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Stochastic Modeling of Overtime Occupancy and Its Application in Building Energy Simulation and Calibration

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Abstract

Overtime is a common phenomenon around the world. Overtime drives both internal heat gains from occupants, lighting and plug-loads, and HVAC operation during overtime periods. Overtime leads to longer occupancy hours and extended operation of building services systems beyond normal working hours, thus overtime impacts total building energy use. Current literature lacks methods to model overtime occupancy because overtime is stochastic in nature and varies by individual occupants and by time. To address this gap in the literature, this study aims to develop a new stochastic model based on the statistical analysis of measured overtime occupancy data from an office building. A binomial distribution is used to represent the total number of occupants working overtime, while an exponential distribution is used to represent the duration of overtime periods. The overtime model is used to generate overtime occupancy schedules as an input to the energy model of a second office building. The measured and simulated cooling energy use during the overtime period is compared in order to validate the overtime model. A hybrid approach to energy model calibration is proposed and tested, which combines ASHRAE Guideline 14 for the calibration of the energy model during normal working hours, and a proposed KS test for the calibration of the energy model during overtime. The developed stochastic overtime model and the hybrid calibration approach can be used in building energy simulations to improve the accuracy of results, and better understand the characteristics of overtime in office buildings.

Keywords: building energy use, building simulation, model calibration, occupant behavior, overtime occupancy, stochastic modeling

1. Introduction

Overtime refers to the time people work beyond normal working hours, such as working during weekends and weekday nights. Overtime is a common phenomenon around the world. According to the report from the International Labor Organization [1], overtime work is conventional in many developing countries. Workers in these countries tend to have longer weekly working hours, often exceeding 48 hours. In China, overtime work is even more common. A survey of 1975 employees shows that almost half of the surveyed employees worked overtime during workdays the week before the survey, and about 40% worked overtime on weekend and holidays [2]. In some developed countries such as Japan, the United States and Germany, overtime work is also observable [3, 4]. The average monthly overtime hours in Japan were officially reported to be 9.4 in 1995 [5]. In Germany, the proportion of overtime hours to total working hours has remained relatively stable at approximately 4% since 1982 [4]. In the USA, 11.5% of the workforce worked overtime for an average of 9 hours per week according to a survey [6].

For people working overtime, building energy and services systems (HVAC, lighting, plug-loads) have to remain operating to provide thermal comfort and ventilation, so a better understanding of overtime is important to building operators and to account for energy use. Building energy use beyond normal working hours can be seen in measured energy use data from surveyed buildings [7, 8]. HVAC systems, especially centralized ones, have to continue to supply ventilation, and cooling or heating for one or more occupants working overtime. This additional load can consume significant amounts of energy if the overtime period is long. Therefore, overtime is one of the main factors in determining building energy use during non-working periods.

The impact of overtime on building energy use is determined by occupant behavior. Building occupants not only contribute to internal heat gains, but also exert direct influence on HVAC system operation, lighting and equipment scheduling, and the indoor environment [9, 10]. In order to accurately simulate the energy use of a building and to estimate energy savings of occupant-controlled technologies, an accurate prediction of occupancy profiles is essential [11, 12]. In current building energy simulations, users are more familiar with factors less related to occupant behavior, such as climate, building envelope, and internal heat gains. The lack of appreciation for occupant behavior is due to its diversity and complexity [9, 13-16]. However, because occupant behavior affects building energy use significantly, it is considered to be one of the most important input parameters influencing the results of building performance simulations [17-21]. Overtime drives both internal heat gains (from occupants, lighting and plug-loads) and HVAC operation during non-working hours (including nights on weekdays, weekends and holidays). Therefore, energy models are difficult to calibrate for non-working hours without considering overtime as an important input. In current building simulations, the internal heat gains and HVAC operation schedules are usually deterministic schedules based on a typical weekday, weekend or holiday, either from measurement or design practice [22-24]. These schedules do not realistically represent overtime schedules due to their stochastic nature, and because of simplistic and idealistic data inputs that are unrepresentative of actual occupancy [25]. As a result, there are large discrepancies between simulated and actual building energy performance. Therefore, inputs of overtime that are more informative and representative of actual occupancy are needed to improve the accuracy of building simulations.

This study focuses on overtime in office buildings using measured data of occupancy and energy use, aiming to provide insights into the following important questions:

(1) What are the characteristics of overtime in office buildings?
(2) How can overtime be described with stochastic models using parameters that can be obtained from surveys or interviews?
(3) How can those stochastic models be applied to improve the accuracy of building energy simulations?
(4) How can overtime models be calibrated? Are the calibration criteria for the overtime periods the same as for normal working periods?

By answering the above questions, more accurate inputs for occupancy schedules and building systems operation can be provided to improve the accuracy of whole-building energy simulations.

