overwriting or adding algorithms in EnergyPlus within the specified aspects of current EMS capability. Use of EMS feature may require advanced knowledge of EnergyPlus and computer programming. EMS is used to model maintenance issues like dirty filters which increase pressure drop across the filter with operating hours.

3) Modifying EnergyPlus source code (Modified Code)

Modifying the existing EnergyPlus source code, the third modeling approach, is used when both direct modeling and EMS approaches cannot be applied to simulate any particular equipment or system deficiencies. This approach requires users to have a thorough understanding of the existing EnergyPlus source code and to write your own custom computer program based on existing code. Such HVAC maintenance issues as cooling coil fouling, outdoor air and return air temperature sensors offset adopt the third approach.

SAMPLED HVAC MAINTENANCE ISSUES

A list of common HVAC maintenance issues are reviewed and selected for the initial modeling and simulations. Based on literature reviews and our understanding of the physics and implications for each maintenance issues, we developed corresponding models and simulation approaches. Table 2 lists the issues with their potential impacts and modeling approach according to maintenance types, including sensor calibration, filter replacement, heat exchanger treatment, mechanical repair and refrigerant charge, are investigated using detailed simulation models.

Each maintenance issue list in Table 2 was modelled using EnergyPlus. A description of the implement model for selected maintenance issues is as follows.

Temperature sensor offset

Control sensors such as supply air temperature (SAT) sensors, zone thermostats, and outdoor air temperature (OAT) sensors may be out of calibration over a long term operation period. In this study, it is assumed that temperature sensors are offset by $\pm 2^{\circ}$ C. For example, if a SAT sensor is offset by $\pm 2^{\circ}$ C and a designed supply air temperature to control is 13°C, the actual supply air temperature due to sensor offset is 11 °C.

Dirty filter

In terms of filter replacement for reactive maintenance, it is assumed that filters in air handler units have not been replaced over a year. Therefore, pressure drop for air handler units has been increased and the maximum additional pressure drop is 500 Pa.

Fouled cooling tower

Cooling towers can become fouled due to unfavourable conditions. The study assumes certain fouling condition that overall heat transfer coefficient is reduced to 85% of design value.

Maintenance Types	Maintenance Issues	Impacts	Simulated Scenarios	Modeling Approach
	Supply air temperature sensor (SAT) offset	controls besting	temperature sensors are offset by ±2°C	Direct modeling, adjust SAT setpoint
Sensor Calibration	Zone temperature sensor offset	and cooling energy		Direct modeling , adjust thermostat settings
	Outdoor air temperature sensor offset			ModifiedCode,modifytheeconomizer controls
Filter replacement	Dirty filter	pressure drop, fan energy, airflow	additional 500Pa of air pressure drop	EMS, adjust fan power for VAV systems
	Fouled cooling tower	efficiency	overall heat transfer coefficient is reduced to 85% of design UA	Direct modeling, adjust cooling tower UA
Heat exchanger	Chiller: fouled tubes	efficiency	chiller COP is reduced by 10%	Direct modeling, adjust chiller efficiency
nt	Boiler: hard water scale	efficiency	boiler efficiency is reduced by 10%	Direct modeling, adjust boiler efficiency
	Fouled heating /cooling coil	efficiency, comfort	overall heat transfer coefficient is reduced to 50% of design UAs	Modified Code, adjust coils UA
	Outdoor air damper leakage	heating and cooling energy	30% OAD leakage	Direct modeling, adjust minimum OA flow
Mechanical repair	Stuck outdoor air damper (OAD)	heating and cooling energy	OAD is stuck at fully open position	EMS, set constant OA flow
	Clogged OA screen	outdoor air flow is less than 100% during economizer mode thus increasing cooling energy	maximum percent of intake fresh air is reduced to 70%	Direct modeling, set maximum OA flow
Refrigerant charge	Chiller: over or under 10% refrigerant charge	efficiency	chiller COP is reduced by 10%	Direct modeling, adjust chiller efficiency

Table 2. List of sampled HVAC maintenance issues

Fouled Chiller/Boiler/Coils

Fouling on heat transfer surfaces of boiler and chiller increases the thermal resistance and leads to reduced heat transfer. For the scenario of chiller/boiler fouling, both chiller COP and boiler efficiency are assumed to be reduced by 10%. For fouled cooling/heating coils, overall heat transfer coefficients are assumed to be reduced to 50% of design UAs.

Outdoor air damper (OAD) leakage

In the study, it is assumed that OAD leakage level is 30%. When the commanded outdoor air fraction is smaller than the leakage level, leaky damper cannot effectively control the air intake.

Stuck outdoor air damper (OAD)

Stuck OAD due to control and mechanical failure is another common fault in field. In this study, OAD is assumed to get stuck at fully open position. Cooling and heating energy penalties are introduced when outdoor air is not favourable for free cooling.

Clogged OA screen

Outdoor air intake screens may get clogged due to unfavourable locations or weather condition. The maximum percent of intake fresh air is assumed to reduce to 70%.



RESULTS AND DISCUSSIONS

Figure 1. The impacts of poor HVAC maintenance on HVAC source energy consumption for a large office building in Chicago, USA

The energy penalty introduced by HVAC maintenance issues varies by a few factors including building and HVAC systems types, vintage (design efficiencies), and climates. In the study, the commercial building reference model (Anon.) for a large-size office building in compliance with ASHRAE Standard 90.1-2004 is used as a baseline representing good maintenance practice. The large-size office building

consists of one basement level and 12 floors above ground served by 4 built-up VAV systems with 2 water-cooled chillers and one natural gas hot-water boiler.

The results, shown in Figure 1, demonstrated the energy penalty introduced by the reactive maintenance practice for the built-up VAV system located in Chicago. The percentages are derived by comparing the total source/primary energy use of HVAC systems for the reactive maintenance practice to those of the good practice (baseline reference model). The maintenance issues with significant energy impacts for Chicago are OA damper stuck at 100% position, blocked OA screen, supply air temperature offset, boiler/chiller fouling, and chiller refrigerant under/overcharge. Although there is no significant energy impact due to heating/cooling coil fouling, the numbers of unmet thermal comfort hours for both heating and cooling are significantly increased due to reduced system cooling and heating capacities. Two combined scenarios (#1 and #2) with different temperature sensor offsets were simulated in the study. The overall energy penalty by combining the sampled maintenance issues including sensor offset by +2 °C can reach 85% of overall HVAC energy consumption for Chicago climate.

Maintananaa Jasuaa	Cooling/Chiller	Heating/Boiler	Fans	Dumps	Cooling
Wannenance Issues	Cooling/Climer	Heating/Boner	raiis	rumps	Tower
OA Damper Leak	-0.04%	8.01%	0.00%	0.67%	0.06%
Clogged OA Screen	13.47%	0.00%	-0.01%	14.88%	16.27%
OA Damper Stuck at 100%	0.79%	183.93%	27.20%	11.37%	0.99%
Filter Replacement	0.57%	-1.24%	63.69%	0.82%	0.60%
Cooling Coil Fouling	1.52%	-0.01%	2.49%	4.14%	-0.12%
Heating Coil Fouling	0.00%	-0.62%	0.05%	2.48%	-0.03%
Cooling Tower Fouling	1.36%	-	-	0.00%	0.11%
Boiler Fouling	-	14.71%	-	-	-
Chiller Fouling	10.24%	-	-	1.00%	1.58%
Refrigerant	10.240/			1.000/	1 5 9 0/
Under/Overcharge	10.24%	-	-	1.00%	1.58%
OAT Offset (+2°C)	0.57%	1.52%	0.00%	-0.14%	-0.59%
OAT Offset (-2°C)	1.20%	-0.01%	2.87%	4.10%	-0.18%
SAT Offset (+2°C)	6.87%	18.08%	-5.05%	12.14%	7.74%
SAT Offset (-2°C)	-7.71%	-7.37%	13.06%	-14.75%	-8.74%
Thermostat Offset (+2°C)	3.83%	-29.02%	21.57%	3.77%	5.00%
Thermostat Offset (-2°C)	-3.05%	22.79%	-25.10%	-5.37%	-1.68%

Table 3. The impacts of poor HVAC maintenance on HVAC end-use energy consumption for a large office building in Chicago, USA

Table 3 shows the impacts of maintenance issues on HVAC end-use energy consumption for chillers, boilers, fans, pumps and cooling towers. In the table, the value in each cell represents the percentage change of HVAC end-use energy consumption relative to that of the baseline model. If OA dampers in the built-up VAV system get stuck at 100%, heating and fan energy uses increase by 184% and

27%, respectively. As variable speed pumps are used in both chilled and hot water loops, pump energy uses have been increased for fouled cooling and heating coils. Cooling tower fouling causes a small increase in cooling energy use (no pump energy increase as the pump is constant speed in the condenser loop). Outdoor air temperature sensor offset interferes control thresholds for various operation modes of air-side economizers and therefore introduces extra energy use for heating and cooling. Supply air temperature sensor offset by +2 °C introduces about 7% cooling penalty, 18% heating penalty due to increased reheat, 5% less fan energy use due to the reduction of overall air flow rates, which SAT sensor offset by -2 °C reduces cooling and heating energy use by increasing the actual controlled supply air temperature.

CONCLUSION

This study applied three different approaches for modeling common HVAC maintenance issues. Sixteen scenarios on individual maintenance issues and 2 combined scenarios were simulated. The results demonstrated that the combined impacts of the selected maintenance issues on building energy use for a large office building in Chicago climate can reach up to 85% of overall HVAC source energy use due to reactive maintenance practice.

Our on-going research focuses on identifying a broader list of HVAC maintenance issues for commercial buildings in various climates, and developing modeling approaches. The research findings can be used to provide a guideline to help practitioners and building operators to gain the knowledge of maintaining HVAC systems in efficient operations, and prioritize HVAC maintenance work plan.

ACKNOWLEDGEMENTS

This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy of the U.S. Department of Energy for the US-China Clean Energy Research Center.

REFERENCES

- ASHRAE. 2012. ASHRAE Guideline 32-2012, Sustainable, High-Performance Operations and Maintenance, Atlanta: American Society of Heating, Refrigerating, and Air-Conditioning Engineers, Inc.
- ASHRAE. 2008. ANSI/ASHRAE 180-200, Standard Practice for Inspection and Maintenance of Commercial Building HVAC Systems, Atlanta: American Society of Heating, Refrigerating, and Air-Conditioning Engineers, Inc.
- CIBSE. 2008. Guide M, Maintenance engineering and management
- Anonymity <u>http://www1.eere.energy.gov/buildings/commercial_initiative/reference_buildings.html</u>, last accessed on June 2012.
- Basarkar M., Pang X. Wang L., Haves P., Hong T. 2012. Modeling and simulation of HVAC faults in EnergyPlus, Proceedings of Building Simulation 2011:12th Conference of International Building Performance Simulation Association, Sydney, 14-16 November.

A novel approach for building occupancy simulation

Chuang Wang, Da Yan (🖂), Yi Jiang

Department of Building Science, School of Architecture, Tsinghua University, Beijing 100084, China

Abstract

Building occupancy is an important basic factor in building energy simulation but it is hard to represent due to its temporal and spatial stochastic nature. This paper presents a novel approach for building occupancy simulation based on the Markov chain. In this study, occupancy is handled as the straightforward result of occupant movement processes which occur among the spaces inside and outside a building. By using the Markov chain method to simulate this stochastic movement process, the model can generate the location for each occupant and the zone-level occupancy for the whole building. There is no explicit or implicit constraint to the number of occupants and the number of zones in the model while maintaining a simple and clear set of input parameters. From the case study of an office building, it can be seen that the model can produce realistic occupancy such as the time of morning arrival and night departure, lunch time, periods of intermediate walking-around, etc. Due to simplicity, accuracy and unrestraint, this model is sufficient and practical to simulate occupancy for building energy simulations and stochastic analysis of building heating, ventilation, and air conditioning (HVAC) systems.

1 Introduction

Building energy simulation tools such as EnergyPlus (Crawley et al. 2001), ESP-r (ESRU 1999), DeST (Yan et al. 2008; Zhang et al. 2008), and TRNSYS (Klein et al. 2004) have been playing more and more important role in building energy conservation since their conception. In past decades, modeling of heat and mass transfer processes, ambient weather data, as well as HVAC (heating, ventilation, and air conditioning) systems in buildings have been the main focus and have been well established. They support the application of simulation technique to predict and evaluate the performance of buildings (indoor climate, energy consumption, etc.). Occupant behavior, as a basic factor in building performance, still remains a big issue because of its stochastic nature in time and space.

In general, the behavior of building occupants can be broken down into two aspects: one is how they occupy the building (when they occupy the building and how many people for each zone), which is denoted by *occupancy*. The

Keywords

building occupancy, occupant movement, stochastic process, Markov chain, energy simulation

Article History

Received: 27 April 2011 Revised: 26 May 2011 Accepted: 28 May 2011

© Tsinghua University Press and Springer-Verlag Berlin Heidelberg 2011

other is how they interact with building devices including windows, doors, blinds, air conditioning terminals, lights, and equipment (TVs, computers, printers, etc.). In most situations, occupants have the right and means to adjust and control these devices, thus, those interactions are closely related to occupancy. For example, lights in a zone might be turned on by occupants when the zone is occupied and might be turned off if there is no occupant. In some smart buildings, occupancy sensors are installed for automatic control of devices according to the occupied status of the monitored space to reduce unnecessary energy use while maintaining the comfort level of the environment. For buildings with occupancy controls, occupancy becomes a key driving factor to accurately predict the energy consumption of the buildings or the impact of such occupancy-based control system on building energy performance.

The load calculation and performance analysis of building HVAC systems depend on accurate accounting of internal heat gains due to occupancy (and associated use of lights and equipment), especially for interior zones in large public

E-mail: yanda@tsinghua.edu.cn

or commercial buildings where the internal heat gains are the most important factor that affects the indoor thermal environment. In such situations, the uncertainty or stochastic variation of internal heat gains usually results in overcooling or overheating during HVAC system operation, and thus plays a decisive role in the performance evaluation of a HVAC system, such as the comparison between CAV (constant air volume) and VAV (variable air volume) system (Yan 2005).

Therefore, how the stochastic characteristic of occupancy in building can be defined and modeled is an important issue that remains to be addressed in building energy simulation.

Currently the most commonly used method in simulation tools to represent occupancy is the so-called schedule, diversity profile or diversity factors (DeST 2008; EnergyPlus 2009; Davis and Nutter 2010), which can describe the time-variation of occupancy. A daily schedule consists of 24 hourly values while a yearly schedule usually consists of 365 daily schedules, in which the hourly values can be estimated from individual experience or onsite survey; the same schedule is usually used for zones that have similar functions. Through this deterministic approach, the average impact of internal heat gains (from occupant, lighting and equipment) on energy consumption and cooling load of the building can be estimated, but it cannot represent the stochastic variations of occupancy in time and space. In addition, the datasets corresponding to occupancy schedule in all its stochastic variety from survey and measurement are still scarce, and even if such datasets were available, since occupancy may vary widely from one building to another depending on the type and size of the building, etc., they may not accurately represent actual occupancy.

Consequently, stochastic models have been proposed to produce synthetic occupancy schedules in a certain way as inputs to simulation tools. A fundamental stochastic model uses the Monte Carlo method (Macdonald and Strachan 2001), which generates an estimation of occupancy for each zone in a building based on the probability distribution of occupancy in each zone (normal distribution used in practice). It is an easy way to consider occupancy uncertainty, regardless of the interactions and relationships of the occupancy at different times in a zone and that in different zones at the same time in a building, which are distinct in reality (e.g., an occupant is likely to stay in the same zone at the next time if he stays there at previous time and he cannot appear at two places at the same time). Thus, this method is too rough for occupancy modeling and usually only used for risk analysis.

In recent years, several advanced models have been proposed to randomly generate plausible sequences of occupancy in buildings. Wang et al. (2005) proposed a probabilistic model to predict and simulate occupancy in single person offices, where non-homogeneous Poisson process model with two different exponential distributions are used to generate the occupancy sequence in a single person office. Based on the examined statistical properties of occupancy, the durations of presence and absence during business hours are both exponentially distributed and the coefficient of each exponential distribution for a single office can be treated as a constant over the workday. Meanwhile, in order to combine the clock-time information into the simulation, the morning arrival time, the night departure time, and the lunch break time are assumed to be normally distributed, which are actually not supported by observations. This method is simple and elegant for single offices, but it is severely limited in describing the relationship of occupancy in different zones due to occupant movement in a building, and thus very hard to extend into other situations.

Page et al. (2008) presented an approach based on the inhomogeneous two-state Markov chain, where the model can generate a time series of the state of presence (in/out, or, present/absent) of occupants within a specific zone of a building, and the transition probabilities of the model, corresponding to arriving, leaving and staying in the respective states, are time-dependent and estimated from the probability of presence (based on aggregate occupancy records) at every time step. In addition, an assumed parameter of mobility describes the probability of state changes. This model is capable of reproducing the important characteristic of occupancy in office buildings such as the morning arrival time, the night departure time, typical long absences and the effective time of presence of the occupant within the zone by a uniform Markov chain. However, it has two major disadvantages: (1) as inputs to the model, the profiles of probability of presence and parameters of mobility are too complex to specify in simulation and to obtain from survey or measurements because of their time dependency; (2) this model does not simulate the movement of occupants from one zone to another, which is distinct in reality and important for occupancy prediction. Even if such efforts can be made, extending the model to multiple zones is much more challenging for determining the time varying entries of high-order transition probability matrix and parameters of mobility for state changes.

The most recent model is proposed by Liao et al. (2011), an agent-based model of occupancy dynamics in a building. This model regards each occupant as an agent and decides the state of an agent (the location of each occupant) at every time step through a set of rules specified by four modules, which can then be collected to generate time-series of zonelevel occupancy. Compared to Page's model, Liao's model maintains a Markov-like property of agent dynamics and is easily scalable to an arbitrary number of zones and an arbitrary number of occupants. The scheduled activities of agents, the zones that each agent can access, the maximum occupancy limits of zones, and a secondary agent that occupies the building for brief periods of time (like visitors) are also involved. This model's prediction accuracy was found to be quite good in the single-occupant single-zone scenario and multi-occupant single-zone scenario, but is poor in the multi-occupant multi-zone scenario. The most time-consuming part in constructing the model is specifying the nominal presence probability profile for each agent in the preliminary state generator module, which consists of the probability time series that an agent occupies a zone at every time step. Due to excessive information, these inputs for the model are hard to obtain especially for multioccupant multi-zone scenarios. For this reason, although it has no limitation in theory when applied to multiple zones, some simplifications have to be made in practice when specifying the nominal presence profiles, such as the zones that each occupant can access only include a primary zone, a secondary zone, a hallway, and a restroom. The frequency and average duration of visiting a restroom per day are assumed to be constant over the workday. Lunch and dinner breaks are strictly specified by fixed schedule rather than random process. These simplifications reduce the capacity of the model and would lead to poor results of the model in a multi-occupant multi-zone scenario.

Additional models have tried to generate the stochastic occupancy in buildings based on occupant activity simulation (Tabak 2008; Goldstein et al. 2010), where the models focused on the chronological sequence of detailed activities, with attributes of a task (e.g., working, meeting, eating), such as frequency, duration, priority, location, facilities, interactions with one another, etc. This method is quite sophisticated and can output many details of human behavior in a building, from which the occupancy is a natural consequence. However, relying on a huge extensive survey or measurement of such detailed activity, this indirect method is not as practical for occupancy simulation as the aforementioned methods.

The above overview indicates that existing models have demonstrated the capacity to realistically reproduce key properties of occupant presence for both the single-occupant single-zone scenario and the multi-occupant single-zone scenario, but have serious limitations when extended to multiple spaces. Furthermore, the excessive inputs of these models due to time dependency or high order of matrix are complex to handle in simulation.

The principal goal of this paper is to present a novel approach for occupancy simulation based on homogeneous Markov chain and demonstrate it in an office building simulation. In this study, occupancy is handled as the straightforward result of occupant movement processes which occur among the spaces inside and outside the building. Thus there is no explicit or implicit constraint to the number of occupants and the number of zones. By using the Markov chain method to simulate this stochastic movement process, the model can generate the location for each occupant and the occupancy for each zone of the building while maintaining a simple, clear set of input parameters. From the case study, it can be seen that the model can produce the realistic occupancy variations in the office building for typical workday with key statistical properties of occupancy such as the time of morning arrival and night departure, lunch time, periods of intermediate walkingaround, etc. In the terms of simplicity, accuracy and unrestraint, this model is sufficient and practical to simulate occupancy for building energy simulations and stochastic analysis of building HVAC systems.

2 Methodology

The goal of the model in this paper is to generate stochastic occupancy schedules with the same statistical characteristic of building occupancy, which can then be used by a building energy simulation tool to further estimate the energy consumption of a building and the performance of a HVAC system.

The basic idea of the model is that building occupancy is a straightforward result of occupant movement processes which occur among the spaces inside and outside the building. The first-order homogeneous Markov chain technique, a widely-used well-established stochastic process method (Ross 1996), was selected for simulating the occupant movement process.

The concept of the first-order homogeneous Markov chain (HMC) technique is that any future state is dependent only on the present state together with the probabilities of the state changing (called Markovian property). These probabilities are held in the transition probability matrix and are time-independent (i.e., fixed). Consider a stochastic process { X_k , $k = 0,1,2,\cdots$ } that takes a set of nonnegative integers $I = \{0,1,2,\cdots\}$ as possible values, HMC (with discrete states and discrete time steps) can be present by

$$P\{X_{k+1} = j \mid X_k = i, X_{k-1} = i_{k-1}, \dots, X_1 = i_1, X_0 = i_0\}$$

= $P\{X_{k+1} = j \mid X_k = i\} = p_{ij}(k) = p_{ij}$

for all states $i_0, i_1, \dots, i_{k-1}, i, j$ and all time steps $k \ge 0$. The fixed value p_{ij} represents the probability that the process will, when in state *i*, next make a transition into state *j*. For the transition probability matrix (denoted by *P* matrix in the sequel) that consists of one-step transition probabilities p_{ij} , we have that

$$p_{ij} \ge 0, \ i, j \in I; \ \sum_{j \in I} p_{ij} = 1, \ i \in I$$
 (1)

HMC has many good statistical analysis features which greatly help set up the model. The interested reader can refer to Ross (1996) for more details on Markov chain.

2.1 General description

The proposed model has a two-level hierarchical structure consisting of a basic module named *movement process* and a high-level module named *events* as shown in Fig. 1. The module of movement process essentially implements a simulation of the Markov chain process and generates the locations of occupants step by step, which can then be used to calculate the occupancy for each zone in buildings. The module of events is used to specify the transition probabilities of Markov chain in specific periods of time, in order to represent the occurrences associated with time.

2.1.1 Movement process

In this paper, the process of occupant movement covers all the occurrences that correspond to the location change of people within a building, such as entering or leaving a specific space, moving around from one space to another, going outdoors for a while, etc. Such a stochastic process results in the variation of building occupancy in time and space. Such processes also may vary widely from one building to another, depending on the type and size of the building, the geographic location and climate, the ethnicity and preferences of the occupants, etc.

Consider a building with n zones that is occupied by m individuals, where a *zone* is an internal space in the building and indexed as $1, 2, \dots, n$; an individual is denoted by *occupant*, i.e., residents in case of a residential building or office workers in case of an office building, etc. The outside of the building is also involved and treated as a specific space indexed by 0, to form a complete movement graph.

Regarding the location of an occupant (in which space the occupant is) at every time step as a random variable, its possible values belong to the set (or a subset) of all spaces' indices $\{0 = \text{outside}, 1 = \text{zone } 1, 2 = \text{zone } 2, \dots, n = \text{zone } n\}$ that correspond to the occupant's accessible range. The movement process of each occupant can thus be described by a Markov chain in which the state of the process is exactly the location of an occupant, and the next location of the occupant is dependent only on the present location and the fixed transition probabilities held in the *P* matrix.

Here the following assumptions have been made: (i) the location of occupant due to movement has a Markovian property; (ii) any location change of occupant due to movement can be finished in one time step; (iii) the movements of each occupant are independent, thus each occupant has his own transition probability matrix.