2. Methodology

2.1. Overview

To investigate the characteristics of overtime, site surveys of office buildings are a natural starting point. Carrie et al. [26] conducted after-hours building walk-throughs to collect data on the power status of office equipment. While the number of buildings audited is sufficient, such kind of data collection cannot capture variations in occupant behavior during all overtime periods, because it requires automated, long-term time-interval monitoring. In this study, actual auto-recorded occupancy data from an office building (Building A) is used.

The overtime data is then analyzed statistically in order to develop a stochastic model that represents the characteristics of overtime with parameters that can be physically measured or obtained via surveys and interviews. The stochastic overtime model can generate occupancy schedules during overtime hours for building energy simulations. Overtime has a direct influence on occupancy and so affects the status of HVAC equipment. This means that actual occupancy schedules and HVAC schedules are both closely related to overtime. Since overtime is stochastic in nature, the generated overtime occupancy schedules and HVAC schedules during overtime periods are also stochastic.

In order to demonstrate the use of the stochastic overtime model and verify its accuracy, a second office building (Building B) is selected for the study. There is no digital system to record overtime information of occupants every day, so direct verification of the overtime model developed from Building A is not possible. Instead, hourly, measured cooling energy consumption data during the entire cooling season is used as a proxy for verification purposes.

A detailed field investigation was first conducted in Building B that examined climate, building envelope, internal loads, HVAC systems and operation, and lighting systems. Information extracted from the collected survey data was then used as input parameters in building energy simulations to better represent the actual building. Further investigation was conducted on a few selected tenants and occupants. Its results were used as inputs to the overtime model to generate detailed overtime information needed for building energy simulation. By comparing measured data with simulated results (both with and without overtime inputs) discrepancies between the building energy simulation and the real building, caused by lack of overtime inputs, can be identified. The overtime model can be verified if the simulated cooling energy consumption meets the acceptance requirements of the calibration criteria. In this study, a hybrid approach to energy model calibration is developed and applied to the calibration of energy models considering overtime. Fig. 1 shows the overall methodology used in this study.

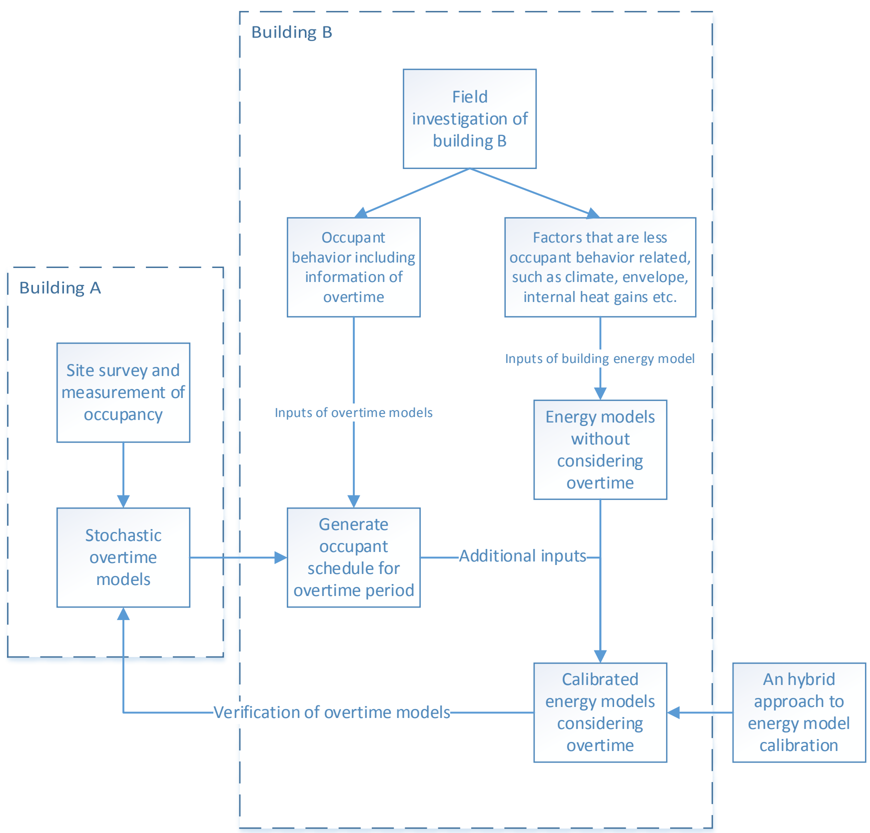


Fig. 1. Overview of the methodology

2.2. Site survey and measurement

Building A is a four-story office building located in Hangzhou, China. It has a total floor area of 7000 m^2, shared by two tenants. The surveyed tenant is a research institute with 47 occupants, occupying the first to third floors of Building A. Each staff member of the surveyed tenant carries a magnetic card. By clicking the card on a reading machine in the entrance, the card holder's accurate time of arrival and departure can be recorded and stored in a computer. The data recorded between November and December of 2010 was used in this study. The normal working hours are 8:00 – 17:00, Monday to Friday. Any working hours after 17:00 on weekdays, and during weekends and holidays are considered to be an overtime period.