The assumption (i) is supported by the experiments of Wang et al. (2005) and Dodier et al. (2006). They measured the occupancy states for some single offices by assembling a sensor network. If the location of an occupant is described by a HMC, the sojourn time of the occupant in any state (i.e., presence/in his office, absence/not in his office during working hours) should be geometrically distributed. From their results, it is approximately geometric for both presence and absence durations of an occupant in business hours. Figures 2 and 3 show the fitted and observed probability distribution of durations of presence and absence for an office in Wang's experiment, with a time interval of 15 minutes. Figures 4 and 5 show the histograms of sojourn times and the fitted probability distribution of durations of presence and absence for two offices in Dodier's experiment, with time intervals of 500 s and 200 s. Both authors concluded that the presence and absence durations are exponentially distributed. However, since the observed data in the experiments are analyzed with a discrete time interval, the exponential distributions are indeed geometric distributions, in a discrete form.

The two experiments, although based on single offices, in a way validate the assumption (i) in our model. It further ensures that the stochastic occupancy model based on occupant movement is reliable in other situations, even for multi-occupant multi-zone scenarios.







Fig. 2 Fitted and observed probability distribution of the presence durations (Wang et al. 2005)



Fig. 3 Fitted and observed probability distribution of the absence durations (Wang et al. 2005)

As for the hypothesis (ii), since the movement of an occupant is essentially a continuous-time process, whether

the location change of an occupant governed by P matrix can be realized depends on his movement speed, especially in a small time step simulation. The transition probabilities of the occupant from the present state to the next state are actually influenced by the limit of movement speed. For the moment, it is not taken into account. Accordingly, to ensure the temporal resolution of the results and to easily integrate with building energy simulation tools, the time intervals for the model can be 5, 10, 12, 15 minutes, or any other submultiples of 60 minutes (i.e., 1 hour that is the usual time step for building energy simulation).

With the above hypotheses, the movement patterns of each occupant can be modeled individually in a simple way even if they may be quite different, and the realistic Markovian properties of occupant movement can be reproduced.

2.1.2 Event mechanism

It is noted that such a HMC can only produce a pure random movement process for each occupant among the spaces (inside and outside of the building), without considering the time factors for the movement occurrences that probably happen for occupants in certain periods of time. Take an office building as an example, in normal conditions the employees would usually go to the office in the morning and leave in the evening, rather than random arrival and departure at any time during the day. Such occurrences of movement associated with time is common for a building with specific function and an occupant with specific career or post, such as in residential buildings, office buildings, etc., which may be called typical movement patterns for such types of buildings and occupants. An event mechanism is proposed to represent and manage the time-triggered occurrences of movement in buildings, in which the movement of occupant is driven by a number of events. In addition, the event mechanism can be also used to treat the relevance of the movements of occupants (e.g., a joint movement such as attending a meeting).



Fig. 4 (a) Frequency distribution of duration of presence, both offices aggregated (78 sojourns of presence, Dodier et al. 2006); (b) fitted and observed probabilities of the presence durations



Fig. 5 (a) Frequency distribution of duration of absence, both offices aggregated (72 sojourns of absence, Dodier et al. 2006); (b) fitted and observed probabilities of the absence durations

An event in the model is an object that corresponds to the specific location change of occupants; for example, the event of walking around, regarded as a basic event in all buildings, corresponds to the location change from one space to another (covering general movements, such as going to the washroom, dropping by another office, etc.). The event of going to the office in the office building corresponds to an occupant's location change from outside (space 0) to the office (a space for his/her own office). Each event has a valid period (with a starting time and an ending time) during which it takes place, and a range of actions on the occupants (i.e., it only influences specific occupants). The event drives occupant movement through *P* matrix exactly by specifying the corresponding elements in the *P* matrix. The probability elements associated with the event are also fixed and time-independent (called "event dependent"). Such transition probabilities can be determined from some statistical indices of the event (see Section 2.2). Each event also has a priority that determines the order of the event taking effect on P matrix in case that several events are valid at the same time (i.e., valid periods of events have intersections) and these events have common elements in Pmatrix. In this situation, such elements of P matrix would be specified with the associated probabilities of the event with the highest priority.

In summary, an event object usually has six properties: starting time, ending time, locations (from one space to another), participants (taking part in the event), transition probabilities (driving the movement of participants), and priority (to resolve conflicts).

With the event mechanism, the Markov chain of occupant movement is indeed inhomogeneous since the transition probabilities in P matrix could be changed at certain times. However, the probabilities are fixed for the remaining periods, so most behaviors of such a Markov

chain look like a HMC during every period split by events. Our method is still labeled as HMC.

A set of events can be made in chronological order according to the typical movement patterns of building and occupant, and it is easily scalable to describe other events, such as long absence, meeting, short visit, working at home, working part-time, and even other scheduled events. Once the list of events is made, the model is completely constructed in form.

2.1.3 Algorithm

Due to the simple structure, the implementation of the model is relatively simple once the building typology, occupant and movement parameters (e.g., the number of occupants, the accessible spaces for each occupant, the set of events with properties, etc.) are determined.

The model was implemented as a MATLAB script. The location of each occupant was simulated independently based on the inputs related to that occupant. For initial states, the occupant is considered to be absent in the case of office buildings (or present in the case of residential buildings) at the initial time step, 00:00 of January 1st. From then on, the time series of occupant location is generated by the transition probability matrix at each time step, which is specified by valid events.

Figure 6 shows how the algorithm works: (0) initialize the states of all occupants at time step 0; for each time step, (1) update the set of active events at present according to the input set of events and their valid periods; (2) update the P matrices of all occupants according to the set of active events, the corresponding elements of P matrix are specified by the active events, and note that the sum of elements in each row of P matrix should equal 1; (3) for each occupant, determine the current state of occupant according to the previous state and the updated P matrix (see Fig. 7 for details, where the MATLAB function *rand* generates a pseudorandom



Fig. 6 The workflow of algorithm (processing stage)



Fig. 7 The simulation script of Markov chain at each time step

value drawn from the standard uniform distribution), and do this for all occupants; (4) calculate the current occupancy for all zones according to the locations of all occupants.

By repeating this procedure step by step, the time series of the location of each occupant and the occupancy of each zone in the building can be generated, without any constraint on the number of occupants and the number of zones.

2.1.4 Reduction and estimation of transition probabilities

The kernel parameters for the model are the transition

probabilities for each occupant. Since the probabilities in the model are time-independent, it greatly reduces the complexity in the time dimension compared to the preexisting models. Actually, all the entries of P matrix for each occupant can be estimated directly from the information that is collected by deploying sensors in the building which track each individual over time as proposed by Tabak (2008). However, it still seems not trivial in simulation to directly input all the entries of P matrices of all occupants in multi-occupant multi-zone scenarios as mentioned by Liao et al. (2011). This is due to the high order of matrices (corresponding to the number of spaces) and the number of matrices (corresponding to the number of occupants). Therefore, a way to further simplify the specifications for such matrices is proposed in this paper.

The most important requirement for the simplified method is the generated P matrix should capture the specific statistical characteristics of building occupancy (i.e., occupant movement). An office building is used as an example to demonstrate the procedure how to apply the present occupancy model to a specific type of building and how to simplify the inputs based on the key statistical characteristic of occupant movement.

2.2 Occupancy modeling in an office building

An office building is a common building type which most occupancy modeling research is focused on. In an office building, a typical movement pattern for the occupants in a workday is going to the office in the morning, having a lunch break at noon, and getting off work in the evening or night (possibly with overtime), which leads to the phased variation of the number of occupants of a typical office building over the workday as shown in Fig. 8. During the working periods, the occupancy for each zone of the building would change since the occupants walk around among the spaces inside and outside of building for a variety of reasons.

In addition to the phased evolution, the occupants' comings and goings for the morning arrival (t_1 to t_2), the



Fig. 8 The occupancy variation of an office building over the workday

lunch break (t_3 to t_4), and the night departure (t_5 to t_6) are all random rather than deterministic (or strictly according to a schedule), which greatly affects the working time of building devices. The indices representing the morning arrival and the night departure are respectively the time of morning arrival and the time of night departure. Those for a lunch break are the time of going out for lunch and the time of coming back to office (it is assumed that the occupants do not have lunch in their own office).

Such a typical movement process of the occupant in an office building can be described by a set of five events: walking around, going to the office, going for lunch, coming back from lunch, and getting off work. Next, an approach to model such events with a specific statistical characteristic and the treatment for events that are not detailed in this paper are discussed.

2.2.1 Walking around

The event of walking around in office buildings corresponds to the general location change from one space to another, among the spaces inside and outside of building (e.g., going to the washroom, walking in the hallway, going outside, dropping by another office, etc.). In most situations, it means a transient movement of an occupant out of his office. Its valid period is usually the same as the business time of a company, e.g., from 8:00 to 17:00.

As discussed above, specifying the P matrix for walking around during the working period is the most challenging work for multi-zone scenarios. Since the present stochastic model should reproduce the specific statistical characteristics of occupant movement, a simplified way can be proposed to determine the probabilities.

From experience, the key statistical characteristic for an occupant walking around is the long-run proportion of time and the expected sojourn time that the occupant stays in each space of the building during the working period. The simplified way to specify P matrix is based on the following mathematical formulations.

The stationary distribution

Let *P* denote the transition probability matrix that corresponds to the process of an occupant moving among the spaces (all zones in the building and outside), which are indexed by $\{0 = \text{outside}, 1 = \text{zone } 1, 2 = \text{zone } 2, \dots, n = \text{zone } n\}$. Suppose the probabilities are fixed and not influenced by any other events in normal conditions.

$$\boldsymbol{P} = (p_{ij})_{(n+1)\times(n+1)} = \begin{pmatrix} p_{00} & p_{01} & \cdots & p_{0n} \\ p_{10} & p_{11} & \cdots & p_{1n} \\ \vdots & \vdots & & \vdots \\ p_{n0} & p_{n1} & \cdots & p_{nn} \end{pmatrix}$$
(2)

In our situations, this Markov chain is irreducible and ergodic. Such a Markov chain has a stationary distribution, denoted by π , $\pi = (\pi_0, \pi_1, \dots, \pi_n)$, where π_i means the long-run proportion of time that the Markov chain is in state *i* (i.e., with what proportion of time the occupant stays in the space *i*). And we have (Ross 1996):

$$\sum_{i=0}^{n} \pi_i = 1 \tag{3}$$

$$\boldsymbol{\pi} = \boldsymbol{\pi} \boldsymbol{P} \tag{4}$$

Based on Eqs. (3) and (4), given the matrix P, the vector π can be determined by solving Eqs. (3) and (4) simultaneously, and expressed as Eq. (5):

$$\boldsymbol{A} = \begin{pmatrix} 1 & 1 & \dots & 1 \\ p_{01} & p_{11} & \dots & p_{n1} \\ \vdots & \vdots & & \vdots \\ p_{0n} & p_{1n} & \dots & p_{nn} \end{pmatrix} \quad \boldsymbol{b} = \begin{pmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \quad \boldsymbol{\pi}^{\mathrm{T}} = \boldsymbol{A}^{-1} \boldsymbol{b}$$
(5)

where π^{T} is the transpose of π_{I} .

The expected sojourn time

The sojourn time in state *i* of Markov chain, denoted by ST_i , is geometrically distributed as expressed in Eq. (6). (Instead, it is exponentially distributed in the continuous-time Markov chain.)

$$P\{ST_i = k\} = p_{ii}^{k-1}(1-p_{ii})$$
(6)

where k is the number of time steps during which the Markov chain is out of state i (measured from the time when the Markov chain is in state i).

The expected sojourn time can be expressed by (Sheng et al. 2008):

$$E(ST_i) = \sum_{k=1}^{\infty} k \cdot \mathbf{P} \{ ST_i = k \} = \sum_{k=1}^{\infty} k \cdot p_{ii}^{k-1} (1 - p_{ii}) = \frac{1}{1 - p_{ii}}$$
(7)

So that,

$$p_{ii} = 1 - \frac{1}{E(ST_i)} \tag{8}$$

Denote the vector of expected sojourn time by *Est*, $Est = (Est_0, Est_1, \dots, Est_n)$, where Est_i means the expected sojourn time that the Markov chain is in state *i* (i.e. how long the occupant stays in the space *i* at a time).

Equations (5) and (8) illustrate the relations between the P matrix and the long-run proportion of time and the expected sojourn time.

Given the long-run proportion of time π and the expected sojourn time *Est* of the occupant in every space, the simplified way to specify *P* matrix can be described as an optimization problem:

$$\min \| (\boldsymbol{A}^{-1}\boldsymbol{b})^{\mathrm{T}} - \boldsymbol{\pi} \|_{2}$$

s.t. $p_{ij} \ge 0, \sum_{j} p_{ij} = 1$
 $p_{ii} = 1 - \frac{1}{Est_{i}}$ (9)

where $\tilde{\pi} = (A^{-1}b)^{T}$ is an estimation of π . This optimization problem can be solved by using the *fmincond* function in MATLAB.

Thus, the *P* matrix with $(n + 1) \times (n + 1)$ entries can be specified by using a set of $2 \times (n + 1)$ parameters, which greatly reduces the space complexity of such inputs. Naturally, the Markov chain governed by this *P* matrix will have the same statistical characteristic of occupant movement that is defined by the long-run proportions of time and the expected sojourn times of the occupant in every space. These two vectors of an occupant are then used as the input of the present model, denoted by "movement vectors" in the sequel.

By using the movement vectors, the input information for the model is easier to collect by deploying tracking sensors or conducting a questionnaire survey of the occupants' behavior. The price of such simplification is that the produced P matrix might lose some inherent information that relates the movement of occupant in the building compared to a directly specified P matrix, since every element of the P matrix has its own meaning. Whether to choose the simplified method or specify the P matrix depends on the user's demand. In the most situations of building occupancy simulation, the detailed specification of P matrix is timeconsuming and not necessary; instead, the movement vectors of occupant are simple, effective, and accurate enough for simulation.

2.2.2 Going to the office and getting off work

The event of going to the office (i.e., morning arrival) of an occupant is regarded as the location change from outside the building to his own office. Thus it only relates the elements of the occupant's transition matrix where the row and the column correspond to outside and his office. The valid period of this event is usually a time span before the business hours, e.g. from 7:00 to 8:30, corresponding to the earliest and latest morning arrival time of office workers.

The morning arrival process can be expressed by a two-state HMC with an absorbing state, which is governed by a fixed 2-by-2 P matrix in Eq. (10).

$$P_{\text{go}_{office}} = \begin{pmatrix} 0 & 1 \\ p_{00} & p_{01} \\ 1 & \begin{bmatrix} p_{00} & p_{01} \\ 0 & 1 \end{bmatrix}$$
(10)

where 0, 1 are respectively the indices of outside and the occupant's office that is known as an absorbing state. The absorbing state means the occupant will definitely enter his office at a certain time, and it means the arrival time of the occupant entering his office when the HMC is in the absorbing state. During the valid period of the event "going to office", the elements of the occupant's P matrix corresponding to outside and his office would be specified with the probabilities in Eq. (10).

Measured from the start of the event of going to the office, the morning arrival time of the occupant is geometrically distributed, and the expected arrival time (denoted by E(FA)) can be expressed by

$$E(FA) = \frac{1}{1 - p_{00}} \quad p_{00} = 1 - \frac{1}{E(FA)} \tag{11}$$

If the arrival time is the same as the on-duty time, $p_{00} = 0$ and E(FA) = 1.

Similarly, the event of getting off work (i.e., night departure) of the occupant corresponds to the location change from his own office to outside the building. Its valid period is usually a time span after the business hours, e.g., 17:00 - 21:00, corresponding to the earliest and latest night departure time of office workers.

The night departure process can be expressed by a twostate HMC governed by the fixed 2-by-2 *P* matrix in Eq. (12).

$$P_{\text{off_work}} = 0 \begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 1 & p_{10} & p_{11} \end{bmatrix}$$
(12)

where 0, 1 are respectively the indices of outside and the occupant's office. Here, outside the building is the absorbing state, which means the occupant will definitely leave his office at a certain time. And it means the departure time of the occupant leaving his office when the HMC is in the absorbing state.

Measured from the start of the event of getting off work, the night departure time of the occupant is also geometrically distributed, and the expected departure time (denoted by E(LD)) can be expressed by

$$E(LD) = \frac{1}{1 - p_{11}} \quad p_{11} = 1 - \frac{1}{E(LD)} \tag{13}$$

If the departure time is the same as the off-duty time, $p_{11} = 0$ and E(LD) = 1.

2.2.3 Lunch break

The lunch break of an occupant can be divided into two events. One is the event of going for lunch, corresponding to the start of lunch break; the other is the event of coming back from lunch, corresponding to the end of lunch break. We suppose the location for the occupant's lunch is out of his office. The two events can be treated similarly like the event of going to office and getting off work.

The process of going for lunch can be expressed by the transition matrix in Eq. (14). Measured with the start of the event of going for lunch (i.e., the earliest leaving time), the expected leaving time for lunch (denoted by (E(LL)) is expressed by Eq. (15).

$$P_{\text{lunch}_{out}} = \begin{pmatrix} 0 & 1 \\ 1 & 0 \\ 1 & p_{10} & p_{11} \end{pmatrix}$$
(14)

$$E(LL) = \frac{1}{1 - p_{11}} \quad p_{11} = 1 - \frac{1}{E(LL)}$$
(15)

The process of coming back from lunch can be expressed by the transition matrix in Eq. (16). Measured with the start of the event of coming back for lunch (i.e., the earliest return time), the expected return time from lunch (denoted by E(LR)) is expressed by Eq. (17).

$$P_{\text{lunch}_back} = \begin{pmatrix} 0 & 1 \\ p_{00} & p_{01} \\ 1 & \begin{bmatrix} p_{00} & p_{01} \\ 0 & 1 \end{bmatrix}$$
(16)

$$E(LR) = \frac{1}{1 - p_{00}} \quad p_{00} = 1 - \frac{1}{E(LR)} \tag{17}$$

2.2.4 Other issues

There are many other things in an office building that have not been discussed in detail in the above paragraphs, such as meetings that happen during a workday, long period absence or leaves or working at home that result in the occupants not entering the office for a whole workday, short visits or working part-time that the visitors or occupants only appear in the building for a short period of workday, tea breaks for some organizations, or the situation that the occupant has his lunch in his office, etc.

The reasons that those situations are not modeled are, on one hand, this paper focuses on the modeling of most typical movement patterns in an office building, it's not necessary to involve too many events; on the other hand, on the basis of our present model, such things can be modeled easily with an external event generator (random or scheduled), whose outputs can be used as the inputs for the model (see Fig. 9). The interactions of occupants, such as going for lunch together, can also be defined in the form of events.

As for the maximum occupancy limits of spaces, a simple rule can be added into the determination of occupant location at each time step, that is, if the space that the occupant would go to has reached its maximum occupancy limit, the occupant would return to his last location rather than enter the zone, i.e., the occupant's location at the current time step would be the same as the previous time step.

2.2.5 Summary

With the events modeled above, a typical movement pattern of occupants over the workday in an office building, i.e., "morning arrival—walking around (working period)— lunch break—walking around (working period)—night departure", can be simulated by a unique Markov chain, in which the transition matrix for each occupant is successively specified with the associated probabilities of events during different periods of the day. Such probabilities for morning arrival, walking around, lunch break, night departure can be determined based on the statistical indices of each event. The simulated results of such a Markov chain will have the same statistical characteristic of events.

Besides the basic information of building and occupant (building typology, occupant number, working schedule, etc.), the particular inputs for the present occupancy model of an office building are clarified as follows.

(1) For walking around, the vectors of long-run proportion of time and expected sojourn time for each space are needed.

(2) For morning arrival, the earliest, the latest and the expected arrival time are needed. For night departure, the earliest, the latest and the expected departure time are needed.



Fig. 9 The integration of event generators within the present model

(3) For lunch break, the earliest, the latest and the expected leaving time for going for lunch, the earliest, the latest and the expected return time for coming back from lunch are needed.

In addition, due to different personalities of occupants, the associated events (or event properties) for each occupant can be different and thus need to be specified individually.

All the above information needs to be collected and calibrated before applying the model.

2.3 Discussion on model calibration and validation

The validation of the proposed stochastic occupancy model, theoretically speaking, should be based on probability, which means the comparison of the probability distribution function (PDF) of the measured and simulated parameters. This requires a long period (usually several years) of measured occupancy data in the real office buildings. But such data are too scarce and not available for most buildings. So the theoretical probabilistic test cannot be carried out due to too few samples. Thus, from the practical point of view, a simple test approach needs to be proposed. For example, the maximum, minimum and average occupancy for each zone inside the building could be chosen as the test parameters and the criterions to calibrate the model. This will be an important work and needs more study in the future.

For the moment, due to the lack of measured data, the proposed model has not been fully validated by comparing the simulated and the measured data. Nonetheless, an illustrative case study can be made to check and test the capacity of the model; whether it can cover the things that affect the occupancy variation in a building and how much it can capture this.

3 Case study

A simple office building is tested to demonstrate the usage and effect of the proposed model. This case is illustrative and the input data are taken from experience. The time step used in the case is 5 min; an occupancy time series of one day is comprised of 288 points.

Through the case, we will check the capacity of the model to represent: (1) the trend of "going to the office—working—lunch break—working—getting off work" in a typical workday; (2) the random arrival time and the smooth increase of building occupancy in the morning; (3) the random departure time (overtime) and the smooth decrease of building occupancy; (4) the random decrease of building occupancy during the lunch break; (5) random movement among the inside and outside spaces during working time.

3.1 Input settings

3.1.1 Building typology

The 2D plan of the office building is shown in Fig. 10. There are 4 office rooms, 1 corridor, and 1 restroom, indexed from 1 to 6; and the outside is indexed by 0. There are 7 spaces in total. All spaces are connected by doors and corridor.

3.1.2 Occupant and movement parameters

There are 3 types of occupants in the building. The occupants in offices 1 and 2 are ordinary workers. The occupants in office 3 are administrative staff (secretary). The occupant in office 4 is a manager (head of the organization). They move among the 7 spaces (i.e., all spaces are accessible for each occupant). The number of occupants for each office is shown in Table 1.

A fixed working schedule from 8:00 to17:00 is specified. Five typical types of events and a scheduled meeting are considered in the workday. The schedule and events in the workday is shown in Table 2.

The exceeding periods of going to office and returning from lunch, compared to the standard schedule, i.e., 7:00 - 8:00, 8:00 - 8:30 and 13:00 - 13:30 respectively means the early morning arrival, the late morning arrival and the late back to the office from lunch. The exceeding period of getting off work, 17:00 - 21:00, means the delay or overtime for night departure.

The events (except meeting) work for all occupants. The expected values for the events are shown in Table 3. Note that these values are accounted in the unit of 5-minute time step. They are only estimations for the statistical index of each event, and used to determine the transition probabilities in *P* matrix and the variations of occupancy ultimately.



Fig. 10 2D plan of the office building

Table 1 Number of occupants in each office

Room No.	Number of occupants	Room No.	Number of occupants
Office 1	6	Office 2	6
Office 3	2	Office 4	1

Schedule	Event	Valid period
	Go to the office	07:00 - 08:30
Moulting times	Leave for lunch	12:00 - 12:30
8:00–17:00 Lunch break 12:00–13:00	Return from lunch	12:30 - 13:30
	Get off work	17:00 - 21:00
	Walk around	08:00 - 12:00,
		13:00 - 17:00
	Meeting	10:00 - 11:30

Table 2 Schedule and events in a working day

The expected value of morning arrival time for going to the office is 7:45; which means, in the 5 min unit the geometric distribution of morning arrival time has an expected value of 9 time steps (measured from 7:00).

The values of long-run proportion and mean sojourn time for different spaces mean: for the occupants in office 1, each of them will spend 90% of business hours in his own office, 3% in the other three offices, 1% in the outside, 1% in the corridor, and 5% in the restroom; the mean sojourn time steps for each space are 24, 3, 2, 2, 2.

With different movement vectors, the differences between the three types of occupants are specified. A manager may have more meetings out of the office, so he/she only spends 60% of business hours in the office and 30% outside, with 1-hour mean sojourn in both spaces. A secretary may tend to move more frequently in the spaces, so he/she only spends 70% of business hours in the office and the remaining 30% occupying other spaces, with 1-hour mean sojourn in the office and 10 min for each other space.