2.3. Overtime models

Overtime is classified into two categories, one is after-work hours on weekdays, and the other is weekends and holidays. Based on overtime characteristics, different mathematical models were used to attempt to represent the two overtime categories. The inputs of the models should be parameters that can be physically obtained through site surveys in office buildings. For instance, by random occupants completing a questionnaire, or interviews of building operators, the average probability of an occupant working overtime can be estimated, as well as the average overtime duration (in hours) on each overtime weekday. The outputs of the models will be parameters that are difficult to obtain by normal site survey. For instance, it is impossible to know the overtime hours of each occupant every day without using a time recording system or other similar equipment.

2.4. Verification of overtime models

Building B is a 20-story office building in Beijing, China, shown in Fig. 2. Its total floor area is 55000 m^2 while the conditioned floor area is 30300 m^2. Cooling is only provided from June 1st to September 30th each year. A site survey was conducted in Building B in 2011 to examine the building envelope, occupant density and schedules, lighting and plug-loads, and HVAC systems. Measured cooling energy consumption data for the building in 2010 was collected. Table 1 summarizes the main characteristics of Building B.

Fig 2. A Photo of Building B.

Table 1. Summary of characteristics of Building B.

	Parameters
Envelope	
Window-wall ratio	North/west: 0.81; East/south: 0.87
Walls construction	370 mm brick wall: Double layered gypsum board + insulation (200 mm polystyrene)
Wall U-factor (W/m^2K)	0.13
Window construction	Double-pane glazing
Window U-factor (W/m^2K)	2.0
Window shading coefficient (SC)	0.47
Internal loads	
Design occupant density ($persons/m^2$)	0.066
Design lighting density (W/m^2)	11.7
Design plug-loads density (W/m^2)	6.0
IT room power (kW)	37.2
HVAC system	
System type	Central built-up VAV systems
Cooling source	Water-cooled centrifugal chillers
Heating source	District Heating
Thermostat setpoints	24℃ Cooling/20℃ Heating
Normal working hours	9:00-18:00, Monday to Friday

Four tenants (using about 10% of the total floor area) in Building B were selected for further investigation. A questionnaire was sent to each occupant about their occupancy during working hours, overtime probability and overtime duration. From the questionnaire results the following can be estimated: the occupant schedule during normal working hours, the average overtime probability, and the average overtime duration. With these as inputs to the overtime models, the hourly occupancy of all occupants in Building B can be determined.

2.5. Simulation Engine

DeST (Designer's Simulation Toolkit) is a whole-building energy modeling program developed by Tsinghua University, China [27-29]. DeST was built upon a state-space multi-zone heat balance calculation method [30, 31] considering detailed heat and mass flows in buildings. It is used in China for practical engineering and research on building simulation to support the design of energy efficient buildings.

2.6. Energy model calibration criteria

ASHRAE Guideline 14-2002 [32] is widely used to calibrate building energy models. The Coefficient of Variation of the Root Mean Square Error (CVRMSE) and the Normalized Mean Bias Error (NMBE) are usually used as acceptance criteria for building models. The CVRMSE and NMBE are determined by comparing predicted results ($\hat{y}$) with the measured data used for calibration (y_i), (n) is the number of data points used in the calibration, and $\bar{y}$ is the average value of y_i. NMBE and CVRMSE are calculated as:

$$NMBE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n \times \bar{y}} \times 100 \tag{1}$$

$$CVRMSE = 100 \times \left[\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 / n\right]^{1/2} / \bar{y} \tag{2}$$

The calibration criteria can be applied to two time scales: monthly and hourly. If monthly data is used during calibration, the NMBE acceptance requirement is 5% and the CVRMSE is 15%. If hourly calibration data is used, then the requirement is 10% for NMBE and 30% for CVRMSE. In this study, hourly calibration criteria and data is used.

ASHRAE Guideline 14 is a useful guide to calibrating energy models with deterministic schedules. Due to the stochastic characteristics of overtime, as further illustrated in this paper, these criteria may not be suitable for the calibration of energy models with stochastic schedules. The overtime model was used to generate occupant schedules during overtime periods which represent the statistics of overtime, but the randomly generated overtime occupancy might not match the actual overtime schedule. To address this gap, a hybrid calibration criterion for building energy models is presented in Section 3.4. Three time periods were used in the building energy model for the purpose of the calibration: (1) normal working hours, (2) overtime during weekdays, and (3) overtime during weekends and holidays. For normal working hours, ASHRAE Guideline 14 is used as calibration criteria; while for overtime during weekdays and during weekends and holidays, a statistical criterion is proposed in this study.

3. Results and discussion

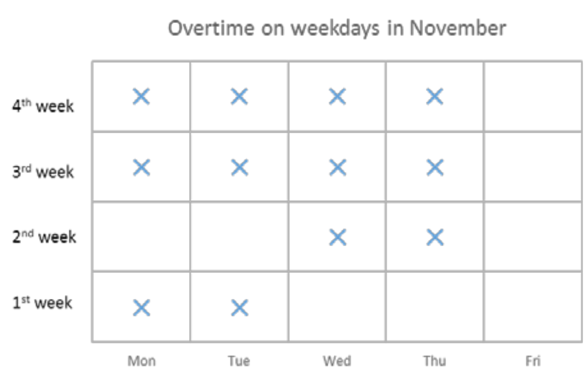
3.1. Characteristics of overtime in reality

Because overtime characteristics are different between weekdays, and weekends and holidays, they are analyzed separately.