To illustrate the effect of meeting events, a scheduled meeting is held in the manager's office from 10:00 to 11:30, and it is attended by two occupants from office 1, two occupants from office 2 and the manager. All the participants are determinate.

Table 3 Expected values for each occupant

3.2 Transition matrix

The transition matrix for each occupant can be determined by the movement parameters according to the equations in Section 2.2. The associated probabilities of events for occupants in office 1 are shown in Fig. 11. Based on those probabilities, the transition matrix would be specified and changed at certain time steps when the events become valid over a workday.

3.3 Results and discussions

The simulation for a workday runs 1000 times consecutively, with different random seeds for each simulation. Figure 12 shows the generated time series of the locations of four occupants in offices 1, 2, 3 and 4. As expected, the four occupants stay in their own offices for most of the time, with different times of morning arrival and night departure, different times of leaving and returning during lunch break, and occasionally out of the office (into other spaces). The scheduled meeting can be seen from that the occupant in office 1 and the manager in office 4 stay in the office 4 during the period of 10:00 - 11:30. The secretary in office 3 seems to move more frequently than others.

3.3.1 Building occupancy

The change of number of occupants in the whole building over a workday is illustrated in Fig. 13, where (a) shows the result of building occupancy for one simulation, (b) shows the results for five successive simulations, (c) shows the maximum, minimum, and average occupancy for each time step from all the simulations, (d) shows the hourly occupancy taking the mean of five-minute results. It can be seen that (1) the trend of "going to the office – working – lunch break – working – going off work" in a typical workday

Event	Statistical index	Expected value		
Go to the office	Morning arrival time	7:45		
Go for lunch	Leaving time		12:10	
Come back from lunch	Return time		12:50	
Get off work	Night departure time		18:00	
Walk around	Long-run proportion of time and mean sojourn time in each room	Office 1	$\pi = [0.01, 0.9, 0.01, 0.01, 0.01, 0.01, 0.05]$ Est = [10min, 2h, 15min, 15min, 15min, 10min, 10min]	
		Office 2	$\pi = [0.01, 0.01, 0.9, 0.01, 0.01, 0.01, 0.05]$ Est = [10min, 15min, 2h,15min, 15min, 10min, 10min]	
		Office 3	$\pi = [0.05, 0.05, 0.05, 0.7, 0.05, 0.05, 0.05]$ Est = [10min, 10min, 10min, 1h, 10min, 10min, 10min]	
		Office 4	$\pi = [0.3, 0.01, 0.01, 0.01, 0.6, 0.02, 0.05]$ Est = [1h, 5min, 5min, 5min, 1h, 10min, 10min]	

0 1 2 3 4 5 6 0 2 3 5 6 1 4 0 $\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$ $0 \begin{bmatrix} 0.5000 & 0.3724 & 0.0247 & 0.0247 & 0.0250 & 0.0260 & 0.0272 \end{bmatrix}$ 1 1 0 0 0 0 0 0 1 0.0042 0.9583 0.0023 0.0023 0.0023 0.0042 0.0263 $\boldsymbol{P} = \frac{2}{3} \begin{vmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{vmatrix}$ 2 0.0244 0.2120 0.6667 0.0234 0.0243 0.0255 0.0237 $P = \frac{2}{3} \begin{vmatrix} 0.0211 \\ 0.0242 \\ 0.2131 \\ 0.0233 \end{vmatrix}$ 1 0 0 0 0 0 0 0.6667 0.0235 0.0241 0.0253 4 1 0 0 0 0 0 0 4 0.0247 0.2110 0.0237 0.0236 0.0246 0.0258 0.6667 5 1 0 0 0 0 0 0 5 0.0257 0.3747 0.0242 0.0243 0.5000 0.0267 0.0245 6 1 0 0 0 0 0 0 6 0.0055 0.4734 0.0052 0.0052 0.0053 0.0055 0.5000 Night time (initial state) Walking around 0 1 0 1 $P_{\text{go_office}} = 0 \quad [0.8889 \quad 0.1111] \quad P_{\text{off_work}} = 0 \quad [1.0000]$ 0 0 1.0000 ' 1 1 0.0833 0.9167 Going off work Going to the office 0 0 1 1 $P_{\text{lunch_out}} = 0$ [1.0000 $P_{\text{lunch_back}} = 0 \quad [0.7368 \quad 0.2632]$ 0 1 0.5000 0.5000 0 1.0000 1 Leaving for lunch Returning from lunch





Fig. 12 The time series of occupants' locations over a workday

15

10

5

0

15

10

5

0 1 2 3 4

5

6

٥

12

24

36

48

60

Hou

(b) Building occupancy for five simulations

72

84

8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24

96

-O- Max

108

Min

Average

120



Fig. 13 Building occupancy over a workday

is reproduced; (2) the total building occupancy reaches maximum gradually, rather than sharply under a fixed schedule; (3) during the working time, the total occupancy varies due to the movement of occupants. Such a workday process changes at every simulation, which is understood as random in everyday life.

3.3.2 Zone occupancy

Figures 14, 15, 16, 17, 18 and 19 show the changes of number of occupants in office 1, office 2, office 3, office 4, corridor 5, and restroom 6 over a workday, where (a) is the result of zone occupancy for one simulation, (b) illustrates the maximum, minimum, and average occupancy for each time step from all the simulations, (c) shows the hourly occupancy results. It can be seen that due to the movement

of occupants from one space to another, the occupancy of zones inside the building stochastically change in time, more or less than the design value. Although the absence probability for each occupant out of his office (i.e., the probability of staying in other spaces) is as small as 0.1, the resulted occupancy variation is remarkable and should not be neglected in building energy simulation. Due to the scheduled meeting, the occupancy in offices 1, 2, and 4 change a lot during the meeting period.

Hour

(d) Hourly occupancy in the whole building

Since the occupancy model is based on the process of occupant movement, the relationships of stochastic occupancy in multiple zones are realistically taken into account. This results in the reasonable occupancy distribution in space, that is, an increase of occupancy in one space usually means a decrease of occupancy in another space while the



Office 2

Max

Min

Min

Average

Average



Fig. 14 Office 1's occupancy over a workday

Fig. 15 Office 2's occupancy over a workday



Fig. 16 Office 3's occupancy over a workday



Fig. 17 Office 4's occupancy over a workday



Fig. 18 Corridor 5's occupancy over a workday

Fig. 19 Restroom 6's occupancy over a workday

total occupancy stays the same. From the simulation results, the occupancy of corridor and restroom are strong coupled with the occupancy of offices and their variations are more significant in time. Even for the spaces with similar function type, the transient occupancy schedules from office 1 to office 4 are not synchronous at each time step (see Fig. 20). Such an uneven distribution of occupancy in space and nonsynchronous change in time would affect the performance evaluation of HVAC systems in simulation.

In general, the stochastic occupancy over a typical workday in an office building can be realistically produced by using the proposed model. Further analysis of simulation results can be made for exploring the validation approach of the model in the future.

4 Conclusions

Building occupancy is a key factor to accurately predict building energy consumption and evaluate the energy saving potential of occupancy-based control system and the performance of HVAC systems. However, it is hard to represent due to its temporal and spatial stochastic nature.

This paper presents a novel approach for occupancy simulation based on the homogeneous Markov chain. In this study, occupancy is handled as the straightforward result of occupant movements among the inside and outside spaces of a building. By using the Markov chain method to simulate the stochastic movement process, the model can generate the location for each occupant and the occupancy for each



Fig. 20 Four offices' occupancy over a workday

zone of the building. Through this approach, the Markovian property of the state of occupant location is retained, which is validated by other experiments, and the relationships of stochastic occupancy in multiple spaces are realistically taken into account. By using the event mechanism, this model is capable of covering most things that affect the occupancy variation in a building and capturing the movement differences of different types of occupants as well.

From the case study of an office building, it can be seen that the model can produce the realistic occupancy variations in the office building for a typical workday with key statistical properties of occupancy such as the time of morning arrival and night departure, lunch time, periods of intermediate walk-around, etc. Especially, it can produce the nonsynchronous change of occupancy in time and the uneven distribution of occupancy in space, which can distinctly affect the performance evaluation of HVAC systems in a simulation.

The model is simple, clear and has no explicit or implicit constraint with the number of occupants and the number of zones. On the strict mathematical basis of geometric distribution, the model builds the relations of the statistical indices of building occupancy such as mean time of morning arrival and night departure, long-run proportion of time and expected sojourn time. Thus it overcomes the issue of specifying the transition matrix for multi-zone scenarios and maintains a simple, clear set of input parameters. In terms of simplicity, accuracy and unrestraint, this model is sufficient and practical to simulate occupancy for building energy simulations and stochastic analysis of building HVAC systems.

The occupancy model's assumption that the location of an occupant due to movement has a Markovian property is supported by some experiments for single offices but more validations need to be carried out in the future. More events such as short visits should be taken into account in office building to capture the stochastic occupancy variations. From a practical point of view, a simple validation and calibration approach needs to be proposed. The capability of the model in other types of buildings, such as residential buildings, should also be tested and calibrated with specific occupant movement patterns.

Acknowledgements

This project is financially supported by the National Natural Science Foundation of China (No. 51008176), the Specialized Research Fund of the Doctoral Program of Higher Education of China (No. 20100002120014), and Tsinghua University Initiative Scientific Research Program (No. 2009THZ0).

References

- Crawley DB, Lawrie LK, Winkelmann FC, Buhl WF, Huang YJ, Pedersen CO, Strand RK, Liesen RJ, Fisher DE, Witte MJ, Glazer J (2001). EnergyPlus: Creating a new-generation building energy simulation program. *Energy and Buildings*, 33: 319 – 331.
- Davis JA, Nutter DW (2010). Occupancy diversity factors for common university building types. *Energy and Buildings*, 42: 1543 1551.
- DeST (2008). DeST-c User Manual. DeST Group, Tsinghua University, China.
- Dodier RH, Henze GP, Tiller DK, Guo X (2006). Building occupancy detection through sensor belief networks. *Energy and Buildings*, 38: 1033 1043.
- EnergyPlus (2009). Input/Ouput Rerference, Version 4.0 Documentation. University of Illinois and Ernest Orlando Lawrence Berkeley National Laboratory, USA.
- ESRU (1999). ESP-r: A building and plant energy simulation environment, User Guide Version 9 Series. ESRU Publication, University of Strathclyde, Glasgow.
- Goldstein R, Tessier A, Khan A (2010). Schedule-calibrated occupant behavior simulation. In: Proceedings of the Symposium on Simulation for Architecture and Urban, Orlande, USA.
- Klein SA, Beckman WA, Mitchell JW, Duffie JA, Duffie NA, Freeman TL, Mitchell JC, Braun JE, Evans BL, Kummer JP, Urban RE, Fiksel A, Thornton JW, Blair NJ, Williams PM, Bradley DE, McDowell TP, Kummert M (2004). TRNSYS 16—A transient system simulation program, User manual. Solar Energy Laboratory, University of Wisconsin-Madison.
- Liao C, Lin Y, Barooah P (2011). Agent-based and graphical modelling of building occupancy. *Journal of Building Performance Simulation*, doi: 10.1080/19401493.2010.531143.
- Macdonald I, Strachan P (2001). Practical application of uncertainty analysis. *Energy and Buildings*, 33: 219 227.
- Page J, Robinson D, Morel N, Scartezzini JL (2008). A generalized stochastic model for the simulation of occupant presence. *Energy* and Buildings, 40, 83 – 98.
- Ross SM (1996). Stochastic Processes, 2nd Edn. John Wiley & Sons, Inc.
- Sheng Z, Xie SQ, Pan CY (2008). Probability and Mathematical Statistics, 4th Edn. Beijing: Higher Education Press. (in Chinese)
- Tabak V (2008). User simulation of space utilisation: system for office building usage simulation. PhD Thesis, Eindhoven University of Technology, Netherlands.
- Wang D, Federspiel CC, Rubinstein F (2005). Modeling occupancy in single person offices. *Energy and Buildings*, 37: 121 – 126
- Yan D (2005). HVAC system simulation and analysis based on uncertain inner heat gains. PhD Thesis, Tsinghua University, China.
- Yan D, Xia J, Tang W, Song F, Zhang X, Jiang Y (2008). DeST—An integrated building simulation toolkit, Part I: Fundamentals. *Building Simulation*, 1: 95 – 110.
- Zhang X, Xia J, Jiang Z, Huang J, Qin R, Zhang Y, Liu Y, Jiang Y (2008). DeST—An integrated building simulation toolkit, Part II: Applications. *Building Simulation*, 1: 193 – 209

Quantitative description and simulation of human behavior in residential buildings

Chen Peng, Da Yan (🖂), Ruhong Wu, Chuang Wang, Xin Zhou, Yi Jiang

Department of Building Science, School of Architecture, Tsinghua University, Beijing 100084, China

Abstract

An in-depth understanding of building energy use requires a thorough understanding of human behavior. This research gives a quantitative description of human behavior in residential buildings. This quantitative description method can be used to forecast the impact of the human behavior on the indoor building environment and energy use. Human behavior influences the energy use directly and indirectly by changing window openings, air-conditioner usage, lighting, etc. This quantitative description method describes these behavioral effects. Behavior can be divided into several types according to the usage with time related, environmentally related and random modes used to quantitatively describe the behavior. The method is then applied to describe a Beijing household with comparison to on-site observations of the resident's behavior and measurements of energy use to validate the method. The results show that the human behavior in the real world can be quantified by the quantitative description method. These simulation tools can greatly facilitate building energy conservation by describing the influence of human behavior on building performance and energy use.

1 Introduction

Human behavior greatly influences building energy use by the way people move, use equipment, open or close windows, building system (e.g., air-conditioning systems and lighting systems) control by the property management personnel and automatic controls. These actions directly and indirectly affect energy use (e.g., electricity, gas, and water). Li et al. (2006) reported that there are significant differences in energy use among different apartments in the same residential building in Beijing. The human behavior such as airconditioning operating times, temperature set points, and window opening/closing habits are quite different with these behavioral differences causing large differences in the electricity use by cooling systems in the same residential building, from 0 to 14.3 kWh/m² with average of 2.3 kWh/m².

Scientists began studying the relationship between human behavior and energy use around 1980s. Sociological models of human behavior were developed, showing that the socialcultural environment, the building and design requirements

E-mail: yanda@tsinghua.edu.cn

Keywords

human behavior, behavioral object, energy use, lifestyle model, time related, environmentally related, random

Article History

and the local climate affected both household lifestyles and

energy use. Technical progress and social change also

Received: 15 April 2011 Revised: 6 August 2011 Accepted: 6 September 2011

© Tsinghua University Press and Springer-Verlag Berlin Heidelberg 2011

influence human behavior (van Raaij and Verhallen 1983; Hitchcock 1993). Further research established that usage times of some appliances, such as washing machines and bathroom heaters, change with the seasons. The average number of household members, their age, and their time spent at home are all factors closely related to energy use in residential buildings (Ouyang et al. 2007). An IEEA study showed that the average operating time of appliances in Europe varied in different countries, which is useful for energy use calculations, but does not describe the human behavior influence on energy use (IEEA 2008). There have also been studies of the interactions between human behavior and building energy use (Mahdavi 2007). The influence of human behavior on building energy use is now a hot issue at

As computer simulations have improved, these tools are being used more to analyze human behavior. Recent research (Hoes et al. 2009) has shown that human behavior

the Annex 53(2010).

can be divided into groups based on the complexity and desired resolution. The information used for building models includes averaged, minimum and maximum values of various parameters. Models considering interactions between energy use and the environment are more complex. Bourgeois (2005) did a comprehensive study of human behavior in buildings and focused on behavior prediction and advanced behavioral modelling. Korjenic and Bednar (2011) found that the lifestyle and occupants' living standard are the mainly reason for the discrepancy between the calculated and measured energy use from the investigation.

Some researchers have used simulations to model certain kinds of behavior in buildings, such as a window opening and appliance usage (Rijal et al. 2007; O'Doherty et al. 2008; Nicol 2001; Reinhart 2004). Yun and Steemers (2008) developed stochastic models to predict window-opening behavior patterns as a function of the indoor temperature, the time of a day and the previous window state through the field study in offices in UK.

Existing building energy simulation software packages pay more attention to the effects of climate, building envelope, systems and equipment than the occupant's actions (Crawley et al. 2001; EnergyPlus 2009; ESRU 1999; Klein et al. 2004; Yan et al. 2008; Zhang et al. 2008). Currently, human behavior



Fig. 1 Factors influencing building energy use

is mostly described by schedule definition, which does not reflect the actual human behavior complexity. The difference between real test data and simulation results is due to human behavior in actual complex situations. Human behavior includes system operation and management, occupant behavior, and indoor environment conditions. These factors work together to influence the building energy use as shown in Fig. 1.

A general relationship between human behavior and building energy use is needed to quantitatively analyze the influence of human behavior. The relationships between buildings and humans are based on three key points as shown in Fig. 2 which was developed to describe human behavior under study.

(1) Ideology to behavioral principles;

(2) Human physiological, psychological and economics feelings;

(3) Impact of human behavior on building energy use.

Different ways are used to classify human behavior depending on the field. This study focuses on the impact of human behavior on building energy use by quantitatively analyzing the influence of human behavior. A human behavior model is constructed for a building simulation software package. This paper includes a comprehensive definition of the quantitative description method including the classification of human behavior and the definition of the ranges of human behavior in a residential building, with a detailed case study to help understand the method.

2 Quantitative description method

2.1 Human behavior classification and description

Different kinds of human behavior lead to great differences in energy use, which is affected by several factors: time, environment, psychology, economic, etc. A quantitative description of human behavior requires that the factors be quantifiable (can be numerically described) and measurable (can be physically measured).



Fig. 2 Relationship between humans and buildings

The two kinds of factors that can be used to quantitatively describe behaviors are time and environment. According to the investigation and discussion above, human behavior in buildings can generally be divided into three categories (Table 1):

(1) time related: actions according to time;

(2) environmentally related: actions to achieve a certain control objective, depending on the environment;

(3) random: actions that depend on uncertain factors or something not quantifiable.

Table 1 Quantitative description method

Туре	Input	Parameters	
Time related	Schedule	Set value	
Actions are based on a speci AC set temperature	the set value, such as the		
Environmentally related	Logic form	Feedback parameters	
Some parameters such as the temperature, are controlled based on logi with specified parameters used with feedback to implement the action			
Random	Frequency or range		
Actions are not regular or may follow unknown or complex rules			

A quantitative human behavior description requires three steps as shown in Fig. 3. First, the object related to the behavior must be identified. Second, investigations are used to classify the behavior and identify which parameters need to be measured, such as hourly TV power and indoor temperatures. Data analysis is then used to describe the human behavior.





Fig. 3 Quantitative description flow chart

Some actions are long life habits, such as opening windows for ventilation. Some adapt to new environments or conditions, such as the use of new electrical equipment. The three human behavior modes can be used to quantitatively describe both human actions in residential buildings, as shown in Table 2 to Table 4.

Human behavior tends to vary periodically in buildings due to the influences of day and night, workdays, weekends and season. Thus, human behavior models need to pay attention to the time period.

2.2 Case study examples

Typical human behavior was investigated with measurements in a residential building in Beijing for the floor plan shown in Fig. 4. The household information is shown in Table 5. The detailed information is in the Electronic Supplementary Material of this paper. There were several face-to-face studies of the behavior of each person in the family. Heat sensors were put in each room to measure the room temperature with power meters used to measure the power used by the appliances, as shown in Table 6. The measurements lasted

Behavioral object	Schedule	Set value		
Window	0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23	On / off		
Example: a housewife, as long as t	he weather conditions are suitable, opens the window for fresh air for an hour every	day from 8: 00 a.m. to 9:00 a.m.		
TV	0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23	On / off		
Example: an office worker turns o	n the TV after work at about 7:00 p.m., turns it off at 11:00 p.m.			
Table 3 Environmentally related mode examples				
Behavioral object	Logic form	Feedback parameters		
Air-conditioner	If FP>29 $^\circ$ C, then turn on with a set value of 26 $^\circ$ C, otherwise keep closed Action time: 19:00 – 24:00 in the summer	FP: indoor temperature		
Example: a resident turns on the air-conditioner when he feels hot at a temperature of about $29^\circ \! \mathbb{C}$				
Lights	If FP<100 lx, then turn on, otherwise turn offFP: interior illuminatAction time: 19:00 – 23:00 annualFP: interior illuminat			
Example: a resident turns on the living room lights when he feels dusky, the illumination is about 100 lx				

Note: 1. Feedback parameters (FPs) must be measurable: for example, temperature, luminance, and concentration of carbon dioxide.

2. The air-conditioning set value is a kind of behavior parameter that must be measured or investigated.

Behavioral object	Frequency	Duration		
Washing machine	2 times/week	1 hour/cycle		
Example: washing machine is used twice a week and each cycle lasts about 1 hour				
Lights 5 times/day 10 min/cycle				
Example: lights in the bathroom are turned on about	t 5 times a day for about 10 minutes each time			





Fig. 4 Household floor plan

Table 5 Household information

	Number	Note
People	5	One couple, a grandmother, a son and a maid
TV	4	Located in the living room, master bedroom, bedroom 1, bedroom 3
Air-conditioner	4	Located in the living room, master bedroom, bedroom 1 and bedroom 2
Computer	1	Located in the master bedroom
Washing machine	1	Located in the kitchen
Refrigerator	1	Located in the kitchen

Table 6 Measuring instruments



for 10 days during the summer, 2010 and 1 month during the winter, 2011. Both instruments were connected to a computer to record and store data.

The real life human activities were divided into the three modes defined in Table 1. The measured data was used to classify the actions.

2.2.1 Time related mode

The investigation showed that the TV usage in bedroom 1 was time related. The usage schedule was found by surveying all members of the household which showed that the occupants of this room usually watched TV three times per day. The power data for June, 2010 and January, 2011 showed that the TV in bedroom 1 was used about 4 hours a day as shown in Fig. 5. The usage times and durations changed a little each day.

The TV usage probability in Fig. 6 shows that the TV is generally used in three time periods from morning to noon, during the afternoon, and at night. The behavior was generalized by the behavior model to quantitatively describe this behavior.

The duration of each period was then calculated from measured data with the duration T, chosen equal to the mathematical expectation for each time period. The start times were selected so that the model periods spanned the largest probability times. Thus, the TV usage time periods in bedroom 1 were then calculated as

$$T = \sum_{i}^{n} x_{i} P_{i}$$

where, x_i : time step, chosen as 1 minute which was the data measurement rate; P_i : usage probability for each time step from the measurements.

Besides the TV usage in bedroom 1, the TV usage in bedroom 3, the AC usage in bedroom 2 and the refrigerator operation were all time related while the AC usage in the master bedroom was environmentally related.

 The refrigerator is on every day, so the probability during each time step was 1 and

$$T = \sum xP = \sum x \times 1 = 24$$

- The AC power usage in bedroom 2 is shown in Fig. 7. The occupant stated that he would turn on the AC once he arrived home and would turn it off when he left. The power usage in Fig. 7 shows the times the resident was at home from the investigation as the green line. The red line is the AC power and the blue line is the indoor temperature. The resident left home at about 7 a.m. and returned at about 3 p.m. The AC power usage then follow this trend,



Fig. 5 Daily TV usage in bedroom 1 (time related)

being on when he was at home and off when he left. This behavior is also described as $T = \sum xP$ where *P* is the probability the resident is at home.

The time related behavior is implemented as

(1) the actions take place at fixed intervals (day, week),

(2) the usage time in each period is the same or nearly the same.



Fig. 6 Usage model for bedroom 1 TV

The behavior schedule is obtained by investigations or measurements. For example, the probability of using the AC or opening windows can be obtained from measured data while the amount of time a person spends at home can be determined through a survey.

2.2.2 Random mode

There were four TVs in the household. The electric used by these TVs was about 1.5 kWh/day, about 20% of the total household electric use. The people reported that the TV usage in the master bedroom was random. The survey showed that the watching TV frequency was approximately once per day with 1 hour per instance on workdays and 2 hours per instance on weekends. The measurements in Fig. 8 show that the occupant does not use the TV every day but the TV is used for more than 4 hours as some days with no clear pattern in the master bedroom.



Fig. 7 AC usage in bedroom 2



Fig. 8 Daily TV usage in the master bedroom (random action)

A statistical analysis showed that the TV in the master bedroom is used an average for one and a half hour a day. Analysis of the behavior probability showed that the resident mostly watches TV between 19:00 and 24:00 (Fig. 9). The random behavior was then characterized by a 1.5 hours period per day.

The Random mode represents complex behavior related to uncertain factors. This information can be obtained only by observing their actions and the cycle of behavior depends on the kind of object. More study is needed about this kind of human behavior.

2.2.3 Environmentally related mode

The investigation showed that the AC usage in the master bedroom was environmentally related as a function of the



Fig. 9 Random action time scales for the master bedroom TV

indoor temperature. The occupant survey showed that they turned on the AC when they felt hot, which they estimate corresponded to an indoor temperature of 29°C and they preferred to set the AC to 26°C.

The feedback and set values (the temperatures) were then found by measuring the indoor temperature and the power usage. As shown by the orange line in Fig. 10, the feedback temperature was 29° C which means that when the resident are active, once the indoor temperature is over 29° C, they will turn on the AC. The measured set temperature was 27° C, which differed from the survey estimate.

As shown in Fig. 11, the two important parameters for the environmentally related mode are the feedback value and the set value. When the temperature exceeds to the feedback value, t_1 , the occupants turn on the AC and set the temperature to t_2 . Thus, this kind of action requires two values to describe the behavior.

The environmentally related mode assumes that:

(1) Behavior is influenced by environmental factors such as temperature or luminance.

(2) The key factors can be measured.

(3) The feedback logic can be described mathematically.

The feedback logic describes a relationship between the environmental factors and the behavior that is seen in the measured data; thus, the environmental parameters and the



Fig. 10 Master bedroom AC usage and temperature variations (environmentally related)


Fig. 11 Environmentally related AC usage behavior

behavior must be measured simultaneously. For example, the temperature and AC power usage must be measured together to analyze the environmentally related AC behavior.

2.3 Quantitative description of the residential building

2.3.1 Physical description

Research on human behavior in buildings seeks to analyze the behavioral influence on the building energy use. The behavioral impact on building energy use is both indirectly and directly related to the building elements such as windows, shades and appliances. Thus, the term "objects" refers to the building elements and the equipment related to energy use which can be controlled by the occupants.

A change in an object's state reflects the human behavior in the building, with the initial conditions in the simulations based on a set of object states. A building-human behavioral model is based on description of the quantitative changes of an object's state. Model simulations are then an effective, scientific way to analyze human behavior in buildings. The objects included in this study are described in Table 7.

2.3.2 Residential building description

Objects are chosen to quantitatively describe the three

 Table 7 Residential building objects

Туре	Description
Building envelope	Adjustable elements, such as windows, curtains and shades
Air conditioning	Equipment or system to keep the air cool and dry
Heating system	Equipment or system to warm the air
Ventilation system	Mechanical system in a building to provide fresh air
Lighting	Artificial sources of visible illumination
Hot water equipment	Supply hot water for bathing, washing, drinking, cooking, etc.
Office appliances	Appliances related to work, such as computers, printers, projectors
Domestic appliances	Appliances for household activities
Elevator	Elevators for transporting people or goods
Others	System services for security, fire control, etc.

different kinds of human behavior. Since each kind of behavior is linked to a certain object, the object is used to describe each kind of behavior. For example, a TV is used to provide a quantitative description of the watching TV behavior.

Human behavior in residential buildings is far more than just interactions with objects. Each family unit in a residential building is defined as a household. There are then many different objects in each room, such as windows, air-conditioners and lamps, which are controlled by people with different action modes in the household which can be functions of the types and positions of the objects in the building.

A lifestyle describes people's own behavioral habits at home, for example, AC use in the summer, opening of windows for ventilation, and washing clothes frequencies. The sum of all the object related behavioral habits in a residence constitute a lifestyle. A lifestyle model is built based on the quantitative description to describe the human behavior in the household.

3 Energy consumption simulations for different lifestyles

3.1 Lifestyle model

The lifestyles in buildings are affected by many factors. Lifestyles can be divided into the three types listed in Table 8 based on differences in life paradigms, professions, economic conditions, etc.

3.2 Quantitative human behavior simulations

Human behavior in residential buildings can be summarized based on the typical lifestyles described in Table 8. The time spent at home will affect the AC usage. While there may be some differences between two families having the same

Table 8 Typical lifestyles in China

Lifestyle	Feature	Example
Energy conscious lifestyle (EC)	People who consider energy consumption to be important will pay more attention to saving electricity, gas, water, etc. in their daily lives. Their actions in the building will seek to use as little energy as possible	Older families, low-income families
Habit related lifestyle (HR)	People who are less concerned about saving energy than living a energy conscious lifestyle	Most white collar families
High quality lifestyle (HQ)	People who have a high demand for indoor environmental quality	Rich and young families

lifestyle mode, the main features of their behavior patterns will be the same. Therefore, one typical family for each lifestyle will be used as examples to build the lifestyle model.

The lifestyle models were built using DeST, a building energy simulation program developed by Tsinghua University (DeST 2008). A special version for human behavior called DeST-m is being developed that includes human behavior as an important input parameter along with the building elements and equipment.

The lifestyle behavior model includes the four layers of action model, object, room and household. The building model in DeST for a residential building in Shanghai chosen for simulation is shown in Fig. 12. The detailed inputs of lifestyles are in the Electronic Supplementary Material of this paper.

The human behavior in the building is then summarized by the household lifestyle. The analysis considers one household in the building.

The human behavior greatly impacts the building environment and energy use. For example, the AC usage times and set temperatures are controlled by the resident. The AC usage for different lifestyles is described in Table 9.

Simulation results for four typical days (two work days and two off days) in the summer of the three kinds of lifestyle are shown in Table 10 for the AC usage, indoor temperature and household load. The AC usage for the energy conscious lifestyle family is the shortest. The temperature during the weekend for the high quality lifestyle family is controlled at 24 $^{\circ}$ C, which results in the highest energy use of the three kinds of lifestyles during these four days.

The different lifestyles result in the different AC usage times and electrical consumption due to differences in the set temperatures as shown in Fig. 13. The household electricity use for all parts of the residence is shown in Fig. 14.

The different lifestyles result in sharp differences in building performance and energy use. In the case of the energy conscious lifestyle, the residents try to save energy and may endure an uncomfortable living environment. They care about how much energy they consume, reducing electric appliance usage by only turning on the AC when they feel really hot. Families with habit related lifestyle will operate objects in the way they think is suitable. Sometimes they will regulate the objects state according to the environment and sometimes they change their habits because of a work schedule change. People with high quality lifestyle consume a great amount of energy to control their living environment. They use the AC and lighting all the time when in the house. The electricity consumption of the household appliances and lighting then are also quite different. Since the high quality lifestyle object usage time is the longest for most appliances (such as the TV, PC and washing machine), their energy use levels are larger than the other two kinds of family lifestyles.



Fig. 12 A six floor residential building model in Shanghai in DeST

 Table 9 AC usage and set temperature for the different lifestyles

Lifestyle	Summer	Winter
EC	If $T_{in}>30$ °C, then turn on, otherwise off Action time: 15:00 – 18:00 in August Set temperature: 28 °C	If $T_{in} < 16$ °C, then turn on, otherwise off Action time: 15:00 – 18:00 in January Set temperature: 18 °C
HR	If $T_{in}>28$ °C, then turn on, otherwise off Action time: set by resident Set temperature: 26 °C	If $T_{in} < 18$ °C, then turn on, otherwise off Action time: set by resident Set temperature: 20 °C
HQ	Work day 01234567891011121314151617181920212223 Off day 01234567891011121314151617181920212223 Set temperature: 24°C	Work day 011234567891011121314151617181920212223 Off day 011234567891011121314151617181920212223 Set temperature: 22°C



Table 10 Impact of different AC usage modes on the room temperature and household load



Fig. 13 Annual AC electrical consumption for different lifestyles



Fig. 14 Annual household electrical consumption for different lifestyles

There are many different kinds of lifestyles besides those listed in this study. The three lifestyles used in this study are typical lifestyles in China. There may be differences in families within the same lifestyle, but they have key common behavioral characteristics. This means that people's behavior in the building can be divided into several categories, each with their own characteristics. We can then model their behavior based on family lifestyles. Additional typical lifestyles are being currently studied in real situations for future work.

4 Conclusions

Human behavior greatly impacts building performance and energy use. Quantitative descriptions of human behavior are then a prerequisite for analyzing and forecasting a person's impact on the building performance and energy use.

This research presents a quantitative description method to define and quantify human behavior. The factors used for the quantitative description should be able to be numerically described and physically measured, such as times and temperatures. Objects usages are divided into a time related mode, an environmentally related mode and a random mode to describe individual human behavior in a residential building by analyzing actual usage. These modes are defined based on key behavioral factors and can be formulated in simulation tools for energy usage analyses of residential buildings.

To make the simulations more workable, human behavior is classified into a relatively small set of typical lifestyles. Each of these lifestyles represents the typical behavior of a certain group of people. Simulations then show that different lifestyles significantly change the building performance and energy use. Other lifestyles will be identified based on investigations and measurements of human behavior in a residential building in future work. Much research still needs to be done to fully understand human behavior in buildings. There is an emerging need to combine quantitative descriptions of human behavior with building simulations to help understand and forecast real building energy use based on on-site measurements and simulations. More case studies will be done to fully optimize the quantitative description method.

Acknowledgements

This project is financially supported by the National Natural Science Foundation of China (No. 51008176), the Specialized Research Fund of the Doctoral Program of Higher Education of China (No. 20100002120014), and Tsinghua University Initiative Scientific Research Program (No. 2009THZ0).

Electronic Supplementary Material: Supplementary material (case study of human behaviors in a household and the examples of the three types of lifestyles) is available in the online version of this article at http://dx.doi.org/10.1007/s12273-011-0049-0.

References

- Annex 53 (2010). Total energy use in building—Analysis and evaluation methods. IEA Energy Conservation in Building and Community Systems Programme, www.ecbcsa53.org.
- Bourgeois DJ (2005). Detailed occupancy prediction, occupancy-sensing control and advanced behavioral modelling within whole-building energy simulation. Ph D Thesis, l'Université Laval, Québec.
- Crawley DB, Lawrie LK, Winkelmann FC, Buhl WF, Huang YJ, Pedersen CO, Strand RK, Liesen RJ, Fisher DE, Witte MJ, Glazer J (2001). EnergyPlus: Creating a new-generation building energy simulation program. *Energy and Buildings*, 33: 319–331.
- DeST (2008). DeST-c User Manual. DeST Group, Tsinghua University, China. (in Chinese)
- EneryPlus (2009). Input/Output Rerference, Version 4.0 Documentation. University of Illinois and Ernest Orlando Lawrence Berkeley National Laboratory, USA.
- ESRU (1999). ESP-r: A Building and Plant Energy Simulation Environment, User Guide Version 9 Series. ESRU Publication, University of Strathclyde, Glasgow.
- Hitchcock G (1993). An integrated framework for energy use and behavior in the domestic sector. *Energy and Buildings*, 20: 151–157.
- Hoes P, Hensen JLM, Loomans MGLC, de Vries B, Bourgeois D (2009). User behavior in whole building simulation. *Energy and Buildings*, 41: 295–302.
- IEEA (2008). Residential monitoring to decrease energy use and carbon emissions in Europe.

- Klein SA, Beckman WA, Mitchell JW, Duffie JA, Duffie NA, Freeman TL, Mitchell JC, Braun JE, Evans BL, Kummer JP, Urban RE, Fiksel A, Thornton JW, Blair NJ, Williams PM, Bradley DE, Mcdowell TP, Kummert M (2004). TRNSYS 16—A transient System Simulation Program, User Manual. Solar Energy Laboratory, University of Wisconsin-Madison.
- Korjenic A, Bednar T (2011). Impact of lifestyle on the energy demand of a single family house. *Building Simulation*, 4: 89 95.
- Li Z, Jiang Y (2006). Characteristics of cooling load and energy consumption of air conditioning in residential buildings in Beijing. *Heating Ventilating & Air Conditioning*, 36(8): 1–6. (in Chinese)
- Mahdavi A, Lambeva L, Mohammadi A, Kabir E, Pröglhöf C (2007). Two case studies on user interactions with buildings' environmental systems. *Bauphysik*, 29: 72–75.
- Nicol JF (2001). Characterising occupant behaviour in buildings: Towards a stochastic model of occupant use of windows, lights, blinds, heaters and fans. In: Proceedings of IBPSA Building Simulation Conference and Exhibition (pp. 1073 – 1078), Rio de Janeiro, Brazil.
- O'Doherty J, Lyons S, Tol RSJ (2008). Energy-using appliances and energy-saving features: Determinants of ownership in Ireland. *Applied Energy*, 85: 650–662.
- Ouyang JL, Gao JL, Luo XY, Ge J, Hokao K (2007). A study on the relationship between household lifestyles and energy consumption of residential buildings in China. *Journal of South China University of Technology (Natural Science Edition)*, 35(z1): 171–174. (in Chinese)
- Reinhart CF (2004). Lightswitch-2002: A model for manual and automated control of electric lighting and blinds. *Solar Energy*, 77: 15–28.
- Rijal HB, Tuohy P, Humphreys MA, Nicol JF, Samuel A, Clarke J (2007). Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings. *Energy and Buildings*, 39: 823 – 836.
- van Raaij WF, Verhallen TMM (1983). A behavioral model of residential energy use. Journal of Economic Psychology, 3: 119 – 143.
- Yan D, Xia J, Tang W, Song F, Zhang X, Jiang Y (2008). DeST—An integrated building simulation toolkit Part I: Fundamentals. *Building Simulation*, 1: 95 – 110.
- Yun GY, Steemers K (2008). Time-dependent occupant behavior models of window control in summer. *Building and Environment*, 43: 1471 – 1482.
- Zhang X, Xia J, Jiang Z, Huang J, Qin R, Zhang Y, Liu Y, Jiang Y (2008). DeST—An integrated building simulation toolkit Part II: Applications. *Building Simulation*, 1: 193 – 209.

Statistical analysis and modeling of occupancy patterns in open-plan offices using measured lighting-switch data

Wen-Kuei Chang¹, Tianzhen Hong² (🖂)

1. Green Energy and Environment Laboratories, Industrial Technology Research Institute, Taiwan, China 2. Environmental Energy Technologies Division, Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA 94720, USA

Abstract

Occupancy profile is one of the driving factors behind discrepancies between the measured and simulated energy consumption of buildings. The frequencies of occupants leaving their offices and the corresponding durations of absences have significant impact on energy use and the operational controls of buildings. This study used statistical methods to analyze the occupancy status, based on measured lighting-switch data in five-minute intervals, for a total of 200 open-plan (cubicle) offices. Five typical occupancy patterns were identified based on the average daily 24-hour profiles of the presence of occupants in their cubicles. These statistical patterns were represented by a one-square curve, a one-valley curve, a two-valley curve, a variable curve, and a flat curve. The key parameters that define the occupancy model are the average occupancy profile together with probability distributions of absence duration, and the number of times an occupant is absent from the cubicle. The statistical results also reveal that the number of absence occurrences decreases as total daily presence hours decrease, and the duration of absence from the cubicle decreases as the frequency of absence increases. The developed occupancy model captures the stochastic nature of occupants moving in and out of cubicles, and can be used to generate a more realistic occupancy schedule. This is crucial for improving the evaluation of the energy saving potential of occupancy based technologies and controls using building simulations. Finally, to demonstrate the use of the occupancy model, weekday occupant schedules were generated and discussed.

Keywords

building simulation, occupancy model, occupancy pattern, occupant schedule, office buildings, statistical analysis

Article History

Received: 10 October 2012 Revised: 19 December 2012 Accepted: 25 December 2012

© Tsinghua University Press and Springer-Verlag Berlin Heidelberg 2013

1 Introduction

Building energy simulation tools have been widely applied in recent years in energy saving proposals for new construction designs and existing building retrofits. However, simulated results sometimes deviate significantly from measured data. Such discrepancies can be attributed to several factors. One of the most important is occupant behavior in buildings. Many studies demonstrate that building occupancy profiles have a significant impact on energy use and the operational controls of buildings. An investigation into the impact of consumer behavior on residential energy demand found that consumer behavior is the most important issue with respect to energy consumption in households (Haas et al. 1998). A simulation of user behavior for the low energy office building design process, which applied a statistical method, found that realistic user behavior should be incorporated into passive cooling design concepts (Pfafferott and Herkel 2007). A methodology that takes into account the variation in occupant behavior and schedules was proposed to estimate the cooling demand in residential units (Tanimoto et al. 2008). Its authors concluded that occupant behavior is a significant factor in residential cooling requirements, though the methodology needs further validation to confirm its plausibility.

Various modeling approaches have been developed for use in building energy performance simulations to predict occupancy characteristics in different types of buildings. A stochastic user behavior model generates a time series of window operations by using Markov chains (Fritsch et al. 1990). However, the lack of adequate measurements makes computing the Markov matrices impossible. The use of stochastic models to capture human behavior and occupant interaction within a building attempts to simulate multiple influences that occupants can have on a building in terms of resource consumption (Page et al. 2008). The results sometimes overestimate and other times underestimate the weekly total energy use and peak demands. A model that combines user presence and interaction in a building showed that improved modeling of user behavior in numerical simulations can optimize overall building performance (Hoes et al. 2009). A model of activity and location schedules was developed, using a system of USSU-User Simulation of Space Utilization, to generate movement patterns that provide a representation of human activities in office building spaces (Tabak 2008). However, there were obvious differences between the observed and predicted human activity behavior related to the number of times a workplace was used during a working day. A model based on Markov chains that simulates the movement of occupants inside an office building can produce more realistic occupancy variations, nonsynchronous change of occupancy in time, and an uneven distribution in space (Wang et al. 2011). However, more validation and calibration approaches must be carried out with specific occupant-movement patterns. Behavioral patterns associated with energy spent on heating were determined statistically, and household and building characteristics were identified (Santin 2011). It appears difficult to establish relationships between behavioral patterns and energy consumption.

Recent years have seen the introduction of systems and devices that can be controlled on a personal basis. These efforts to improve energy efficiency and increase energy savings include lighting, office equipment, thermostats for heating, ventilation, and air conditioning, windows, and blinds. Accurately estimating the savings and impacts of these systems and technologies requires the accurate prediction of how often and how long occupants stay in their offices. Therefore, the impact of occupancy profile on building energy performance becomes more important. The occupancy pattern defined in the present study is the frequency of an occupant leaving his/her cubicle and the corresponding duration of the absence. It is part of the broader occupant behavior which includes occupant's interactions with building envelope and energy systems. A method for obtaining realistic and stochastic occupancy is a key concern for building energy simulations, in order to precisely evaluate the performance of occupancy-based controls. Currently, most simulation tools apply fixed or predefined occupancy schedules to represent the time when occupants are present. However, occupancy pattern can change significantly according to the season, weather, time,

and personality. It is therefore not surprising that simulated energy use deviates from actual consumption in most situations. Although various occupancy models have been developed to predict occupancy profiles in buildings, they usually lack validation from adequate field-measured data.

This study uses statistical methods to analyze lightingswitch data collected from the open office spaces of an office building to identify variations in occupancy patterns. Various occupancy patterns and characteristics are identified, and a robust occupancy model is being developed to generate more realistic occupant schedules. The results of this study can be used to understand further and evaluate the impact of occupancy patterns on building energy performance, and to improve the accuracy of predicting the actual energy use of buildings with simulation tools.

2 Data collection

A total of 200 lighting-switch sensors were installed in open office cubicles on three floors of an office building. The numbers of switches installed on each floor are listed in Table 1. Each cubicle had a single, workstation-specific suspended fixture with a built-in occupancy sensor. The sensor detected occupant movement and controlled the lighting switch for each cubicle. The light was activated (switched on) if the cubicle was occupied, and deactivated (switched off) if unoccupied. All occupancy sensors were calibrated and control systems were commissioned before data were collected. The lighting control system recorded a daily log of sensor switch events, including the presence and absence of occupants, every five minutes. Switch events were recorded as 1 or 0, indicating the cubicle was occupied or unoccupied, respectively. In this study, each cubicle was assumed to be unoccupied until the occupant arrived for the first time in the morning. After the first occupancy event, the data was filled in with 1 or 0, based on the most recent event for each cubicle.

This study used data collected for weekdays, weekends, and holidays from May through November in 2011. In a small number of cases there may be some errors in the data due to sensor sensitivity and coverage. Switch sensors sometimes are triggered by people walking past cubicles, or fail to trigger if occupants remain overly static in their

 Table 1
 Number of lighting switches on three floors of an office building

Building floor	Number of switches	
Floor A	104	
Floor B	47	
Floor C	49	
Total	200	

cubicles. Although these cases cannot be excluded in this study, their occurrence is relatively infrequent and should not have a noticeable impact on the results. The collected data for weekdays were processed in parallel with data for weekends and holidays to provide a more accurate view of occupancy profiles. The goal was to obtain general occupancy trends and patterns for a large number of office cubicles to allow for comparisons across each floor. Data were processed for as many valid days as possible, including time periods during and after commissioning. Exclusions were made due to missing or incomplete switch data files and insufficient switch number information. Some days were excluded due to the control system going offline temporarily, which resulted in incomplete data collection. The final data used in this study includes 76 weekdays and 34 weekend days and holidays.

3 Analysis methods

Once the collected data were finalized, they were statistically analyzed to identify occupancy patterns during weekdays and weekends. The number of daily absences and their durations were determined, and the occupancy variations were distinguished.

The switch-on events were recorded every minute. Therefore, the presence duration of each occupant can be obtained by accumulating the number of switch-on events. The total monthly presence hours were calculated by adding up the daily presence hours. The average daily presence hours of each occupant were determined by dividing the total presence hours in each month by the number of datacollection days in that month. Thus, the profiles of occupant presence hours of the three floors were determined. Additionally, the daily occupancy profiles of each floor during weekdays and weekends were obtained by averaging the probabilities of switch-on events for each cubicle each month.

A total of 200 occupancy patterns of three floors are illustrated according to the probabilities of switch-on events. Different occupant's behavior results in different occupancy patterns. Based on the variations of each occupancy pattern curve, these 200 occupancy patterns were classified into five types: a single-square curve (Fig. 4(a)), a one-valley curve (Fig. 4(b)), a two-valley curve (Fig. 4(c)), a variable curve (Fig. 4(d)), and a flat curve (Fig. 4(e)). A valley was identified when the switch-on profile started to drop and then rise when the difference between the maximum and minimum switch-on percentage values exceeded 20%. A single-square curve occupancy pattern was defined if there wasn't a valley apparent from the switch-on profile. Similarly, the one-valley curve and two-valley curve occupancy patterns were defined if the valley occurred once or twice in the switch-on profile, respectively. Finally, the variable curve occupancy pattern was defined if the valley occurred twice or more. After all occupancy patterns were determined, the occurrence percentages of each occupancy pattern could be calculated by counting the frequency of each occupancy pattern for each floor. By accumulating the probabilities of the five patterns individually, and then dividing by the total number of each occupancy pattern, the average occupancy pattern was determined. Daily working hours were divided into four two-hour time periods. The occurrence times of each occupancy pattern for each time period on the three floors were collected to determine the occurrence percentages of each occupancy pattern, and the relationships between occupancy and working time period.

The number of daily absences and absence durations of each occupancy pattern were calculated to further understand the characteristics of each occupancy pattern. Switch-off events tracked when the occupant vacated the cubicle. Accumulating these events provided time and duration information and allowed further understanding of their relationship. According to the results, a noticeable valley usually occurred during noon in the occupancy patterns. Therefore, daily working hours were re-divided into three time periods: 8–11:30 a.m., 11:30 a.m.–1:30 p.m., and 1:30–6 p.m. The number of daily absences and absence durations in each time period were summarized to investigate when the valley occurred in the occupancy pattern.