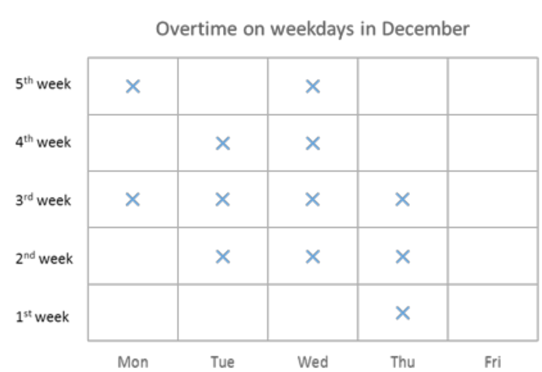
3.1.1. Overtime during weekdays

In Building A, each occupant's arrival and departure time were recorded every day to determine their overtime frequency and duration of overtime work. Taking three occupants as an example, Fig. 3 shows their weekday overtime occurrences in November and December (a cross indicates overtime). Considering individual days or weeks, overtime appears to occur randomly, which means that overtime could happen on any weekday, and the number of overtime days per week also varies. For each individual, the overtime occurrence and frequency vary from day to day, and week to week. It can be seen that the first occupant has the most overtime, followed by the second and then the third.

Fig. 4 shows the daily number of occupants working overtime on weekdays in Building A, which varies significantly from day to day. Fig. 5 shows the frequency distribution of the same data which can be approximated by a bell curve, which usually indicates a normal or binomial distribution. Fig. 6 shows the daily overtime durations for the three occupants on weekdays. Overtime hours are very uncertain between calendar days and also occupants. Fig. 7 illustrates the frequency distribution of overtime duration for all three occupants working overtime. From Fig. 7, it can be observed that there is a peak frequency of 37.4% for overtime duration between 0 and 0.5 hours. Further, there is more than a 50% probability that each overtime occurrence is less than one hour in duration, and rarely does overtime exceed 4 hours in duration.