4 Results

The profiles of occupant presence hours for each floor are shown in Fig. 1. The working time is divided into four periods, every two hours. The percentages of occupant presence hours for each floor were very different. For Floors A and C, most occupants, 40% and 31% respectively, stayed in their cubicles for 4 to 6 hours per day. Only a few occupants stayed over 6 hours. On Floor B, occupancy pattern was significantly different from Floors A and C. Most occupants, about 66%, on Floor B stayed in their cubicles for around 2 hours per day. There was no one staying for more than 6 hours. The average presence hours of Floor B were almost half those of Floors A and C. This may indicate that different agencies with different job categories work on different floors. The occupants of Floor B may work half-time, or work at home or outside the office part of the time. Therefore, a working occupant may not always be in his or her cubicle. Furthermore, this study observed that occupancy patterns were influenced slightly by the location of the cubicle. Longer occupancy periods occurred in more isolated cubicles that had more privacy, or cubicles that were near windows. However, job category may have more impact on occupancy pattern than location of the cubicle.



Fig. 1 Profile of presence hours for each floor: (a) Floor A; (b) Floor B; (c) Floor C

Unfortunately, private information like job category for each occupant was not available for this study.

The average daily weekday switch-on profile of each floor is shown in Fig. 2. In general, the occupants of each floor arrived at and departed from the office between 6 a.m. and 6 p.m. on weekdays. The switch-on percentage of each floor increased in the morning and reached a peak value at around 9 a.m. The maximum values of Floors A, B, and C are about 48%, 16%, and 32%, respectively. A higher switch-on percentage means higher occupancy. The increase in switchon rate of Floor A was greater than that of Floors B and C. Figure 2 also shows that the switch-on percentage of each floor has an obvious drop at around noon, attributed to occupants leaving the office for lunch. Also, it can be seen that the switch-off rate of Floor A is greater than that of the other two floors. The occupants of each floor began to leave work approximately between 3 p.m. and 4 p.m. Compared with the decrease in switch-on rate of Floors B and C, the decrease in switch-on rate of Floor A is greater. In addition, several spikes occurred after 6 p.m. This can be attributed to the cleaning crews in the evening. The cleaning schedules of Floors A, B, and C are 6:35 p.m. to 8 p.m., 5:05 p.m. to 6:30 p.m., and 9:25 p.m. to 10:50 p.m., respectively. The spikes occur within these time periods and the switch-on percentage of each floor is about 5%. As for weekends, the average daily profiles of switch-on events for each floor are shown in Fig. 3. Compared with the weekday profiles, the weekend switch-on percentages are quite low for all three floors. The switch-on percentage of Floor A was less than 3%



Fig. 2 The average daily weekday profile of switch-on events for each floor



Fig. 3 The average daily weekend profile of switch-on events for each floor

and for Floors B and C was almost equal to 0%. Therefore, this study only focuses on the investigation and analysis of data collected for weekdays.

The numbers of lighting-switch sensors installed on Floors A, B, and C were 104, 47, and 49, respectively. This led to 200 occupancy profiles. The collected occupancy profiles can be classified into five patterns by occupancy variation, presence duration in the cubicle, and occupant personality, as shown in Fig. 4. These occupancy patterns are very different from one another. In Fig. 4(a), the pattern looks like a single-square curve. The percentage of occupants stay in the cubicle is more than 60% within daily working hours except two time periods: one from 6 to 8 a.m. when occupants arrive at the office, and the other from 4 to 6 p.m. when occupants get off work. Figure 4(a) indicates that occupants leave their cubicles fewer times and with shorter duration during working hours. Alternatively, this pattern can be interpreted as the stationary time in which an occupant does not leave or enter their cubicle frequently. Several spikes occur after 6 p.m., the reason for which is discussed in our description of Fig. 3. Figure 4(b) shows an occupancy pattern similar to Fig. 4(a), except for an observable deep valley occurring at midday for a period of approximately 1 to 1.5 hours. This can result from the occupant leaving for lunch. The occupant leaves the cubicle after approximately 11:30 a.m. for lunch and then returns to the cubicle at approximately 1 p.m. This pattern can be interpreted as the occupant not leaving or entering the cubicle frequently, but leaving for lunch at midday. Figure 4(c) shows two



Fig. 4 The occupancy patterns: (a) single-square curve; (b) one-valley curve; (c) two-valley curve; (d) variable curve; (e) flat curve

noticeable valleys in this pattern. In addition to the valley that occurs around noon, another valley appears in the morning. This can be attributed to a longer absence by the occupant, such as attending a meeting or leaving the building. However, the valley observed in this study not only occurs in the morning but also in the afternoon (although it is not shown in Fig. 4(c)). Figure 4(d) shows a significant variation in the pattern. There is no regular pattern as with Figs. 4(a)–(c). This pattern shows the occupant leaving the cubicle frequently during work time and being absent for longer amounts of time. Figure 4(e) shows a flat occupancy pattern; the cubicle seldom appears occupied and the occupied duration is short. This can be attributed to a cubicle used

for public usage, such as a print station, coffee shop, or office supply room. This kind of pattern will not be discussed further in this study.

Based on the number of occupants on each floor in Fig. 2, the occupancy patterns of all occupants were further identified. Figure 5 shows occurrence percentages of each occupancy pattern for the three floors. The designations of Patterns 1 to 5 shown in this figure correspond to Figs. 4(a) to (e) as discussed above, and these designations will be further used in later discussion. Compared with Floor B, the occurrence percentages of each pattern are similar for Floors A and C. Pattern 2 is the most typical occupancy pattern, about 45% and 39% for Floors A and C, respectively.



Fig. 5 The occurrence percentages of each occupancy pattern: (a) Floor A; (b) Floor B; (c) Floor C

For Floor B, however, the highest occupancy pattern is Pattern 5, with an occurrence percentage of about 38%. This significant difference can be attributed to different agencies working on different floors, as discussed above.

The occurrence percentages for each occupancy pattern for the three floors in four time periods are listed in Fig. 6. Circles displayed in this figure indicate the occurrence times of the pattern. Larger circles represent higher occurrence times. Occurrence percentages of Pattern 2 for each floor were found to be higher than those of other patterns when occupants stayed in their cubicles for 2 to 8 hours per day. This indicates that most occupants of each floor left for lunch during the noon hour. The second highest is Pattern 1, which represents occupants who did not leave or enter their cubicles frequently. Additionally, the occurrence percentages of Pattern 1 for each floor were higher than those of Patterns 2 to 4 when occupants stayed in their cubicles for less than 2 hours per day.

The analysis results described above are occupancy patterns that only represent the overall characteristics of cubicles occupied on each floor. It is still very approximate for use as an occupancy schedule in building simulation tools. For example, the switch-on percentage of Pattern 1 was about 60% during the working hours of 8 a.m. to 6 p.m. This indicates that the probability of an occupant in the cubicle was about 60%. However, the number of daily absences and absence durations still cannot be obtained via this occupancy pattern. An occupant's number of daily absences and absence durations can have significant impact on energy usage and cause substantial differences between measured and simulated energy use. To obtain more accurate simulation results, a more realistic occupancy schedule-including presence and absence durations of occupants, and the number of absences in the cubicle-is required for use in the simulation. Therefore, the number of daily absences and absence durations of each occupancy pattern were further identified and detailed, as follows.

Figure 7 represents the accumulated number of daily absences within the 76-day period for Patterns 1 to 4. The days when the occupant did not arrive at the office are excluded. For example, if the number of daily absences and the number of occurrences were 4 and 9, respectively, this



Fig. 6 The occurrence percentages of each occupancy pattern in four time periods for each floor: (a) Floor A; (b) Floor B; (c) Floor C. Larger circles represent more occurrences

represents a total of 9 days when the occupant left the cubicle 4 times per day. In this figure, it can be found that



Fig. 7 The accumulated number of daily absences for each occupancy pattern in a 76-day period for Patterns 1–4

the maximum number of occurrences of each occupancy pattern shifted and decreased with the number of daily absences. The most typical numbers of daily absences of each pattern are 1, 4, 5, and 9. For Pattern 1, there are a total of 5 days when the occupant never left the cubicle. Although the peaks of the other patterns were less than that of Pattern 1, each of the total number of absences of Patterns 2, 3, and 4 was almost greater than those of Pattern 1, except the cases with none or one daily absence. More daily absences indicate that the occupant entered or left the cubicle more frequently.

The accumulated numbers of durations of each absence within the 76-day period for each pattern is shown in Fig. 8. The absence durations concentrate in a 10-to-29-minute span for all occupancy patterns except Pattern 4. For Patterns 1 and 2, most absence periods were 10 to 19 minutes in duration, and their occurrence percentages were 41% and 37%, respectively. For Pattern 3, most absences lasted 20 to 29 minutes, and the percentage was 56%. For Pattern 4, most absences were 0 to 9 minutes, and the percentage was 62%. For all patterns, occurrence times decreased with longer absence minutes. It can be deduced that for shorterduration absences, the occupant leaves the cubicle to take a break, go to the restroom, or walk around. Longer periods can be attributed to meetings, lunch, or outside business.



Fig. 8 The accumulated number of occurrences of absence duration for each occupancy pattern over a 76-day period

The outlines of occupancy profiles in Patterns 1 to 3 were similar except for one and two significant valleys in Patterns 2 and 3. To further understand occupancy patterns, Pattern 2 was further investigated as follows. The working time in a day was divided into three periods: 8 to 11:30 a.m., 11:30 a.m. to 1:30 p.m., and 1:30 to 6:00 p.m. The total number of absences and average absence durations for these time periods for Pattern 2 are illustrated in Figs. 9(a) and (b). The number of absences shown here are the accumulated numbers within the 76-day period, and the absence durations are the average values. The number of absences increased as the day progressed. The occupant left the cubicle more often and with a shorter duration in the afternoon. This may be due to the dwindling concentration of an occupant or increasing fatigue, resulting in the occupant walking around or going to the restroom more often. The average absence duration from 11:30 a.m. to 1:30 p.m. was significantly longer than the others, as this is the lunch period. However, the average absence durations from 8 to 11:30 a.m. and 1:30 to 6:00 p.m. were almost the same.

The accumulated numbers of absence minutes of each time period for Pattern 2 is illustrated in Fig. 10. The most typical absence duration for all three time periods was 10 to 19 minutes. The percentages for each time period were 43%, 25%, and 45%. Figure 10 shows that occurrence times decrease with longer absence minutes. This corresponds to the result mentioned before. However, the occurrence times



Fig. 9 Total number of absences and average absence duration of three time periods for Pattern 2 over a 76-day period: (a) number of absences; (b) absence duration in minutes



Fig. 10 The accumulated number of occurrences of each absence duration for occupancy Pattern 2 for three time periods over a 76-day period

of absence minutes for different time periods can be further distinguished. For the time periods of 8 to 11:30 a.m. and 1:30 to 6:00 p.m., the curves dropped drastically after a peak and then descended slowly. Compared with the period of 1:30 to 6 p.m., more absences of longer duration occurred from 8 to 11:30 a.m. It can be deduced that there were more meetings or longer events in the morning. For the time period 11:30 a.m. to 1:30 p.m., the curve declined more smoothly after the peak and the times of longer absences were higher than the other two time periods. This figure indicates that the occupant may spend over 10 minutes and sometimes almost 2 hours for lunch.

5 Discussion

Cubicle occupancy for a typical 8-hour weekday for the three floors mostly begins between 8 and 9 a.m., with a dip around noon, and then begins to decrease from 4 to 6 p.m. Spikes, caused by the late-night cleaning crews after most occupants have left in the evening, are also observed. Weekend occupancy levels for cubicles on all three floors are fairly low and can be neglected. Furthermore, weekday occupancy levels for Floor B are very different from the other two floors, which can be attributed to different agencies working on different floors, with occupants on Floor B working part time, going out for business more often, or working from home part of time. Due to privacy and security concerns, no further data is available to allow further verification.

200 occupancy patterns for the three floors were collected in this study. These collected patterns can be classified into five patterns according to occupancy variation, appearance duration in the cubicle, and occupant personality. The five identified occupancy patterns are: Pattern 1 (single-square curve), Pattern 2 (one-valley curve), Pattern 3 (two-valley curve), Pattern 4 (variable curve), and Pattern 5 (flat curve). Statistical results show that the most common occupancy among all occupants is Pattern 2, which indicates that most occupants leave their cubicles for lunch around noon, in addition to other longer events, such as attending meetings or going outside. The second most popular occupancy is Pattern 1, in which occupants do not leave or enter their cubicles frequently. Additionally, the occurrence percentages of Pattern 1 for each floor are higher than those of other patterns when occupants stayed in their cubicles for less than 2 hours per day.

The number of absences and absence duration for each occupancy pattern are identified. More daily absences mean an occupant moves in and out of the cubicle more frequently. The most typical numbers of daily absences for Patterns 1 to 4 are 1, 4, 5, and 9, respectively. Additionally, the absence durations for each absence are mostly from 10 to 29 minutes for all occupancy patterns. The number of absences decreases with the longer absence duration for all patterns. For a short absence duration, it can be deduced that an occupant leaves the cubicle to take a break, go to the restroom, or walk around. On the other hand, a longer period can be attributed to an occupant attending a meeting, having lunch, or going outside.

Finally, the working time in a day is divided into three periods for further analysis of occupancy patterns. Occupants leave the cubicle more often in the afternoon but for shorter durations. In other words, the occupants leave the cubicle less often but for longer. The average absence at midday is longer due to lunch. However, the average absence durations in the morning and afternoon are almost the same.

This study also observes that occupancy patterns are slightly influenced by cubicle location. Longer occupancy periods occur in more isolated cubicles that have more privacy or are near windows. However, job category may have more influence on occupancy pattern than cubicle location. Due to privacy concerns, no data is available to further relate job characteristics to occupancy patterns.

6 Occupancy model and schedule generation

Based on the results, a stochastic occupancy model of each pattern is developed with three key elements: (1) the cumulative distribution function (CDF) of the number of daily absences, (2) the CDF of each absence duration, and (3) the probability distribution function (PDF) of the start time of each absence.

For an open-plan office with a certain number of cubicles, assuming one occupant per cubicle, a profile of occupancy patterns must first be determined by energy modeling. Then occupancy schedules for a weekday can be generated by the following steps, using Patterns 1 and 2 as examples. First, a uniform-distribution random number between 0 and 1 is generated, and it is used as an input to the inverse function of the CDF of the number of daily absences in Fig. 11(a) to find the corresponding number of daily absences. For each absence, a uniform-distribution random number between 0 and 1 is generated, and it is used as an input to the inverse function of the CDF of the daily absence duration in Fig. 11(b) to find the corresponding daily absence duration in minutes. Finally, for each absence, a uniform-distribution random number is generated and used to calculate the start time of each absence. After that, the end time of each absence can be determined by adding the absence durations previously calculated. For Pattern 1, according to Fig. 4(a), the absence start time can be assumed to be uniformly distributed between 8 a.m. and 4 p.m. For Pattern 2, the absence start time is not uniformly distributed, as there is a deep valley at around noon, as shown in Fig. 4(b). Therefore, the distribution of number of absences is determined by the relative probability of occurrence in the three time periods: morning, noon, and afternoon, based on Fig. 12. For each absence in either of the three time periods, the same procedure as Pattern 1 is used to determine the absence start time.

Three generated weekday occupant schedules of Pattern 1 are shown in Fig. 13. The value 1 in the figure indicates the occupant is in the cubicle, while 0 indicates the occupant is away from the cubicle. It can be seen that for Pattern 1,



Fig. 11 The curves of occurrences, probability distribution function (PDF), and cumulative distribution function (CDF) of Pattern 1: (a) number of daily absences; (b) absence duration

there is mostly one daily absence, lasting 10 to 30 minutes. Three generated weekday occupant schedules of Pattern 2 are shown in Fig. 14. As with the occupant schedules of



Fig. 12 The curve of cumulative distribution function (CDF) of daily absence section for Pattern 2



Fig. 13 Three generated weekday occupant schedules for Pattern 1



Fig. 14 Three generated weekday occupant schedules for Pattern 2

Pattern 1, most absence durations last 10 to 30 minutes, but the number of daily absences are increased to 3 or 4, and one absence occurs during noon.

7 Conclusions

This study statistically analyses information collected from 200 cubicle offices on three floors of a commercial office building. It used measured lighting-switch data to represent the occupancy status of cubicles. Occupancy levels were identified and occupancy profiles were classified into five patterns as displayed in Figs. 4(a)-(e). The number of daily absences and absence durations for each occupancy pattern were further calculated and analyzed. Based on these results, a mathematical model to describe the occupancy patterns, including the probability distributions of the number of absences and absence duration, was developed. The occupancy model can be used to generate more realistic occupant schedules for open-plan cubicle offices, for use in building energy simulations. In addition to lunch breaks, more occupancy events such as meetings, short visits, walking around, and late-night cleaning can be taken into account in the model to better capture the stochastic nature of actual occupancy variations in the building. These more detailed occupancy schedules can replace the fixed or predefined ones currently used in building energy simulations to better assess the impact of occupancy patterns on building energy performance, and to improve the accuracy of simulated results. This method can also be used to validate and enhance other building occupancy models. However, more case studies and measured data analyses are needed. The analysis methods used in this study can also be adapted to study the occupancy patterns of private offices and other building types, such as residential.

Acknowledgements

The authors thank Joy Wei and Abby Enscoe for providing the lighting-switch data and answering our questions. This work was supported by the U.S. Department of Energy under the U.S.-China Clean Energy Research Center for Building Energy Efficiency, and it was co-sponsored by the Bureau of Energy, "Ministry of Economic Affairs, Taiwan".

References

- Fritsch R, Kohler A, Nygard-Fergusono M, Scartezzini JL (1990). A stochastic model of user behavior regarding ventilation. *Building* and Environment, 25: 173 – 181.
- Haas R, Auer H, Biermayr P (1998). The impact of consumer behavior on residential energy demand for space heating. *Energy and Buildings*, 27: 195 – 205.
- Hoes P, Hensen JLM, Loomans MGLC, de Vries B, Bourgeois D (2009). User behavior in whole building simulation. *Energy and Buildings*, 41: 295 – 302.
- Page J, Robinson D, Scartezzini J (2008). A generalized stochastic model for the simulation of occupant presence. *Energy and Buildings*, 40: 83 – 98.
- Pfafferott J, Herkel S (2007). Statistical simulation of user behavior in low-energy office buildings. *Solar Energy*, 81: 676 682.
- Santin OG (2011). Behavioral patterns and user profiles related to energy consumption for heating. *Energy and Buildings*, 43: 2662 2672.
- Tabak V (2008). User simulation of space utilisation: System for office building usage simulation. PhD thesis, Eindhoven University of Technology, The Netherlands.
- Tanimoto J, Hagishima A, Sagara H (2008). A methodology for peak energy requirement considering actual variation of occupant's behavior schedules. *Building and Environment*, 43: 610 – 619.
- Wang C, Yan D, Jiang Y (2011). A novel approach for building occupancy simulation. *Building Simulation*, 4: 149 – 167.

Occupant Behavior: Impact on Energy Use of Private Offices

Tianzhen Hong^{1,*}, Hung-Wen Lin²

¹ Environmental Energy Technologies Division, Lawrence Berkeley National Laboratory, Berkeley, USA

² Green Energy and Environment Research Laboratories, Industrial Technology Research Institute, Taiwan

ABSTRACT

Measured energy use of buildings demonstrated large discrepancies even between buildings with same function and located in similar climates. Among various factors contributing to the discrepancies, occupant behavior is a driving factor. Occupant behavior is also one of the most significant sources of uncertainty in the prediction of building energy use by simulation programs. How occupants set the comfort criteria (including thermal, visual, and acoustic), interact with building energy and services systems, and response to environmental discomfort directly affect the operation of buildings and thus their energy use. This study employs building simulations to evaluate the impact of occupant behavior on energy use of private offices with single occupancy. Typical occupant behavior we studied includes how an occupant sets comfort criteria, operates lights, office equipment, space thermostat, and HVAC systems. The behaviour is categorized into three workstyles: 1) austerity – occupants are proactive in saving energy, 2) standard - average occupants, and 3) wasteful occupants do not care about energy use. The simulation results demonstrate the impact of occupant behavior on building energy use is significant, and even so at the energy end use levels such as lighting, space cooling and heating. For a typical single-occupancy office room, compared to the standard or reference workstyle, the austerity workstyle consumes up to 50% less energy, while the wasteful workstyle consumes up to 90% more energy.

Three methods are proposed to model occupant behavior depending upon the complexity: 1) use EnergyPlus directly, 2) use the advanced feature of EnergyPlus - Energy Management System, and 3) use modified code of EnergyPlus. Our study provides a method to evaluate energy impact of occupant behavior, which can be a good tool for decision makers of behavioral programs that target energy savings in buildings.

KEYWORDS

Building simulation, Energy use, EnergyPlus, Occupant behavior, Office buildings

^{*}Corresponding author email: thong@lbl.gov

INTRODUCTION

Occupant behavior affects the building energy use directly and indirectly by opening/closing windows, turning on/off or dimming lights, turning on/off office equipment, turning on/off heating, ventilation, and air-conditioning (HVAC) systems, and setting indoor thermal, acoustic, and visual comfort criteria. Measured energy use of buildings demonstrated large discrepancies even between buildings with same function and located in similar climates. Among various factors contributing to the discrepancies, occupant behavior is a driving factor. Occupant behavior is also one of the most significant sources of uncertainty in the prediction of building energy use by simulation programs due to the complexity and inherent uncertainty of occupant behavior. With the trend towards low energy buildings that reduce fossil fuel use and carbon emissions, getting occupants actively involved during the design and operation of buildings is a key to achieving high energy performance without scarifying occupant comfort or productivity. Pilot projects demonstrated that low energy systems, such as natural ventilation, shading to control solar heat gains and glare, daylighting to dim lights, and demand controlled ventilation, especially need the interactions and collaborations of occupants. Energy savings from 5 to 30% were achieved by behavioral studies that motivate changes to occupant behavior.

In the last decade, new designs target net-zero energy buildings which emphasize the importance of energy efficiency technologies, integrated design, building operation and maintenance, and occupant behavior. Good operation practice and high design efficiency in buildings could lower the energy use (Mahdavi et al. 2008, Linden et al. 2006). Santin (2011) looked at the relationship between user behavior and space heating energy use, and concluded that behavior patterns could be used in building energy calculations and usage profiles with different behavior could be discerned.

Mahdavi (2008) described an effort to observe control-oriented occupant behavior in a few office buildings in Austria. His results imply the possibility of identifying certain patterns of user control behavior as a function of indoor and outdoor environmental parameters such as illuminance and irradiance. However, his observations also underscore the need for typologically differentiated occupancy and control action models for different buildings. Parys (2009) evaluated various lighting and blind control systems in combined with four types of user behavior in office buildings in Belgium. His simulation results demonstrated that the energy savings of a daylight dimming system in an individual office decrease by about 10% when the occupant behavior is accounted for.

On windows operating, Haldi (2008) and Rijal (2008)'s study are based on the presumption that the main driver of occupant window intervention is occupant discomfort. The adaptive thermal comfort model by Humphrey and Nicol (1998), proposed that the occupants' comfort temperature changes with the monthly outdoor

air mean temperature from a number of surveys conducted world-wide for natural ventilated buildings. Although the adaptive comfort model was original obtained for naturally ventilated buildings, it can be adapted for mechanically cooled spaces. Rijal (2008) proposed a method of implementing Humphrey's observations of occupant window opening behaviour in a building simulation model, assuming that occupants only interact with windows when they are thermally uncomfortable, defined as 2°C above the upper bound or below the lower bound of the adaptive comfort temperature.

Peng et al (2012) presents a quantitative description method of human behavior in residential buildings. The method can be used to predict the impact of the human behavior on the indoor environment and energy use. It was applied to a household in Beijing with comparisons to on-site observations of the occupants' behavior and measurements of energy use for validation.

The objective of this study is to identify, understand, and categorize occupant behavior that can have significant impact on energy use of private offices, and evaluate how different types of occupant behavior affect the energy use by building simulations. The study applies to private offices with single occupancy, assuming the occupant has freedom to interact and change his indoor environment. Open offices or private offices with multiple occupants involve the complexity of group behavior, which is not covered in the study.