(a1) Occupant A



(a2) Occupant A

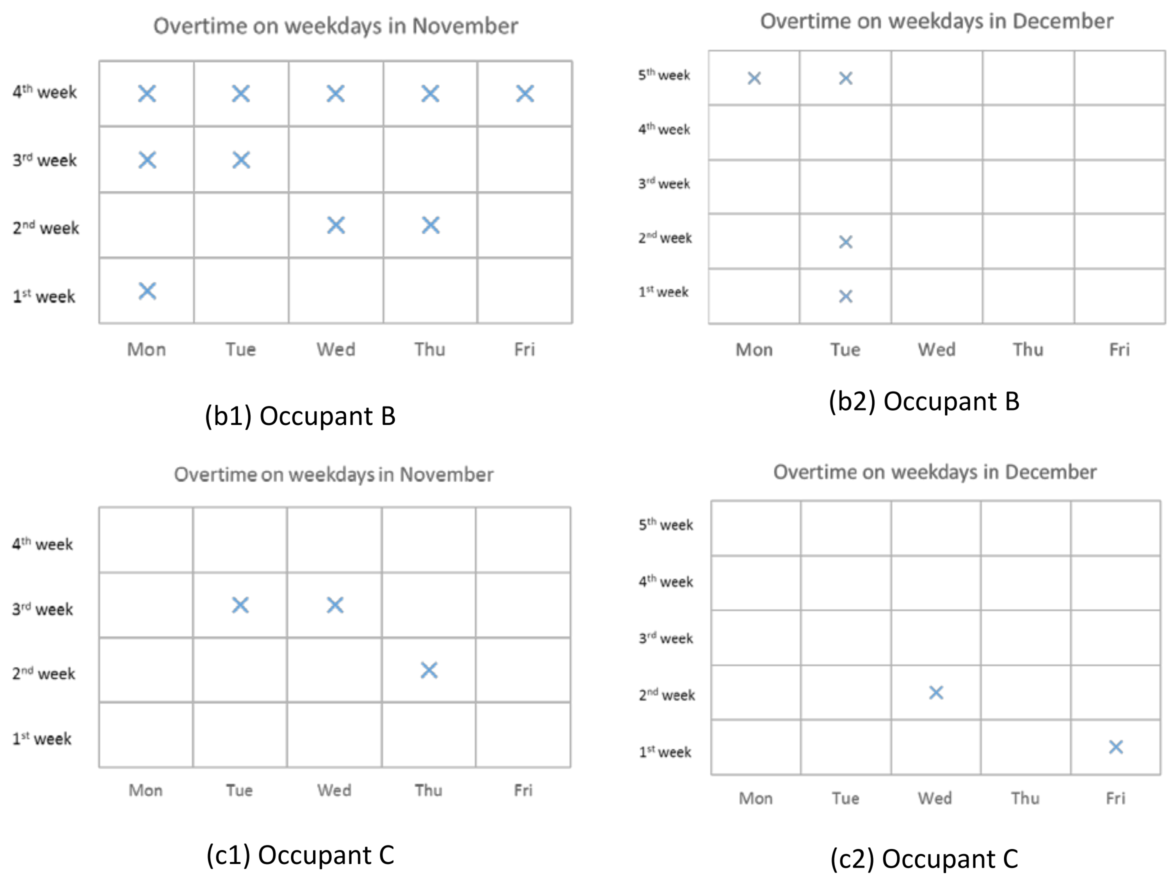


Fig. 3. Occupants' weekday overtime occurrences in November and December: a1, b1, c1 are in November and a2, b2, c2 are in December.