RESEARCH METHODS

First, occupant behavior in private offices is categorized into three different workstyles according to the level of energy is used to provide comfort for the occupants: 1) the Austerity workstyle with occupants being proactive in saving energy; 2) the Standard workstyle representing most occupants in terms of average energy use behavior; and 3) the Wasteful workstyle with occupants consuming energy at will, lacking motivation to reduce energy use. The three types of occupant behavior is based on literature review and occupants surveys like the post occupancy survey done by Center of the Built Environment, University of California at Berkeley; they aim to represent general situation. Then building simulations using EnergyPlus (USDOE 2012) version 7.0 are employed to quantify and evaluate the impact of the three workstyles on energy use of private offices. To look at the influence of climate, three U.S. typical climates are studied.

The energy metric used in the study is the source or primary energy use by the individual office, which includes the source energy of the natural gas for heating, and the source energy of electricity for cooling, ventilating, lighting, and office equipment (plug-load).

Characteristics of the private offices

Three adjacent and equal size private offices, located on the south facade of a middle story of a medium size office building, are selected for the study. Each office has only one exterior wall (with a window) facing south, and has a rectangular shape with a floor area of 15 m². The private office is occupied by only one person, and is served by a constant air volume HVAC system with heating from a gas furnace and cooling from a direct-expansion unitary system. The efficiency levels of the building envelope, lighting, and HVAC are set to meet the minimum requirements of ASHRAE Standard 90.1 (2004). The internal loads, including the interior lighting power and plug loads (both at 10.76 W/m^2), and operation schedules (Figure 1) stay the same across climates. The building operates 6am to 10pm, while the typical private office is occupied 8am to 5pm. Cooling and heating thermostat of the private offices are set to 24°C and 21°C respectively. The occupant is assumed to take three breaks: half hour in the morning, one hour lunch, and half hour in the afternoon. The middle office is occupied by one person with standard workstyle, while the adjacent two offices are each occupied by one person with austerity and wasteful workstyle respectively. The interior walls of the three offices are insulated well to ignore heat transfer from adjacent offices.



Figure 1. Schedules of lighting, plug-load, and people

Climate zones

Three climates, Miami (Hot and Humid), San Francisco (Coastal, Mild), and Chicago (Cool Summer, Cold Winter), are selected in this study to represent typical climates in the U.S. Table 1 lists the climate zone information for the three representing cities based on ASHRAE Standard 90.1-2010. In the table, HDD18 is the Heating Degree Days with a base temperature of 18°C, and CDD10 is the Cooling Degree Days with a base temperature of 10°C.

Tuble 1. Churacteristics of selected cities and citmule 20hes				
Cities	ASHRAE Climate Zones	HDD18	CDD10	
Miami	Hot –Humid, 1A	200	9474	
San Francisco	Warm-Marine, 3C	3016	2883	
Chicago	Cool-Humid, 5A	6176	3251	

Table 1. Characteristics of selected cities and climate zones

The TMY3 weather data was used in the EnergyPlus simulations. The TMY3 weather data represented typical weather conditions during 1991 to 2005 and was available for download at EnergyPlus web site (USDOE 2012).

Occupant behavior

Typical occupant behavior related to energy use is studied and summarized in Table 2, including:

• Cooling setpoint

The Standard occupant prefers a room air temperature of 24°C during cooling. The Austerity occupant prefers a warmer temperature of 26°C, while the Wasteful occupant likes a cooler temperature of 22°C. The lower the cooling setpoint, the higher the cooling energy use.

• Heating setpoint

The Standard occupant prefers a room air temperature of 21°C during heating. The Austerity occupant prefers a lower temperature of 18°C, while the Wasteful occupant likes a warmer temperature of 23°C. The higher the heating setpoint, the higher the heating energy use. Note that the heating setpoint of the Wasteful occupant is actually higher than the cooling setpoint, which is not unusual for people with such workstyle.

• Adaptive comfort

Adaptive comfort theory allows the indoor cooling comfort temperature to be adjusted upward based on the monthly average outdoor air temperature. Hot climates with higher monthly average outdoor air temperatures would have higher indoor comfort temperatures. The Austerity occupant adjusts the cooling setpoint based on the adaptive comfort model, while the Standard or Wasteful occupant does not. As shown in Figure 2, for Miami climate, the cooling setpoint in July and August can be adjusted as high as 26.5°C, which is 2.5°C higher than the constant setpoint 24°C. This reduces the cooling energy use.





- For the Austerity occupant, he turns off lights and HVAC, and turns down plug-load 30% when he leaves office for break. The Standard occupant operates lights, HVAC, and office equipment according to schedules (Figure 1). The Wasteful occupant leaves everything 100% on during breaks.
- Daylighting controls

The Austerity occupant dims lights to 50% or completely turns them off if adequate daylight meets the visual comfort. The other two occupants do not response to daylight.

• HVAC operation time

Compared to the standard HVAC operation schedule, the Austerity occupant turns on HVAC one hour late at 9am and turns off one hour early at 4pm. The Wasteful occupant sets the HVAC operation the same as the whole building - from 6am to 10pm.

• Cooling startup control

The Austerity occupant turns on cooling only when he feels warm, which usually occurs when the space air temperature reaches 28°C. When the cooling is turned on, cooling setpoint temperature of 24°C is maintained. This is demonstrated in Figure 3 for a hot summer day. The other two occupants set the startup temperature the same as the cooling setpoint.



Figure 3. Cooling startup control

1 uble 4 . Occupant bend	ivior calegorizea inio	iniee worksiyles	
Occupant behavior	Austerity workstyle	Standard workstyle	Wasteful workstyle
Cooling setpoint (°C) 26		24	22
Heating setpoint (°C)	18	21	23
Adaptive comfort	Yes	None	None
Occupancy controls If unoccupied, turn off lights and HVAC, turn down plug-load 30%		Scheduled	Leave everything on: lights, HVAC, and plug-load
Daylighting Control 3 Steps Dimming		None	None
HVAC operation timeTurn on 1 hour late and turn off 1 hour early: 9am to 4pm		Scheduled on: 8am to 5pm	Same as the whole building schedule: 6am to 10pm
Cooling startup control Cooling startup control Cooling turns on when space air temperature reaches 28°C, then maintains at 24°C. Cooling turns off when unoccupied.		Follow HVAC operation schedule (8am to 5pm) to maintain 24°C. Same as above.	Follow HVAC operation schedule (6am to 10pm) to maintain 24°C. Same as above.
Combined	All above behavior	All above behavior	All above behavior

Table 2. Occupant behavior categorized into three workstyles

Modeling approaches

Three different approaches using EnergyPlus, in order of difficulty, are used in the study to model the occupant behavior discussed before:

1) Direct modeling with EnergyPlus

Occupant behavior, including cooling setpoint, heating setpoint, daylighting control, and HVAC operation time, is modelled directly with EnergyPlus by changing corresponding inputs from the base cases for the Standard occupant. The advantage of this approach is easy implementation.

2) Using the energy management system (EMS) in EnergyPlus

EMS is an advanced feature of EnergyPlus and designed for users to develop customized high-level, supervisory control routines to override specified aspects of EnergyPlus modeling in the EMS program. EMS has certain limitations and its use requires advanced knowledge of EnergyPlus and computer programming. EMS is used to model occupant behavior of adaptive comfort and Occupancy control. The Occupancy control can also be modelled directly by pre-calculating the new schedules for lights, HVAC, and office equipment, but the Direct Modeling approach would not work if the occupant schedule is stochastic.

3) Modifying EnergyPlus source code

Modifying the existing EnergyPlus source code, the third modeling approach, is used when both the Direct Modeling and EMS approaches cannot be applied. This approach requires users to have a thorough understanding of the EnergyPlus data structure and existing source code before being able to modify code. This is the most difficult approach but offers the most flexibility to model complex occupant behavior. This approach is used to model the Cooling start up control.

RESULTS AND DISCUSSIONS

The simulation results are presented as percentage changes of source energy of the Austerity workstyle and Wasteful workstyle compared to the Standard workstyle for individual occupant behavior as well as the combined behavior. Figures 4 to 6 show the results for the three climates.



Figure 4. Changes of source energy in San Francisco climate



Figure 5. Changes of source energy in Chicago climate



Figure 6. Changes of source energy in Miami climate

From these results, it can be seen that:

• The combined Austerity workstyle and Wasteful workstyle have significant impact on energy use of the private office. Compared to the Standard workstyle, the Austerity workstyle can save 42%, 50%, and 48% of source energy in San Francisco, Chicago, and

Miami respectively; while the Wasteful workstyle consumes 89%, 81%, and 74% more energy for the three climates respectively.

- For the Austerity workstyle, the Cooling startup control, the Occupancy control, and the Cooling setpoint have the most energy savings. While for the Wasteful workstyle, the Cooling startup control is the same as the HVAC operation time, and the Cooling setpoint cause the most increase of energy use.
- The impact of Heating setpoint is relatively small because the heating source is natural gas which is valued much less in source energy compared to other end uses in electricity.
- The adaptive comfort model based Austerity occupant behavior can save 30% of source energy for the hot climate of Miami.
- Occupant behavior that leads to longer HVAC operation time and lower cooling setpoint increase of energy use significantly.
- Occupant behavior that leads to delay the cooling (Startup control), higher cooling setpoint (including Adaptive comfort), and turning off or down equipment when unoccupied reduce energy use significantly.

CONCLUSION

This study identified and evaluated a few typical occupant behavior related to operation and control of energy service systems of private offices. The behavior is categorized into three workstyles – Austerity, Standard, and Wasteful – according to the potential impact on energy use. The simulation results demonstrate that occupant behavior has significant impact on energy use of private offices – the combined Austerity workstyle can save up to 50% of source energy, while the combined Wasteful workstyle can increase energy use by 89% compared to the Standard workstyle.

Three approaches to modelling occupant behavior using EnergyPlus are discussed. Our on-going research focuses on occupant behavior in operating windows and shading devices, and implementing our behavior models in EnergyPlus for public use.

It is a different topic, well worth exploring but outside our expertise, on how to motivate occupants to change from Standard workstyle to Austerity workstyle to save energy. There have been many pilot behavioral programs presented in the Behavior, Energy, and Climate Change conference (Anon.).

ACKNOWLEDGEMENTS

This work was supported by the U.S. Department of Energy under the US-China Clean Energy Research Center on Building Energy Efficiency. It is also part of our research activities for the IEA ECBCS Annex 53: Total Energy Use in Buildings – Evaluation and Analysis Methods. This work was co-sponsored by the Bureau of Energy, Ministry of Economic Affairs, Taiwan.

REFERENCES

Anonymity <u>http://beccconference.org/</u>, last accessed on 30 July, 2012.

- USDOE. 2012. EnergyPlus, http://www.energyplus.gov/, last accessed on 31 July, 2012.
- Mahdavi A, Mohammadi A, Kabir E, and Lambeva L. 2008. Shading and lighting operation in office buildings in Austria: a study of user control behavior, *Building Simulation*. 1: 111-117.
- Linden AL, Carlsson-Kanyama A, and Eriksson B. 2006. Efficient and inefficient aspects of residential energy behaviour: what are the policy instruments for change? *Energy Policy*. 34: 1918-1927.
- Santin OG. 2011. Behavioural patterns and user profiles related to energy consumption for heating, *Energy and Buildings*. 43: 2662-2672.
- Haldi F and Robinson D. 2008. On the behaviour and adaptation of office occupants, *Building and Environment*. 43(12): 2163–2177.
- Rijal HB, Tuohy P, Nicol JF, Humphreys MA, Samuel A, and Clarke J. 2008. Development of an adaptive window-opening algorithm to predict the thermal comfort, energy use and overheating in buildings, *Journal of Building Performance Simulation*. 1(1): 17–30.
- Humphreys MA and Nicol JF. 1998. Understanding the adaptive approach to thermal comfort, *ASHRAE Transactions*. 104 (1): 991 1004.
- ASHRAE. 2004. *ANSI/ASHRAE Standard 90.1-2004*, Energy standard for buildings except low-rise residential buildings, Atlanta: American Society of Heating, Refrigerating, and Air-Conditioning Engineers, Inc.
- ASHRAE. 2010. *ANSI/ASHRAE Standard 55-2010,* Thermal environmental conditions for human occupancy, Atlanta: American Society of Heating, Refrigerating, and Air-Conditioning Engineers, Inc.
- Parys W, Saelens D, and Hens H. 2009. Impact of occupant behavior on lighting energy use, *Proceedings of Building Simulation 2009*, Glasgow, UK, pp 1143-1150.
- Peng C, Yan D, Wu RH, Wang C, Zhou X, and Jiang Y. 2012. Quantitative description and simulation of human behavior in residential buildings, *Building Simulation*, 5(2): 85-94.

DATA ANALYSIS AND MODELING OF LIGHTING ENERGY USE IN

LARGE OFFICE BUILDINGS

Xin Zhou¹, Da Yan^{1,*}, Xiaoxin Ren¹, Tianzhen Hong²

¹Department of Building Science, School of Architecture, Tsinghua University, Beijing, China ²Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, CA 94720, USA

ABSTRACT

Lighting consumes about 20 to 40% of total electricity use in large office buildings in the U.S. and China. In order to develop better lighting simulation models it is crucial to understand the characteristics of lighting energy use. This paper analyzes the main characteristics of lighting energy use over various time scales, based on the statistical analysis of measured lighting energy use of 17 large office buildings in Beijing and Hong Kong. It was found that the daily 24-hour variations of lighting energy use were mainly driven by the schedule of the building occupants. Outdoor illumination levels have little impact on lighting energy use in large office buildings due to the lack of automatic daylighting controls and relatively small perimeter areas. A stochastic lighting energy use model was developed based on different occupant activities during six time periods throughout a day, and the annual distribution of lighting power across those periods. The model was verified using measured lighting energy use of one selected building. This study demonstrates how statistical analysis and stochastic modeling can be applied to lighting energy use. The developed lighting model can be adopted by building energy modeling programs to improve the simulation accuracy of lighting energy use.

KEYWORDS

building simulation, energy use, lighting, modeling, occupant behavior, office buildings, Poisson distribution

INTRODUCTION

Lighting energy use in large office buildings is as high as 20% to 40% of the building total in both China and the U.S. This has caught the attention of practitioners, researchers, and policy makers. Studies have shown that the two main factors affecting lighting energy use are outdoor illumination and occupant behavior. From other researchers' field studies and simulations, it was concluded that lighting energy use has a correlation with outdoor illumination. When the outdoor illumination is above a certain level, people around perimeter zones with access to natural light are less likely to use artificial electrical lights, and the artificial illumination needed to meet design illuminance levels is lower (Reinhart and Voss 2003, Li et al 2006, Galasiu and Atif 2002, Li and Lam 2001, Maitreya 1997). However, other researchers also found that occupants have a crucial influence on the lighting energy use. Through case studies of actual buildings, Yun et al (2012a) found that in open-plan offices, the usage of lighting was not influenced by outdoor illumination. Instead it had a close relationship with the indoor activities of occupants. Meanwhile, Yong et al (2012b) formulated

^{*} Corresponding author. E-mail address: yanda@tsinghua.edu.cn

the concept that outdoor illumination has no statistical significance with lighting energy use, and the operation of lighting was strongly correlated to the time of day. Other studies also found that operation of lights by occupants only depended on whether the room is occupied, and is independent of outdoor illumination (Love 1998, Lindelof and Morel 2006).

Currently, most research on lighting energy use is focused on small office and residential buildings. The analysis methods and conclusions from this research provide some hints to help understand the lighting energy use in large office buildings. In China, a common method to predict lighting energy use involves combining lighting power density information with lighting schedules. However, the generation of lighting schedules is too simplified and lacks verification against measured data (Yun and Steemers 2008). This leads to a large discrepancy between simulated and measured lighting energy use (Bluyssen 2009, Norford et al 1994). Furthermore, the annual variation of actual lighting energy use is not captured. More complex lighting energy use models have been reviewed. Hunt (1979) introduced a stochastic model to calculate the probability of turning on lights after the arrival of occupants. He concluded that the probability of occupants turning on artificial lights increases only when the illumination of the working surface is below 100 lux. Newsham (1995) developed the Lightswitch model that followed a stochastic approach and simulated user occupancy at the workplace based on measured field data in an office building in Ottawa, Canada. Reinhart (2004) improved the Lightswitch model to Lightswitch-2002 to calculate the probability of occupants arriving and leaving offices, and the related probability of turning on and off lights. Meanwhile, in Reinhart's study, based on the model, the amount of energy savings under different lighting control strategies was evaluated. Joakim Wide n et al (2009) used Markov chains to estimate the probability of occupant movement. Then the probability of turning on lights was modeled as a decision based on the lighting level and occupant movement. Since these studies were mainly based on small office buildings (Hunt 1979, Reinhart 2004) and residential buildings (Wide'n et al 2009), there is a strong need to conduct more research on lighting energy use in large office buildings if energy use targets are to be met.

Based on large quantities of measured data from several large office buildings, this paper analyzes the characteristics of total amount and distributions of lighting energy use in large office buildings. Due to the lack of detailed information on the physical characteristics of lighting systems in these buildings, this paper focuses on daily and seasonal lighting energy use patterns. Daily 24-hour lighting curve, annual distribution of lighting power, and main influencing factors of lighting energy use are first identified and discussed through statistical analysis of hourly data. Then a stochastic model is developed which effectively capture random characteristics of lighting energy use. The model accounts for the time-varying nature of lighting energy use, including peaks in usage at certain times of the day. In this study, the general lighting energy use features of large office buildings are analyzed and discussed in depth, and the main influencing factors and distributions of lighting energy use are clarified more distinctly.

RESEARCH METHODS

The research method in this paper is shown in Figure 1. First, the two main factors influencing lighting energy use - outdoor illumination and occupant behavior - are analyzed. To determine the influence of outdoor illumination on lighting energy use, the lighting energy use between different seasons and different building levels (above-grade areas and basements) is compared. The effect of occupant behavior is analyzed by comparing lighting energy used on different types of day

(workdays, weekends, holidays), and by comparing lighting energy use under different occupancy schedules. Then, based on the understanding of main influencing factors of lighting energy use, further discussion about the feature of lighting energy use curve in large office buildings can be gained through the analysis of measured lighting energy use from dozens of large office buildings with energy sub-metering systems. The analysis is mainly focusing on four aspects: 1) annual total energy use; 2) monthly distribution; 3) daily feature; and 4) annual distribution. More in-depth analysis is conducted to decode the annual distribution feature and the time-relevant properties between different time periods. A whole-building lighting energy use model is developed based on the results from the analysis of lighting energy use and lighting profiles at various time scales. The model is then applied to a case study to simulate the lighting energy use, and the simulated results are compared with measured data to verify the model.



Figure 1 Research route

RESULTS

- **1** Analysis of influencing factors
 - 1.1 The influence of outdoor illumination

1.1.1 Comparison of lighting energy use between the basement and the above-grade floors

The lighting energy use is shown in Figure 2. The red line in the figure represents the daily mean lighting energy use. The edges of the blue boxes are placed at the 25% and the 75% quartiles. The maximum and minimum data points are also shown. It reveals that the outdoor illumination has no obvious effect on the shape of the average lighting power curves in large office buildings.





1.1.2 Comparison of lighting energy use between seasons

To further study the influence of outdoor illumination, the lighting energy use between different seasons is compared as shown in Figure 3. It can be concluded that outdoor illumination has no noticeable influence on the total lighting energy use.



Figure 3 Weekly profiles of average lighting energy use for the four seasons

1.2 The influence of occupant behavior

To assess the influence of occupant behavior on lighting energy use, the power draw between workdays and weekends for the same lighting branch is compared and shown in Figure 4 and Figure 5. As there are many more occupants in the building on workdays, the lighting power on workdays is higher than weekends. Different occupancy events such as arriving at work, going out for lunch, and leaving work can be detected from the workday lighting power curve. While during weekends, the discrete range of lighting energy use is much larger, and a homogeneous lighting schedule cannot be detected due to the uncertainty of overtime work and other events.





Figure 4 Average lighting power draw on workdays



Note: the red lines are the hourly averages; the green lines represent data at 5% and 95% probability; the blue boxes show the first and third quartiles; the vertical dashed blue lines show the range

2 General characteristics of lighting energy use

Based on measured data of 17 large office buildings in Beijing and Hong Kong, general characteristics of the lighting energy use are analyzed.

2.1 Annual lighting energy use

The electricity end-use intensities are calculated and shown in Figure 6. It can be seen that the offices in Hong Kong have greater electricity use intensity.



Figure 6 Electricity use intensity of large office buildings in Beijing and Hong Kong Note: Power refers to utilities equipment like elevators; AC refers to HVAC equipment.

2.2 Monthly distribution of lighting energy use

Table 1 shows the months with the maximum and minimum daily lighting energy use for the 17 buildings. It cannot be judged statistically from the results which months have the greatest or least daily lighting energy use.

Buildings	The month with the maximum daily lighting energy use	The month with the minimum daily lighting energy use	Buildings	The month with the maximum daily lighting energy use	The month with the minimum daily lighting energy use
А	7	4	Н	3	8
В	7	9	Ι	12	1
С	12	5	J	11	8
D	4	5	Κ	12	1
Е	11	5	М	2	3
F	7	10	Ν	7	12
G	12	10	0	8	2
R	9	5			

Table 1 Months with maximum and minimum daily average lighting energy use

2.3 Daily distribution of lighting energy use

The hourly lighting energy use for a typical workday for Building F is shown in Figure 7. The curve has dual peaks and can be divided into six time periods: 1)Night Period; 2)Going-to-work Period;; 3)Morning Period; 4)Noon-Break Period; 5)Afternoon Periodl; 6)Off-Work Period.



Figure 7 Curve of lighting power for a typical workday

The six periods can be divided into two categories:

1. Constant Power

Morning Period, Noon-break Period, Afternoon Period and Night Period are periods that can be represented by a flat curve with a constant lighting power. Table 2 lists the maximum coefficient of variation for each of the four periods. It indicates that the variation can be ignored.

Table 2 Maximum coefficient of variation for the four constant power time period	ods
--	-----

				=
	Morning Period	Noon-break Period	Afternoon Period	Night Period
Coefficient of variation V_{σ}	0.22	0.13	0.25	0.31

Note: $V_{\sigma} = \sigma/x$, where V_{σ} is the coefficient of variation, σ is the mean square deviation, and x is the average value

2. Variable power

The daily distribution of lighting energy use during the Going-to-Work and Off-Work periods satisfies an exponential curve. Wang et al (2005) proved, with measured data, that the probability of

a certain number of people (represented by k) arriving during a certain time period fits a Poisson distribution:

$$P\{X = k\} = \frac{\lambda^k}{k!} e^{-\lambda}$$

 $\lambda = \frac{1}{T}$, where T is the average time before k people arrive the office. So the probability of some

people arriving during a certain time period fits $P = P\{k > 0\}$, which is an exponential distribution. And the probability of lighting turning on is related to the probability of people arriving. During the Off-Work Period, the probability of people leaving the office can be represented by an exponential distribution, which means that the probability of people in the office is calculated as $P = 1 - P\{k > 0\}$.

Taking Going-to-Work period as an example, using the least square regression model, confidence level α = 0.05 is assumed, and the functional form is set to the exponential distribution. The results are shown in Figure 8. From the regression curve, almost all the data is within the confidence interval, which proves that the curve fitting is good.



Figure 8 The daily regression curve during the Going-to-Work Period [λ =0.89]

3 Annual distribution of lighting energy use

From the spread of hourly lighting use from a single lighting branch shown in Figure 9, it can be seen that during one year the lighting energy use during these periods is not constant.



Figure 9 Annual hourly lighting energy use

Regression analysis is used to verify the distribution characteristic, as shown in Figure 10. Most data are within the confidence interval, which proves that the annual variations of the lighting power during each of four periods can be represented with a normal distribution.





Figure 10 The normal distribution of the lighting power

DISCUSSION

A model of the whole-building lighting energy use was developed based on the daily lighting curves and the annual distribution properties. This model is applicable to large office buildings, where the lighting energy use has almost no relationship with outdoor illumination, but has a close relationship with the occupancy schedule. Only the lighting energy use on a typical workday is simulated here. The simulated results of a lighting branch in Building A are shown in Figure 11. With the consideration that simulation aims to represent the most typical scenarios in reality, the data edges of this quartile graph are the data points at the probabilities of 95% and 5%. It can be seen that the simulated daily lighting curve agrees quite well with the curve from the measured data. The annual distributions of each period are also described.



Figure 11 Comparison between the simulated and measured lighting energy use

CONCLUSION AND IMPLICATIONS

This paper analyzed the main characteristics and major influencing factors of lighting energy use in large office buildings, based on measured lighting energy use of 17 large office buildings in Beijing and Hong Kong. It is important to describe the daily lighting profiles accurately in order to represent the various characteristics of lighting energy use in large office buildings. A stochastic lighting model was developed to quantify the uncertainty of occupant behavior. This paper focused on the description of lighting energy use curves.

Main findings in this study include:

- 1. In large office buildings, the lighting energy use is mainly affected by the occupant schedule, and the influence of outdoor illumination is very limited.
- 2. In large offices, the time when lights are turned on is closely correlated with the time when most occupants arrive. While turning off lights is related to the time most occupants leave. Accurate prediction of the presence of occupants in offices is crucial to predict lighting energy use.
- 3. Lighting is a major electric end-use in large office buildings. The annual lighting energy use per square meter is similar for large offices in Beijing and Hong Kong.
- 4. Poisson and normal distributions can accurately describe the stochastic properties of daily lighting power curves and annual variations.
- 5. A whole-building lighting energy use model is developed based on daily lighting curves and annual distribution of lighting power levels. The model is verified using measured lighting energy use from an actual building.

Future work can be done to improve the simulation accuracy of the annual distribution of lighting power levels for the Going-to-Work and Off-Work periods. A lighting model for weekends can also be developed and verified.

REFERENCES

- Bluyssen, P.M. (2009) The Indoor Environment Handbook: How to Make Buildings Healthy and Comfortable, Earthscan, London.
- California Energy Commission (2006) California Commercial End-Use Survey. PIER report, CEC-400-2006-005.
- Galasiu, A.D. and Atif, M.R. (2002) Applicability of daylighting computer modeling in real case studies: comparison between measured and simulated daylight availability and lighting consumption. Building and Environment, 37, 363–377.
- Hunt, D. (1979) The use of artificial lighting in relation to daylight levels and occupancy. Building and Environment, 14, 21-33.
- Joakim Wide'n, Nilsson, A.M., Wa[°]ckelga[°]rd, E. (2009) A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand. Energy and Buildings, 41(10), 1001–1012.
- Li, D.H.W., Lam, T.N.T., and Wong, S.L. (2006) Lighting and energy performance for an office using high frequency dimming controls. Energy Conversion and Management, 47, 1133-1145.
- Li, D.H.W. and Lam, J.C. (2001) Evaluation of lighting performance in office buildings with daylighting controls. Energy and Buildings, 33, 793–803.
- Lindelöf, D. and Morel, N. (2006) A field investigation of the intermediate light switching by users. Energy and Buildings, 38, 790–801.
- Love, J.A. (1998) Manual switching patterns observed in private offices. Lighting Research and Technology, 30, 45–50.
- Maitreya, V. K. (1997) Daytime artificial lighting in office buildings in India. Building and Environment, 12, 159–163.
- Newsham, G.R., 1995. Lightswitch: A stochastic model for predicting office lighting energy consumption. In: Proceedings of Right Light Three, 3rd European Conference on Energy Efficient Lighting, Newcastle, UK, pp. 59–66.
- Norford, L.K., Socolow, R.H., Hsieh, E.S., and Spadaro, G.V. (1994) Two-to-one discrepancy between measured and predicted performance of a 'low-energy' office building: insight from a reconcillation based on the DOE-2 model. Energy and Buildings, 21, 121–131.
- Reinhart, C.F. (2004) Lightswitch 2002: a model for manual control of electric lighting and blinds. Solar Energy, 77 (1), 15–28.
- Reinhart, C.F. and Voss, K. (2003) Monitoring manual control of electric lighting and blinds. Lighting Research and Technology, 35, 243–260.
- Wang, D., Federspiel, C.C., and Rubinstein F. (2005) Modeling occupancy in single person offices. Energy and Buildings, 37, 121-126.
- Yun, G.Y., Kong, H.J., Kim, H., and Kim, J.T. (2012a) A field survey of visual comfort and lighting energy consumption in open plan offices. Energy and Buildings, 46, 146–151.
- Yun, G.Y., Kong, H.J., Kim, H., and Kim, J.T. (2012b) Effects of occupancy and lighting use patterns on lighting energy consumption. Energy and Buildings, 46, 152–158.
- Yun, G.Y. and Steemers, K. (2008) Time-dependent occupant behaviour models of window control in summer. Building and Environment, 43, 1471–1482.

A detailed loads comparison of three building energy modeling programs: EnergyPlus, DeST and DOE-2.1E

Dandan Zhu¹, Tianzhen Hong², Da Yan¹ (🖂), Chuang Wang¹

1. Department of Building Science, School of Architecture, Tsinghua University, Beijing 100084, China 2. Environmental Energy Technologies Division, Lawrence Berkeley National Laboratory, One Cyclotron Road, Berkeley, CA 94720, USA

Abstract

Building energy simulation is widely used to help design energy efficient building envelopes and HVAC systems, develop and demonstrate compliance of building energy codes, and implement building energy rating programs. However, large discrepancies exist between simulation results from different building energy modeling programs (BEMPs). This leads many users and stakeholders to lack confidence in the results from BEMPs and building simulation methods. This paper compared the building thermal load modeling capabilities and simulation results of three BEMPs: EnergyPlus, DeST and DOE-2.1E. Test cases, based upon the ASHRAE Standard 140 tests, were designed to isolate and evaluate the key influencing factors responsible for the discrepancies in results between EnergyPlus and DeST. This included the load algorithms and some of the default input parameters. It was concluded that there is little difference between the results from EnergyPlus and DeST if the input values are the same or equivalent despite there being many discrepancies between the heat balance algorithms. DOE-2.1E can produce large errors for cases when adjacent zones have very different conditions, or if a zone is conditioned part-time while adjacent zones are unconditioned. This was due to the lack of a strict zonal heat balance routine in DOE-2.1E, and the steady state handling of heat flow through interior walls and partitions. This comparison study did not produce another test suite, but rather a methodology to design tests that can be used to identify and isolate key influencing factors that drive the building thermal loads, and a process with which to carry them out.

1 Introduction

Computer simulation is an important and proven method to help understand and analyze the thermal performance of buildings, and predict their operational energy consumption. Since the 1960s, many building energy modeling programs (BEMPs) have been developed to perform building energy simulation, for instance, the widely-used DOE-2 (DOE-2 1980), EnergyPlus (Crawley et al. 2001), ESP (ESRU 1999), and DeST (Yan et al. 2008; Zhang et al. 2008). DOE-2 was developed at the Lawrence Berkeley National Laboratory with funding from the U.S. Department of Energy (USDOE) after the energy crisis in the late 1970s and is still the most widely-used BEMP in the U.S. This includes its use as a stand-alone calculation engine and with graphical user interfaces (GUI) such as VisualDOE (VisualDOE 2004), EnergyPro (EnergyPro 2011), eQuest (eQuest 2009), and EnergyGauge (EnergyGauge 2012). EnergyPlus is a next generation BEMP developed, supported and maintained by a team led and funded by USDOE since 1996. EnergyPlus is based on the load algorithms of BLAST and the system algorithms of DOE-2. New features and enhancements were added to support innovative, low-energy building designs and operational controls. Development of ESP-r started in 1974 at the University of Strathclyde and is primarily used in Europe. DeST (Designer's Simulation Toolkits) is a BEMP developed at Tsinghua University since the late 1980s with the aim of aiding teaching, research and the practical use of building energy analysis and simulation in China.

BEMPs play a significant role in the design of energy

building energy modeling program, building thermal loads, comparison, DeST, DOE-2.1E, EnergyPlus

Article History

Received: 15 November 2012 Revised: 6 February 2013 Accepted: 18 February 2013

© Tsinghua University Press and Springer-Verlag Berlin Heidelberg 2013 **Research Article**

efficient envelopes and HVAC (heating, ventilation, and air-conditioning) systems for new buildings and retrofitting existing buildings, the development of building energy codes and standards, and defining and implementing building energy rating/labeling programs. However, the issue that large discrepancies exist in simulation results between different BEMPs, even for the same building modeled by the same person, leads many users and stakeholders to lack confidence in building simulation methods and the results from BEMPs. This is a major barrier for the wider adoption and effective application of building energy simulation, and represents a challenge to the industry. The large discrepancies of simulation results between different BEMPs mainly come from three factors as Fig. 1 illustrated: first is the simulation engine that is the unchangeable core; second is the GUI to



Fig. 1 The top three influencing factors for the discrepancies in simulation results between different BEMPs

the simulation engine that usually simplifies, hides or hardwires some inputs that can be important; third is the fact that users may model the building or system inaccurately as they are not familiar with the chosen BEMP, or input poor data due to constraints of budget and resources. In order to address the issue of large discrepancies between different BEMPs, the impact of the above three factors must be identified and quantified.

This paper mainly discusses why and how different BEMPs produce different simulation results. As the building load calculation forms the basis of building energy and thermal performance simulations, this paper focuses on detailed comparisons of loads calculation between the three BEMPs: EnergyPlus, DeST, and DOE-2.1E, with the goal to identify and quantify the influences of the simulation engines and input values or algorithms. EnergyPlus was chosen because it is widely used and continuously being developed and supported by USDOE. DOE-2.1E was chosen as it is still widely used in the U.S. DeST was chosen due to its emerging use in China and a few Asian countries and regions. Toplevel key features of DOE-2.1E, DeST and EnergyPlus are summarized in Table 1.

Our findings can be a valuable reference for decision makers to determine which BEMP to use for various applications including development and compliance calculations for building energy codes and standards. Another separate paper will discuss the methodologies and findings from a detailed comparison of the same three BEMPs in HVAC systems and central plant modeling.

Feature	DOE-2.1E	DeST	EnergyPlus
Developer	LBNL/USDOE	Tsinghua University, China	USDOE
Development and support	No more development or support	On-going	On-going
User	Worldwide	Mostly in China	Worldwide
Input	Text, BDL	Database, Microsoft Access	Text, IDF
Output	Summary & hourly reports	Summary & hourly reports	Extensive summary & detailed reports with user specified time steps
GUI	Simulation engine only; 3rd party GUIs available	Coupled with AutoCAD	Simulation engine only; 3rd party GUIs available
Algorithm	Surface heat transfer: CTF; zone weighting factors	Zone heat balance: state space method	Surface heat balance: CTF; zone heat balance
Time step	1 hour, fixed	1 hour, fixed	1 to 60 minutes (15 minutes is used in this paper)
Weather data	Hourly	Hourly	Hourly or sub-hourly
HVAC	28 pre-defined systems	A few pre-defined systems	User configurable with some limitations
User customization	User functions	N/A	Energy management systems
Co-simulation	N/A	N/A	External interface
Language	Fortran 77	C++	Fortran 2003
Limitation	Lack zone air heat balance, linear systems	Limited user customization, linear systems	Potentially long run-time for large models
Licensing	Free download; source code available	Free download; source code not open to public	Free download; open source

 Table 1
 Comparison of top-level key features of DOE-2.1E, DeST and EnergyPlus

2 Methodology

The comparisons of the features and capabilities of twenty major BEMPs were summarized to help understand their functions, advantages and disadvantages from a simple overview (Crawley et al. 2008). Many efforts to test simulation results from EnergyPlus (Henninger and Witte 2011a, b, c), DeST (2006), and DOE-2.1E (IEA 1995; Sullivan 1998; Henninger and Witte 2006; Meldem and Winkelmann 1995) have been undertaken by their development teams. These tests employed three testing approaches: analytical tests, comparative (inter-program) tests, and empirical tests. These tests demonstrated that the three BEMPs had the basic capability to simulate dynamic thermal processes and the energy performance of buildings. LBNL performed comparative tests between DOE-2.1E and EnergyPlus based on the test cases defined in the Alternate Calculation Method Manual of California Building Energy Efficiency Standards Title 24 in order to evaluate the possibility of using EnergyPlus as the reference simulation engine for development and compliance calculations of future revisions of Title 24 (Huang et al. 2006). A key finding was that the simulation results were highly sensitive to seemingly minor differences in inputs and model algorithms. Another comparison (Andolsun and Culp 2010) of EnergyPlus and DOE-2.1E was undertaken using case studies that ranged from a sealed box to a detailed residential building. Andolsun and Culp demonstrated that EnergyPlus under-estimated total building loads by 16%-17% compared to DOE-2.1E as incremental loads were added, and air infiltration reduced the differences of loads calculation results between the two BEMPs. Another study (Waddell and Kaserekar 2010) compared the results of solar gains, cooling load calculations, and the transition from the solar gains to cooling loads, from a few BEMPs including EnergyPlus, eQuest, IES, and TRACE 700. These comparisons uncovered that large discrepancies existed in the results from DOE-2.1E and EnergyPlus which were not well understood, nor did they explain what the key influencing factors could be.

Previous building simulation comparisons have generally resulted in standard test suites or case studies, which present the discrepancies between the simulation results, but do not address specific reasons for the discrepancies from the view of calculation algorithms or model inputs. In this paper, new sets of in-depth tests were designed and carried out as complement to the ASHRAE Standard 140 tests. To further identify and understand the differences and their effects on simulation results, new test cases were designed by modifying inputs of the ASHRAE Standard 140 tests, based on deep understandings of load calculation algorithms, modeling assumptions, and defaults of inputs of the three BEMPs. It should be noted that all test cases in Standard 140 were set to be continuously (24 hours per day) conditioned by mechanical cooling and heating systems. However, it is very common that heating or cooling is only used during some specific hours, or only in specific zones of a building. This means that the heat transfer between unconditioned and conditioned spaces needs to be accurately accounted for in the heat balance calculation. Therefore, test cases with two adjacent spaces were added, and extreme thermal conditions and practical engineering conditions were applied to test possible limitations of the three BEMPs. Figure 2 summarizes the method used to develop the tests and perform the comparisons. For all test cases, EnergyPlus Version 7.0, DeST Version 2011-11-23 and DOE-2.1E114 were used. For all EnergyPlus tests, the CTF (conduction transfer function) method was used with a simulation time-step of 15 minutes.

3 Results from the ASHRAE Standard 140 tests

ASHRAE Standard 140-2007 (ASHRAE 2007), Standard Method of Test for the Evaluation of Building Energy Analysis Computer Programs, is based on the work previously performed by the International Energy Agency (IEA) under the Building Energy Simulation Test (BESTEST) and Diagnostic Method (IEA 1995). ASHRAE Standard 140 defines a standard method of tests that can be used for identifying



Fig. 2 Methodology to build the tests and perform the comparisons

and diagnosing predictive differences from whole building BEMPs that may possibly be caused by algorithmic differences, modeling limitations, input differences, or coding errors. So, the load calculation comparison based on ASHRAE Standard 140 tests is carried out first in our study. The results for DOE-2.1E were obtained from ASHRAE Standard 140; results for EnergyPlus 7.0 were obtained from the EnergyPlus development team; while results for DeST were produced during this study as earlier tests were limited and outdated.

All test cases use single-zone models except Case 960. Inputs including weather data, building construction, envelope materials, infiltration, internal loads, and mechanical system are controlled in each of the three BEMPs according to ASHRAE Standard 140-2007. Case 600 is the base test, Cases 610 to 650 are low-mass tests, Cases 900 to 960 are highmass tests, Cases 600FF to 950FF are free flow tests and the remaining are additional test cases (Cases 195 to 320, Cases 395 to 440 and Cases 800 to 810). The outputs from these test cases were annual heating and sensible cooling loads, peak heating and cooling sensible loads, and zone air temperatures for the cases without mechanical heating or cooling systems. The annual heating loads for the low-mass building are showed in Fig. 3, where each bar represents a different BEMP, from DOE-2, BLAST (BLAST 1991), ESP, SRES/SUN, SERIRES, S3PAS, TRNSYS (http://sel.me.wisc.edu/trnsys), TASE (Aittomäki and Kalema 1976), ENERGYPLUS, or DEST. BEMPs participating in the ASHRAE Standard 140 comparison are listed in Table 2.

One method to see how well DOE-2.1E (the output of DOE2.1E-RevWindow), DeST, and EnergyPlus predict building loads is to see if their results fall within the range of spread of results from other BEMPs. Tables 3 to 7 show



Fig. 3 Annual heating loads for the 600 series low-mass tests from the ASHRAE Standard 140-2007

Code name	Computer program	Developer	Implemented by
BLAST	BLAST-3.0 level 193 v.1	CERL, U.S.	NREL, U.S.; Politecnico, Torino, Italy
DOE-2.1D	DOE-2.1D 14	LANL/LBNL,U.S.	NREL, U.S.
ESP	ESP-RV8	Strathclyde University, U.K.	De Montfort University, U.K.
SRES/SUN	SERIRES/SUNCODE 5.7	NREL/Ecotope, U.S.	NREL, U.S.
SERIRES	SERIRES 1.2	NREL, U.S. and BRE, U.K.	BRE, U.K.
S3PAS	S3PAS	University of Sevilla, Spain	University of Sevilla, Spain
TASE	TASE	Tampere University, Finland	Tampere University, Finland
TRNSYS	TRNSYS 13.1	University of Wisconsin, U.S.	BRE, U.K.; Vrije Universiteit, Brussels, Belgium
DOE-2.1E	DOE-2.1E	LANL/LBNL, U.S.	GARD Analytics, U.S., using NREL input files
DOE2.1E-RevWindow	DOE2.1E-RevWindow	LANL/LBNL, U.S.	GARD Analytics, U.S., using Window 4 data file which more closely matches specification
BLAST3.0-334	BLAST3.0 level 334	CERL, U.S.	GARD Analytics, U.S., using NREL input files
ENERGYPLUS	EnergyPlus ver.7.0.0.036,Nov 2011	U.S. Dept. of Energy	GARD Analytics, U.S.
DEST	DeST 2011-11-23	Tsinghua University, China	Tsinghua University, China

Table 2 BEMPs participating in the ASHRAE Standard 140 comparison (Henninger and Witte 2011b)
Table 3 Comparison of annual heating loads for various ASHRAEStandard 140 tests

Annual heating load (MWh)									
Case	Description	Min.	Max.	DOE-2	.1E	DeS	Г	Energy	Plus
600	Base case	4.296	5.709	4.994	у	5.007	y	4.364	у
610	South shading	4.355	5.786	5.042	у	5.042	y	4.398	у
620	East/west window orientation	4.613	5.944	5.144	у	5.292	у	4.512	y1
630	East/west shading	5.050	6.469	5.508	у	5.570	у	4.813	y1
640	Thermostat setback	2.751	3.803	2.995	у	3.127	у	2.667	y1
650	Night ventilation	0.000	0.000	0.000	у	0.000	у	0.000	у
900	High-mass base case	1.170	2.041	1.301	у	1.894	у	1.163	y1
910	High-mass south shading	1.512	2.282	1.559	у	2.266	у	1.427	n
920	High-mass east/west window orientation	3.261	4.300	3.312	y	4.025	y	3.087	n
930	High-mass east/west shading	4.143	5.335	4.249	y	4.485	y	3.785	n
940	High-mass thermostat setback	0.793	1.411	0.838	y	1.270	y	0.727	n
950	High-mass night ventilation	0.000	0.000	0.000	у	0.000	y	0.000	у
960	Sunspace	2.144	3.373	2.216	y	2.835	y	2.322	y

 Table 4
 Comparison of annual cooling loads for various ASHRAE

 Standard 140 tests
 \$140 tests

Annual cooling load (MWh)									
Case	Description	Min.	Max.	DOE-2	2.1E	DeS	Г	Energy	Plus
600	Base case	6.137	8.448	8.054	у	5.924	y1	7.006	у
610	South shading	3.915	6.139	5.874	у	4.873	у	4.976	у
620	East/west window orientation	3.417	5.482	5.256	у	3.847	у	4.384	у
630	East/west shading	2.129	3.701	3.235	у	2.879	у	2.952	у
640	Thermostat setback	5.952	8.097	7.713	у	5.759	y1	6.710	у
650	Night ventilation	4.816	7.064	6.678	у	4.625	y1	5.538	у
900	High-mass base case	2.132	3.669	3.390	у	2.296	у	2.683	у
910	High-mass south shading	0.821	1.883	1.738	у	1.202	у	1.350	у
920	High-mass east/west window orientation	1.840	3.313	3.169	у	2.401	у	2.683	у
930	High-mass east/west shading	1.039	2.238	1.823	у	1.696	у	1.745	у
940	High-mass thermostat setback	2.079	3.546	3.272	у	2.262	у	2.606	у
950	High-mass night ventilation	0.387	0.921	0.749	у	0.455	у	0.571	у
960	Sunspace	0.411	0.895	0.855	у	0.537	у	0.732	у

Table 5 Comparison of peak heating loads for various ASHRAEStandard 140 tests

Peak heating load (kW)								
Case	Description	Min.	Max.	DOE-2.1E	DeS	Т	Energy	Plus
600	Base case	3.437	4.354	3.767 y	3.986	у	3.732	у
610	South shading	3.437	4.354	3.755 y	3.954	у	3.720	у
620	East/west window orientation	3.591	4.379	3.785 y	3.962	у	3.726	у
630	East/west shading	3.592	4.280	3.762 y	3.963	у	3.703	у
640	Thermostat setback	5.232	6.954	5.656 y	5.991	у	6.265	у
650	Night ventilation	0.000	0.000	0.000 y	0.000	у	0.000	у
900	High-mass base case	2.850	3.797	3.248 y	3.600	у	3.140	у
910	High-mass south shading	2.858	3.801	3.256 y	3.612	у	3.139	у
920	High-mass east/west window orientation	3.308	4.061	3.508 y	3.776	у	3.453	у
930	High-mass east/west shading	3.355	4.064	3.536 y	3.801	у	3.475	у
940	High-mass thermostat setback	3.980	6.428	5.322 y	5.723	у	4.785	у
950	High-mass night ventilation	0.000	0.000	0.000 y	0.000	у	0.000	у
960	Sunspace	2.410	2.863	2.603 y	2.601	у	2.691	у

Table 6 Comparison of peak cooling loads for various ASHRAEStandard 140 tests

Peak cooling load (kW)									
Case	Description	Min.	Max.	DOE-2	2.1E	DeS	Г	Energyl	Plus
600	Base case	5.965	7.188	6.965	у	6.151	у	6.678	у
610	South shading	5.669	6.673	6.482	у	5.964	у	6.274	у
620	East/west window orientation	3.634	5.096	4.679	v	3.819	v	4.005	v
630	East/west shading	3.072	4.116	3.834	y	3.270	y	3.446	y
640	Thermostat setback	5.884	7.126	6.903	у	6.116	у	6.614	у
650	Night ventilation	5.831	7.068	6.843	у	5.973	у	6.479	у
900	High-mass base case	2.888	3.932	3.778	у	3.469	у	3.320	у
910	High-mass south shading	1.896	3.277	2.703	у	2.953	у	2.640	у
920	High-mass east/west window orientation	2.385	3.505	3.342	у	2.844	у	2.835	у
930	High-mass east/west shading	1.873	3.080	2.638	у	2.527	у	2.332	у
940	High-mass thermostat setback	2.888	3.932	3.778	у	3.497	у	3.320	у
950	High-mass night ventilation	2.033	3.170	2.917	у	2.586	у	2.451	у
960	Sunspace	0.953	1.422	1.048	у	1.085	у	1.213	у

		Maximum annual	hourly zone to	emperature (°	C)					
		Min.	Max.	DOE-2.1E		DeST	DeST		EnergyPlus	
600FF	Base case	64.90	75.10	73.40	у	65.49	у	66.03	у	
650FF	Night ventilation	41.81	46.40	45.50	у	42.39	У	43.65	у	
900FF	High-mass base case	63.24	73.50	71.70	у	63.67	У	64.31	у	
950FF	High-mass base case	35.54	38.50	37.10	у	35.67	у	36.90	у	
960FF	Sunspace	48.88	55.34	51.60	у	55.54	y1	52.93	у	
	Minimum annual hourly zone temperature ($^\circ \mathbb{C}$)									
		Min.	Max.	DOE-2.1E		DeST		EnergyPlus		
600FF	Base case	-18.80	-15.57	-17.70	у	-18.60	у	-17.51	у	
650FF	Night ventilation	-6.38	-1.65	-2.00	у	-4.50	у	-2.39	у	
900FF	High-mass base case	-23.00	-21.10	-21.00	у	-22.91	у	-23.08	y1	
950FF	High-mass base case	-20.20	-17.80	-17.80	у	-19.97	у	-20.34	y1	
960FF	Sunspace	-2.82	5.80	6.00	y1	0.48	у	2.44	у	
		Average annual h	nourly zone ter	nperature (°C	2)					
		Min.	Max.	DOE-2.1E		DeST		EnergyP	lus	
600FF	Base case	24.22	27.40			24.43	у	26.19	у	
650FF	Night ventilation	24.45	27.50			24.45	у	26.40	у	
900FF	High-mass base case	17.99	20.80			17.81	у	18.87	у	
950FF	High-mass base case	14.00	15.30			13.88	y1	14.62	у	
960FF	Sunspace	26.43	30.50			29.92	у	29.51	у	

 Table 7 Comparison of hourly zone temperatures for various ASHRAE Standard 140 tests

the results of the three BEMPs with an extra column for each of the three BEMPs to indicate whether its results fall within the ranges. The columns of the Min. and Max. represent respectively the minimum and maximum results from all of the tested BEMPs except DOE-2.1E, DeST and EnergyPlus. An indicator of "y" means that the test results are within the [Min., Max.] range, a "y1" means the results are not within the [Min., Max.] range but are within the 5% relaxed range [Min./1.05, Max. × 1.05], while an "n" means the results are outside of the relaxed range [Min./1.05, Max. × 1.05].