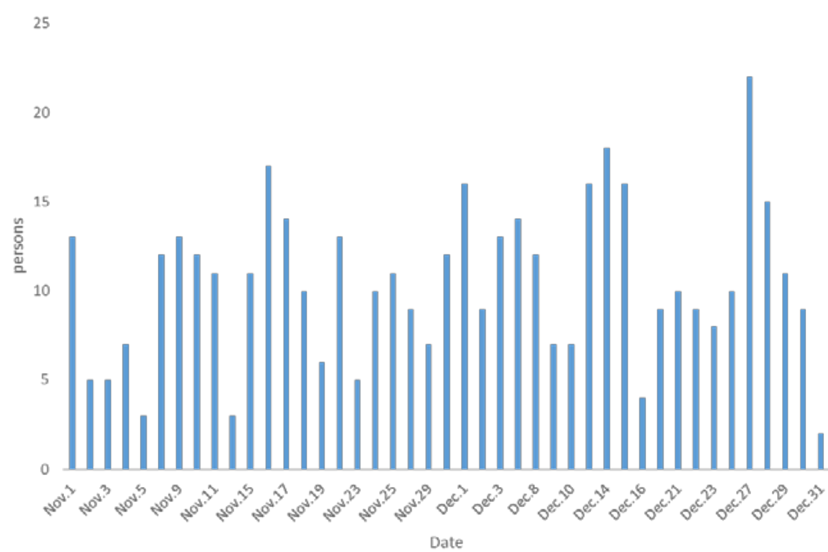


Fig. 4. Number of occupants working overtime during weekdays

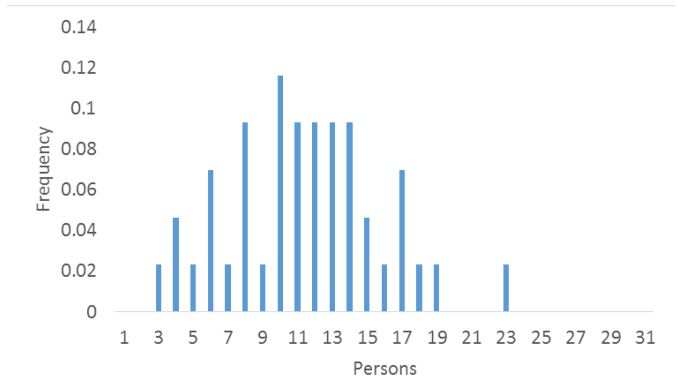


Fig. 5. The frequency distribution of the number of occupants working overtime

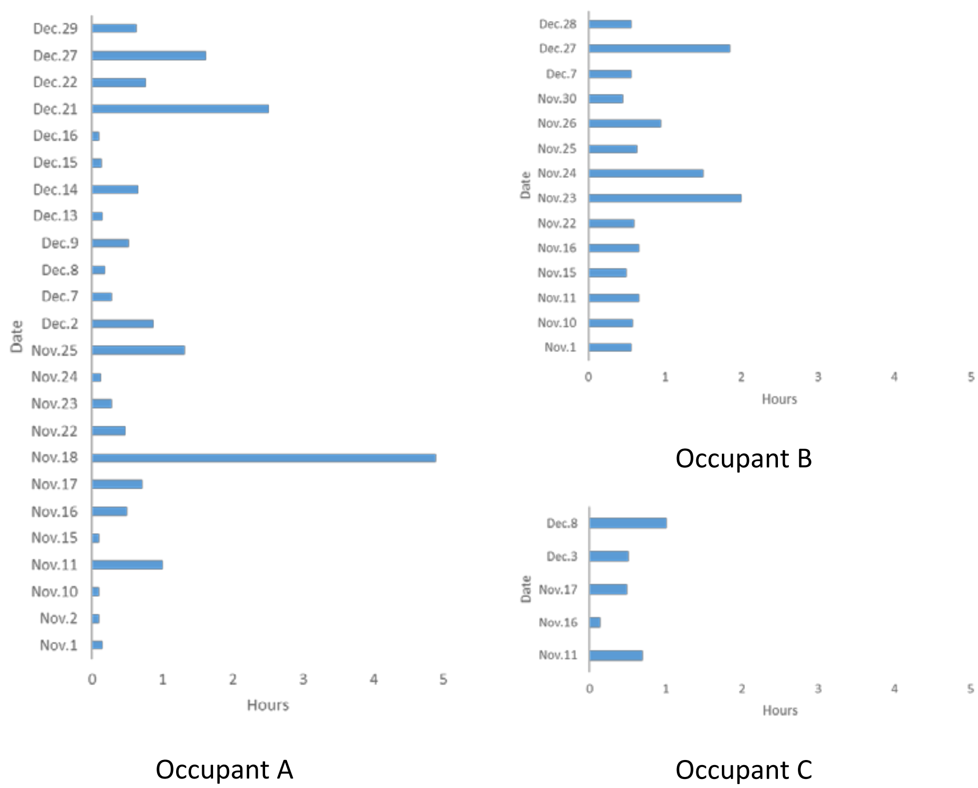


Fig. 6. Overtime durations for three building occupants during weekdays

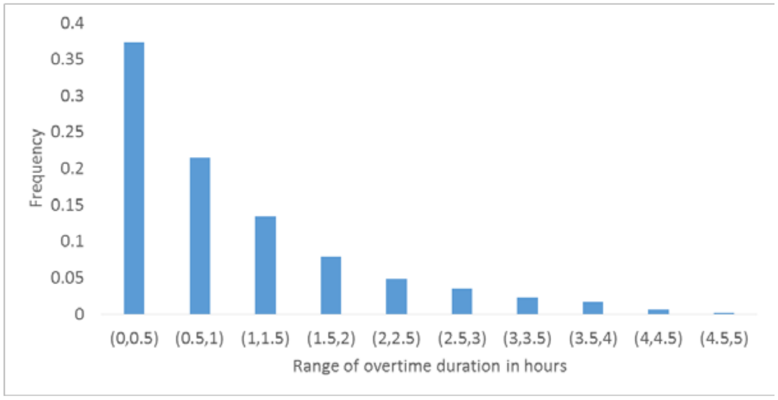


Fig. 7. The frequency distribution of overtime durations

3.1.2. Overtime during weekends and holidays

There are 16 weekend days during the two surveyed months for Building A. Taking a weekend day as an example, there are six occupants working overtime. Fig. 8 illustrates their overtime start times and durations. It can be seen that their start times vary significantly from approximately 9:00 to 14:00. This is quite different from weekdays, when start times are consistent (immediately after normal working hours). Meanwhile overtime durations vary widely in length, from approximately two to eight hours. The number of occupants working overtime during each weekend or holiday is stochastic (similar to weekdays) as illustrated in Fig. 9 which shows a minimum of zero and a maximum of seven occupants working overtime in November and December.

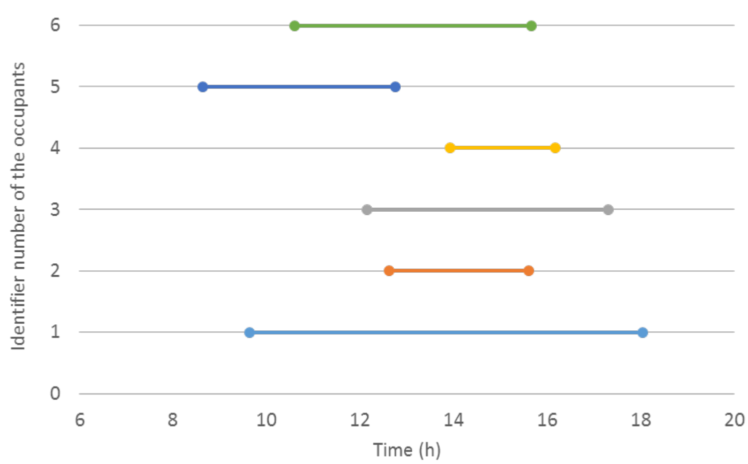


Fig. 8. Start time and duration of overtime for six occupants on a weekend day

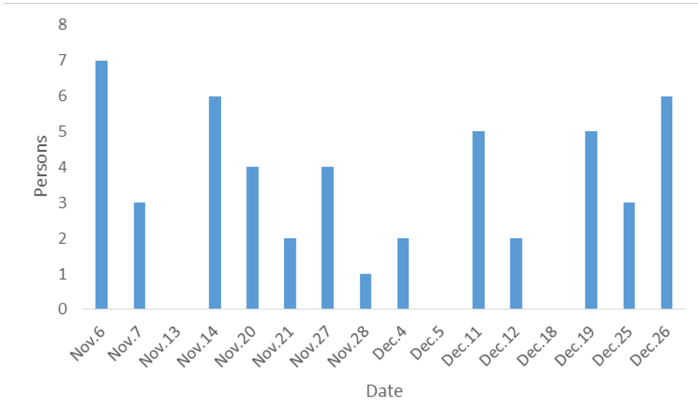


Fig. 9. Number of occupants working overtime during weekends and holidays

3.2. Stochastic overtime models

Based on previous analyses of overtime during weekdays and weekends/holidays, there is a need to develop stochastic models to represent the different characteristics of overtime during those two different periods.

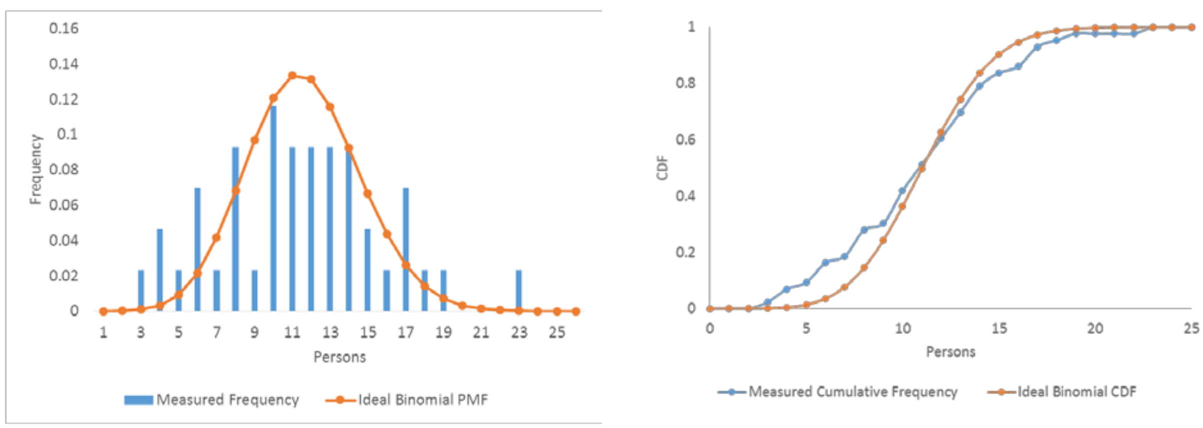
3.2.1. Overtime model for weekdays

In the measured data, there are 45 weekdays and 1808 person-time (one occupant with one overtime occurrence counts as one person-time) of overtime, which is sufficient to perform a statistically significant analysis. In order to determine hourly occupancy schedules during overtime on a weekday, two parameters are necessary: (1) the number of overtime occupants on that weekday and (2) the overtime duration (in hours) for each occupant. Although each occupant's overtime probability is different, it is not necessary to specify which occupant works overtime. Instead, at the tenant level, three inputs are needed to generate the tenant's hourly occupancy, including the average overtime probability, the total number of occupants and the average overtime duration.

According to Section 3.1.1, the distribution of the number of overtime occupants approximates to a normal or binomial distribution. However, considering the discrete nature of the number of overtime occupants, a binomial distribution is more realistic. The two parameters of a binomial distribution, n and p, are the number of trials and the success probability of each trial, respectively. In this study, n represents the number of occupants, while p represents the average probability of overtime occurring.

In order to test the rationale of the hypothesis distribution for measured data, the one-sample Kolmogorov-Smirnov test (KS test) is used as the test method in this study. The KS test is a non-parametric test for the equality of continuous, one-dimensional probability distributions that can be used to compare a sample with a reference probability distribution (one-sample KS test), or to compare two samples (two-sample KS test) [33]. The KS test quantifies a discrepancy between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution, or between the empirical distribution functions of two samples. The null distribution of this statistic test is calculated under the null hypothesis that the samples are drawn from the same distribution.

For the hypothesis that the number of overtime occupants follows a binomial distribution, the KS test result h is 0, demonstrating that the hypothesis is accepted. Fig. 10 also shows a good match between a binomial distribution and the measured frequency of number of overtime occupants using a PMF (Probability Mass Function) and CDF (Cumulative Distribution Function), respectively.



(a) (b)

Fig. 10. Comparison of a standard binomial distribution with the measured frequency of the number of overtime occupants: (a) Probability Mass Function; (b) Cumulative Distribution Function.

The distribution of the duration of overtime on weekdays, shown in Fig. 11, approximates well to an exponential distribution. The only parameter of an exponential distribution is λ, representing the mean value. In this case λ is equal to 1.095. Again using the KS test to examine the distribution, the result h is 0 shows that an exponential distribution is a reasonable approximation to describe overtime duration on weekdays. Fig. 11 shows a comparison between an exponential distribution and the measured frequency of overtime hours, indicating good agreement. Therefore, an exponential distribution can be used to describe overtime duration, with the only parameter being the average occupants' overtime duration.