From the comparison of the ASHRAE Standard 140 test results, we can conclude that the simulation results from the three BEMPs mostly fall within the ranges except the heating loads results for the high-mass cases 910, 920, 930, and 940, where EnergyPlus calculated smaller annual heating loads than DOE-2.1E and DeST. EnergyPlus results for these four cases are about 10% lower than the minimum of the ranges. The largest percent differences are in the annual heating loads from test case 940 high-mass with thermostat setback, where EnergyPlus gave the lowest annual heating loads of 0.727 MWh while DeST gave the highest result of 1.27 MWh, a 42.7% difference, even though the absolute difference is not the largest (0.938 MWh in Case 920). The largest percent differences are in the annual cooling loads from test case 950 high-mass night ventilation, where DOE-2.1E gave the highest annual cooling loads of 0.945 MWh while DeST gave the lowest result of 0.455 MWh, a 39.3%

difference, even though the absolute difference is not the largest (2.130 MWh in Case 600). For peak heating and cooling loads in Tables 3 and 4, the results from the three BEMPs all fall within the ranges, but there are still large difference of 16.4% in Case 940 peak heating loads and 18.4% in Case 620 peak cooling loads.

Even though test cases from ASHRAE Standard 140 are very simple, there are still large discrepancies in the results from the three BEMPs, especially the annual heating loads for the high-mass test cases. The ASHRAE Standard 140 tests did not provide adequate details to explain or isolate the influencing factors that drive the discrepancies.

4 In-depth tests

In this part, new sets of in-depth tests were carried out as complement to the ASHRAE Standard 140 tests. Firstly, influencing factors that drive the differences between EnergyPlus and DeST are isolated by modifying inputs of the ASHRAE Standard 140 tests. DOE-2.1E (DOE-2 1982) lacks strict heat balance calculations of zone and surfaces. It calculates the interior surface heat exchange by using the combined convective and radiative heat transfer coefficients, rather than calculating the convection from surfaces to zone air, and long-wave radiation between interior surfaces separately. Thus, input values for DOE-2.1E cannot be matched well with EnergyPlus and DeST, and in Section 4.1 EnergyPlus and DeST are compared by in-depth tests. Secondly, double-zone cases were added up to test the ability of the three BEMPs calculating the heat balance calculation accurately when heating or cooling is only used during some specific hours, or only in specific zones of a building in Sections 4.2 and 4.3. As DOE-2.1E uses the adjacent space temperature from the previous time step to calculate the heat transfer from adjacent spaces, some errors may come up if two adjacent spaces are not both conditioned, or if there is a large temperature difference between two adjacent spaces. Thus, these comparisons are very useful for the three BEMP's applications in practical engineering conditions.

4.1 Control input values based on ASHRAE Standard 140 tests

4.1.1 Specification of test cases

A series of tests were designed to identify the influence of different modeling assumptions between DeST and EnergyPlus, as shown in Table 8. When using default values or algorithms in EnergyPlus and DeST, there are large discrepancies in the surface convection coefficients, as shown in Figs. 4 and 5. DeST assumes constant values of convection coefficients for both the inside and outside surfaces (DeST 2006), while EnergyPlus calculates these coefficients using correlations with indoor and outdoor air temperatures and wind speeds (EnergyPlus 2011). In all test cases except C10, the exterior and interior surfaces convection coefficients for EnergyPlus were set to be the same constant values as those used in DeST.

C1 is the simplest case and can be calculated analytically. It assumes no solar absorption, no long-wave radiant

Table 8 In-depth test cases

Case	Description
C1	Case 195 + suspended in outdoor air + solar/visible absorptance and infrared emissivity equal zero + the outdoor air temperature was always kept at 10° C
C2	C1+the outdoor air temperature was exactly the same as case 195
C3	Case 195 (surfaces convection coefficients for EnergyPlus were set as DeST defaults)
C4	C3 + solar absorptance equals 0.6
C5	C4 + infrared emissivity equals 0.9
C6	C5 + internal gains
C7	C6 + infiltration
C8	C7 + the thermostat control strategy of Case 600
С9	C8 + south windows of Case 600
C10	CO + defende de serviter en entre de la construction de férier terier En entre

C10 C9 + default algorithms for surfaces convection coefficients in Energy-Plus (exactly the same as Case 600 in ASHRAE Standard 140)



Fig. 4 Hourly exterior surface convection coefficients of the south wall from Case 195 in ASHRAE Standard 140



Fig. 5 Hourly interior surface convection coefficients of the south wall from Case 195 in ASHRAE Standard 140

exchange between interior surfaces, and constant outdoor air temperature. C3 is the same as Case 195 except the surface convection coefficients are set to the constant value used in DeST. Based on C3, other influencing factors such as internal gains, air infiltration, thermostat control strategy, and a south-facing window were added step by step to build the final C10 test case.

4.1.2 Results and discussions

Annual heating and cooling loads for the ten test cases are summarized in Figs. 6 and 7.



Fig. 6 Annual heating loads of test Cases C1 to C10 from EnergyPlus and DeST



Fig. 7 Annual cooling loads of test Cases C1 to C10 from EnergyPlus and DeST

The hourly heating load of test case C1 can be calculated analytically to obtain the result of 0.50 kW, as Table 9 illustrates. The hourly results from EnergyPlus and DeST are both 0.50 kW, matching the analytical one well.

Case C2 considers the hourly variation of outdoor air temperature and the simulation results indicate little differences between DeST and EnergyPlus, as shown in Fig. 8.

Comparing the simulation results from EnergyPlus and DeST for Cases C1 to C9, we find that the largest discrepancy occurred after south-facing windows were added. The solar transmittance at different incident angles for the doublepane window are almost the same in DeST and EnergyPlus, which are also close to the values provided in ASHRAE Standard 140, as shown in Fig. 9. This indicates that the window algorithm should cause little difference between the results from DeST and EnergyPlus. However, when comparing the solar radiation on the southern exterior surface and window-transmitted solar as shown in Fig. 10, we find

Table 9 The UA calculation of Case C1

	h_out	R	h_in	Area	U-factor	UA
	$(W/(m^2 \cdot K))$	$((m^2 \cdot K) / W)$	$(W/(m^2 \cdot K))$	(m ²)	$(W/(m^2 \cdot K))$	(W/K)
Light wall	23.3	1.789	3.5	75.6	0.47	35.70
Light floor	0	25.254	4	48	0.04	1.88
Light roof	23.3	2.993	1	48	0.25	11.89
Total						49.48



Fig. 8 Hourly heating loads for Case C2



Fig. 9 Solar transmittance at various incident angles



Fig. 10 Annual solar radiation on the south wall and the annual window-transmitted solar

that the annual solar radiation on the south wall from DeST is about 5.1% smaller than from EnergyPlus, while the window-transmitted solar radiation is 7.0% smaller. This helps explain why cooling loads from DeST are lower than EnergyPlus as less solar radiation enters the room.

The main reason for this discrepancy is the time point used for the solar position calculation and the sky diffuse solar radiation model. DeST (2006) uses the beginning of the hour for solar calculations during the hourly time step simulations, while EnergyPlus (2011) performs interpolation of solar radiation data from weather input files, and uses the end of each sub-hourly time step for the solar calculations. For the sky diffuse solar radiation model, EnergyPlus takes into account the anisotropic radiance distribution of the sky, while DeST uses an isotropic model.

Comparing the results between C9 and C10, we can find that another main influencing factor is the surface convection coefficients. EnergyPlus calculates the coefficients considering the variations of indoor and outdoor conditions, while DeST uses constant values as required by the linear system structure of its state-space heat balance method. As both exterior and interior surface convection coefficients are smaller in EnergyPlus than in DeST, EnergyPlus produces lower annual heating loads and higher annual cooling loads.

In conclusion, the differences between annual heating or

cooling loads from EnergyPlus and DeST can be controlled below 10% if inputs including default values or algorithms are matched, although EnergyPlus and DeST have difference in their load calculation algorithms and modeling assumptions. Therefore, matching inputs are the key when using different BEMPs.

4.2 Double-zone cases under extreme thermal conditions

4.2.1 Specification of test cases

DOE-2.1E has limitation in the heat balance calculation, especially multiple zones under different thermal conditions. To see how this limitation affects DOE-2.1E simulation results, Case EC1 was designed for the three BEMPs. A building has two adjacent rectangular spaces each with dimensions 10 m wide \times 10 m long \times 3 m high, as shown in Fig. 11. Zone 1 is conditioned with a special thermostat setting while Zone 2 is un-conditioned.

The construction of the exterior walls, roof and floor are the same as Case 600 and the interior walls are the same as Case 960 in ASHRAE Standard 140 tests. All solar/visible absorptance and thermal emissivity coefficients are set to zero, so only convective heat transfer between the outdoor air and the two indoor zones is considered. Surface convection coefficients are specified as the same constant values for DOE-2.1E, EnergyPlus, and DeST. The outdoor air temperature and ground temperature are always kept at 10°C. Each zone has no internal gains or air infiltration.

4.2.2 Results and discussion

The air temperature of Zone1 varied periodically (switched between 29.8°C and 16.2°C hourly) all year round controlled by a scheduled air-conditioning system, as shown in Fig. 12. The air temperature of Zone 2 was then calculated, as shown in Fig. 13, which shows that the results from DeST and EnergyPlus were always constant, but DOE-2.1E gave fluctuating air temperatures between 13.8 and 14.4°C. This is mainly due to the fact that DOE-2.1E uses the adjacent



Fig. 11 Building model of Case EC1



Fig. 12 Temperature settings of Zone 1



Fig. 13 Simulated temperature of Zone 2

zone temperature from the previous time step to calculate the heat transfer between adjacent zones, and the heat flow through the interior walls and partitions is treated as steady-state.

4.3 Double-zone cases under practical engineering conditions

The results from Case EC1 implied that DOE-2.1E has limitations in accurately calculating heat transfer between adjacent zones. Further tests were designed to ascertain the influence of this under practical engineering conditions.

4.3.1 Specification of test cases

Three new tests were created. Case SC1 is the base test and its results are used as the baseline for Cases SC2 and SC3 (Table 10). The building model of all the three cases includes two zones and each zone has dimensions 10 m wide \times 10 m long \times 3 m high (Fig. 14), with a window area of 12 m² on the south facade.

Weather data was the same as for Case 600. The constructions of the exterior walls, roof and floor, as well as the properties of the double-pane window, were the same as for Case 600. The interior wall was the same as for Case 960 in ASHRAE Standard 140 tests. Infiltration was always 0.5 air changes per hour, DeST and EnergyPlus use constant values,

Case	Description
SC1	Base test, both zones are conditioned 24 hours a day
SC2	Zone 1 with office daytime occupancy (Fig. 15); Zone 2 empty and unconditioned
SC3	Zone 1 with bedroom nighttime occupancy (Fig. 16); Zone 2 empty and unconditioned



Fig. 14 Building model of Case SC1



Fig. 15 Office daytime schedule used in SC2



Fig. 16 Bedroom nighttime schedule used in SC3

while DOE-2.1E uses the AIR-CHANGES/HR method which calculates the infiltration based on the wind speed. Internal heat gains from people, lighting, and equipment were assumed as constant. Table 11 lists the input assumptions for the internal heat gains. The inputs for "people heat level" were equivalent for the three BEMPs though their input values were not the same.

Solar and visible absorptances were set to 0.6, thermal emissivity to 0.9, and ground reflectance to 0.2 in the three BEMPs. Surface convection coefficients, solar distribution,

Table 11 Internal heat gains for Case SC1

	DOE-2.1E	DeST	EnergyPlus
People	0.1 person/m ² Sensible heat: 66 W Latent heat: 71 W	0.1 person/m ² Sensible heat: 66 W Latent heat: 0.102 kg/h	0.1 person/m ² Active level: 137 W Sensible heat fraction: 0.48
People heat distribution	Default weighting factors	Default distribution	Same as DeST
Lighting	10 W/m ²	10 W/m ²	10 W/m ²
Lighting heat distribution	Default lighting type	Default distribution	Same as DeST
Equipment	5 W/m^2	5 W/m^2	5 W/m ²
Equipment heat distribution	Default weighting factors	Default distribution	Same as DeST

and time step were set to the default values or algorithms in each BEMP.

DeST and EnergyPlus use ideal air systems and DOE-2.1E uses a "two pipe fan coil" system. The system used in DOE-2.1E was set to be a 100% convective air system, 100% efficient with no duct losses, and with adequate cooling and heating capacities, which is very close to an ideal air system. The air systems were always on and the zone thermostat set-point for Case SC1 was always 21.1°C. In Cases SC2 and SC3, the set-point for heating was 20°C and for cooling was 27°C. SC2 was exactly the same as SC1 except that Zone 1 used an office daytime schedule and Zone 2 was empty and unconditioned (no internal gains).

SC3 is exactly the same as SC2 except that Zone 1 used a bedroom nighttime schedule.

4.3.2 Results and discussion

In DOE-2.1E, hourly heating or cooling loads are calculated by the LOADS subprogram, first assuming constant space temperature, then adjusted by the SYSTEMS subprogram to consider the thermostat settings, outdoor air ventilation, etc. The loads from the SYSTEMS subprogram are used in our study.

Comparing the results of different BEMPs from SC1 to SC3, heating loads were always close but cooling loads were not. From the results of SC1 (Fig. 17), the monthly cooling loads of the three BEMPs were very close. Comparing SC1 with SC2 and SC3 (Figs. 18 and 19), we can see that the monthly cooling loads of DeST and EnergyPlus were always close, but the results of DOE-2.1E deviate more significantly. In SC1 there was no heat transfer between adjacent zones, so its results can be used as the benchmark where the biggest difference between annual cooling loads from DOE-2.1E and EnergyPlus was 10.3%. In SC2 the annual cooling load of DOE-2.1E was 35.0% higher than DeST and 18.2% higher than EnergyPlus. In SC3 the annual cooling loads were very small compared to SC1 and SC2 (Fig. 20), so the percentage



Fig. 17 Monthly sensible cooling loads of SC1



Fig. 18 Monthly sensible cooling loads of SC2



Fig. 19 Monthly sensible cooling loads of SC3



Fig. 20 Annual sensible cooling loads from SC1 to SC3

differences, even though very high, are not very meaningful. These results reveal that DOE-2.1E has serious limitations in accurately accounting for multi-zone heat balance and part-time operation of HVAC systems, especially for the nighttime air-conditioning case SC3.

From the monthly heating results (Figs. 21 to 23) from the three BEMPs, DeST and EnergyPlus always have close simulation results across all three test cases, but DOE-2.1E's results are always lower, mainly due to the differences in default values and algorithms used. For all three cases SC1 to SC3, the annual heating loads (Fig. 24) from DOE-2.1E were about 20% lower than those from EnergyPlus or DeST.



Fig. 21 Monthly heating loads of SC1



Fig. 22 Monthly heating loads of SC2



Fig. 23 Monthly heating loads of SC3



5 Discussions and conclusions

This study compared the capability and simulation results of EnergyPlus, DeST and DOE-2.1E for performing building thermal load calculations, to evaluate the impact of the different simulation engines. Algorithms used to calculate the thermal loads play an important role, but keeping inputs to energy models exactly the same or equivalent is even more important to guarantee consistent results from different BEMPs. All the three BEMPs have the basic capability for performing building load calculations, and the discrepancy in load results from DeST and EnergyPlus was reduced to less than 10% if the surface convection coefficients were set exactly the same as those in ASHRAE Standard 140 test cases.

To differentiate this study from previous work, it did not produce another test suite, but rather a methodology to design tests and a process to carry out these tests. A few in-depth tests, built upon the ASHRAE Standard 140 tests, were designed and performed to identify and quantify the key influencing factors that drive the discrepancies in results from EnergyPlus, DeST and DOE-2.1E. It was verified that DOE-2.1E has limitations in handling heat transfer between adjacent zones, with large errors emerging for cases when adjacent zones have very different conditions, or if a zone is part-time conditioned while adjacent zones are unconditioned.

The simulations done in the study were based on EnergyPlus version 7.0 and DeST version 2011-11-23. The latest available is EnergyPlus 7.2 and DeST 2013-01-15. The solar position algorithm in DeST is improved in the new version, which is an important feedback from this comparison study. DeST V2011-11-23 used the beginning of the hour for solar calculations during the hourly time step simulation. We got the measured direct normal solar radiation per minute from the Beijing Weather Station and calculated the direct solar radiation on east/west/south/north facing surface per minute as well as accumulated value per hour as the standard value. Then we tried different points (the beginning, the middle and the end) of the hour during the hourly time step and also different sub-hourly time steps for the solar calculations. Comparing the hourly result of different methods with the standard value, we finally chose the middle of the hour and the hourly time step considering the accuracy and computation speed for DeST in version 2013-01-15. The differences of load results between DeST and EnergyPlus will be reduced as the solar radiation on exterior surfaces has smaller discrepancy now. One major change in EnergyPlus from version 7.0 to 7.2, directly related to loads calculation, is the correction of exterior surface convection coefficients for windows, including the use of near-window wind speeds rather than the weather station wind speeds and the use of new coefficients for the empirical correlation (Booten et. al 2012). This change to EnergyPlus increases heating loads, which will reduce the discrepancy in heating loads between EnergyPlus and DeST.

Although the study provides new methods and results in comparing simulation programs, it serves as a good starting point for a much bigger study that is needed to fully justify which program is better, or under which situation, users should use which programs.

This study covers the loads comparison between EnergyPlus, DeST and DOE-2.1E. A future paper will discuss the methods and findings from comparing the HVAC models across the three programs.

Acknowledgements

This study was a joint effort between Tsinghua University, China and Lawrence Berkeley National Laboratory, USA under the US-China Clean Energy Research Center on Building Energy Efficiency. It was co-sponsored by the Energy Foundation under the China Sustainable Energy Program.

References

- Aittomäki A, Kalema T (1976). TASE—A Computer Program for Energy Analysis of Buildings. Technical Research Centre of Finland (VTT), Laboratory of Heating and Ventilating. (in Finnish)
- Andolsun A, Culp CH (2010). A comparison of EnergyPlus to DOE-2.1E: Multiple cases ranging from a sealed box to a residential building. In: Proceedings of SimBuild, New York, USA.
- ASHRAE (2007). ANSI/ASHRAE Standard 140-2007, Standard Method of Test for the Evaluation of Building Energy Analysis Computer Programs. Atlanta, USA: American Society of Heating, Refrigerating and Air-Conditioning Engineers.
- BLAST (1991). BLAST User Reference, Vols. 1, 2. Urbana, USA: University of Illinois.
- Booten C, Kruis N, Christensen C (2012). Identifying and Resolving Issues in EnergyPlus and DOE-2 Window Heat Transfer Calculations, NREL/TP-5500-55787.
- Crawley DB, Hand JW, Kurnment M, Griffith BT (2008). Contrasting the capabilities of building energy performance simulation programs. *Building and Environment*, 43: 661 – 673.

- Crawley DB, Lawrie LK, Winkelmann FC, Buhl WF, Huang YJ, Pedersen CO, Strand RK, Liesen RJ, Fisher DE, Witte MJ, Glazer J (2001). EnergyPlus: Creating a new-generation building energy simulation program. *Energy and Buildings*, 33: 319 – 311.
- DeST (2006). Simulation Method for Building Thermal Environment-DeST. Beijing: China Architecture and Building Press, 2006. (in Chinese)
- DOE-2 (1980). DOE-2 Reference Manual Version 2.1, LBL-7689-M Ver.2.1, LBL-8706 Rev.1.
- DOE-2 (1982). DOE-2 Engineers Manual Version 2.1A, LBL-11353.
- EnergyGauge (2012). EnergyGauge User Manual 2010. Florida Solar Energy Center, USA.
- EnergyPlus (2011). Engineering Reference Version 7.0 Documentation. University of Illinois and Ernest Orlando Lawrence Berkeley National Laboratory, USA.
- EnergyPro (2011). EnergyPro User's Manual, Version 5, July, 2011. EnergySoft, LLC, USA.
- eQuest (2009). eQuest Introductory Tutorial, Version 3.63, April, 2009. James J. Hirsch & Associates, USA.
- ESRU (1999). ESP-r: A building and plant energy simulation environment, User Guide Version 9 Series. ESRU Publication, University of Strathclyde, USA.
- Henninger RH, Witte MJ (2006). Test Report of LBNL DOE-2.1E119 Based on ANSI/ASHRAE Standard 140-2004. Lawrence Berkeley National Laboratory, USA.
- Henninger RH, Witte MJ (2011a). EnergyPlus Testing with ASHRAE 1052-RP Toolkit—Building Fabric Analytical Tests. Available: http://apps1.eere.energy.gov/buildings/energyplus/energyplus_te sting.cfm. Accessed Nov. 2011.

- Henninger RH, Witte MJ (2011b). EnergyPlus Testing with Building Thermal Envelope and Fabric Load Tests from ANSI/ASHRAE Standard 140-2007. Available: http://apps1.eere.energy.gov/buildings/ energyplus/energyplus_testing.cfm. Accessed Nov. 2011.
- Henninger RH, Witte MJ (2011c). EnergyPlus Testing with HVAC Equipment Component Tests. Available: http://apps1.eere.energy.gov/ buildings/energyplus/energyplus_testing.cfm. Accessed Nov. 2011.
- Huang J, Bourassa N, Buhl F, Erdem E, Hitchcock R (2006). Using EnergyPlus for California title-24 compliance calculations. In: Proceedings of SimBuild, Cambridge, MA, USA.
- IEA (1995). Building Energy Simulation Test (BESTEST) and Diagnostic Method. National Renewable Energy Laboratory, USA.
- Meldem R, Winkelmann F (1995). Comparison of DOE-2 with Measurements in the Pala Test House, LBL-37979. Lawrence Berkeley National Laboratory, USA.
- Sullivan R (1998). Validation Studies of the DOE-2 Building Energy Simulation Program, LBNL-42241. Lawrence Berkeley National Laboratory, USA.
- VisualDOE (2004). VisualDOE 4.0 User Manual, March, 2004. Architectural Energy Corporation, USA.
- Waddell C, Kaserekar S (2010). Solar gain and cooling load comparison using energy modeling software. In: Proceedings of SimBuild, New York, USA.
- Yan D, Xia J, Tang W, Song F, Zhang X, Jiang Y (2008). DeST—An integrated building simulation toolkit, Part I: Fundamentals. *Building Simulation*, 1: 95 – 110.
- Zhang X, Xia J, Jiang Z, Huang J, Qin R, Zhang Y, Liu Y, Jiang Y (2008). DeST—An integrated building simulation toolkit, Part II: Applications. *Building Simulation*, 1: 193 209.