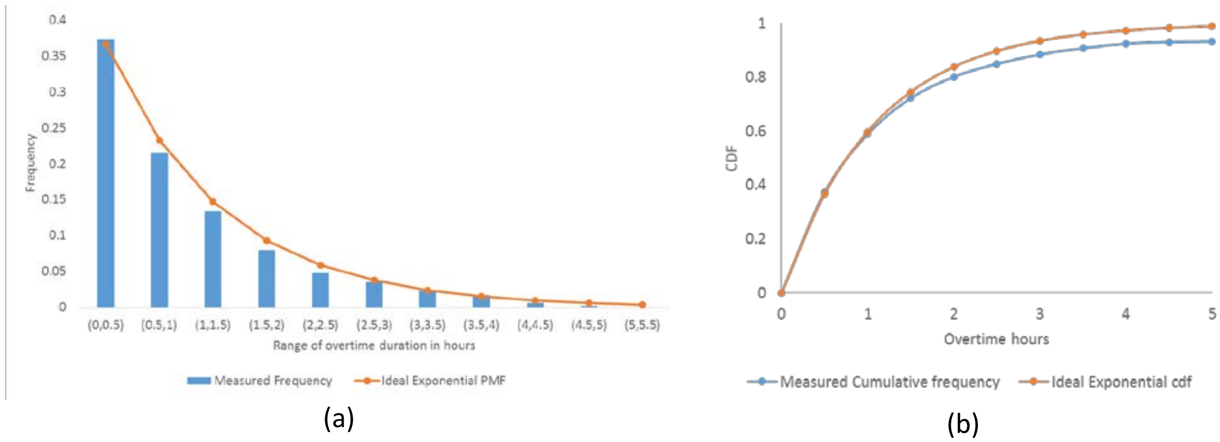


Fig. 11. Comparison of an exponential distribution with measured frequency of overtime duration: (a) Probability Density Function; (b) Cumulative Distribution Function.

In summary, the overtime model for weekdays contains two parts. One is a binomial distribution for the number of overtime occupants, which has two parameters: n for the number of total occupants, and p for the average probability of overtime. The other is an exponential distribution describing each occupant's overtime duration on a weekday, which has a single parameter representing the occupants' average overtime duration.

For a building tenant on a specific calendar day, the number of occupants working overtime can be generated from a binomial distribution. While for each occupant working overtime on that day, their overtime duration can be generated from an exponential distribution. The number of occupants working overtime and their overtime duration can then be aggregated into an hourly occupancy schedule.

3.2.2. Overtime model for weekends and holidays

According to Section 3.1.2, the number of daily overtime occupants and overtime duration for each occupant vary during weekends and holidays. Additionally, the overtime start time for each occupant varies significantly. Unfortunately, the dataset only has 16 weekends/holidays and 50 person-time of overtime, which is insufficient for a statistically significant analysis. However, overtime work during weekend and holidays is less important than the weekdays based on measured data from Buildings A and B. In Building A, the overall person-time of overtime on weekends and holidays (50) is much smaller than on weekdays (1808). In Building B, as shown in Section 3.4, the total cooling energy consumed during overtime on weekends and holidays is about 40% of the total cooling energy consumed during all overtime periods (Table 5).

Thus, for overtime on weekends and holidays, a simplified model was used in this study. First the average overtime probability is calculated from surveyed data on occupants. Then this probability is applied as a multiplier to the occupant schedule during normal working hours on weekdays to derive the occupant schedule for weekends and holidays.

3.3. A hybrid approach to energy model calibration

Ideally, recorded occupancy data from other buildings is needed to verify the accuracy of the overtime models developed from data on Building A. Unfortunately no such data is available for this study so direct verification of the overtime models is not possible. However, occupancy during overtime period leads to extended cooling consumption, so measured hourly cooling energy consumption data during the entire cooling season can be used as a good proxy for overtime occupancy for verification purposes. Then how do we determine whether the overtime models are accurate? In other words, what should be the calibration criteria of a building energy model with overtime inputs?

From Sections 3.1 and 3.2, overtime occurs randomly with a certain probability distribution. The hourly occupancy schedule generated from the stochastic overtime model on weekdays varies from day to day. It would not match exactly any occupancy schedule during the overtime of a particular weekday. Therefore, the simulated hourly energy use during overtime periods also varies from day to day, and would not match the measured hourly energy use, but rather the energy use probability distribution. The hourly calibration criteria from ASHRAE Guideline 14 is based on direct comparison between hourly simulated and measured energy use which cannot be applied to the overtime periods. A new model calibration criterion is needed for the overtime periods that have strong stochastic characteristics.

Since overtime occupancy schedules have a certain probability distribution, building energy consumption during overtime periods should also follow some probability distribution. This requires a new statistical approach to calibrate overtime models. By testing the equivalence of two probability distributions for the simulated and measured cooling energy consumption, the accuracy of overtime models can be verified and energy models can thus be calibrated. Moreover, because both the number of overtime occupants and the overtime durations are daily parameters of the stochastic overtime models, simulated hourly results during overtime periods can be aggregated on a daily basis and used for model calibration.

The two-sample KS test is one of the most useful and general non-parametric methods for comparing two samples, as it is sensitive to differences in both location and shape of the empirical cumulative distribution functions of the two samples [33]. The two-sample KS test will be used to compare the probability distributions of the measured and simulated daily cooling energy consumption of Building B during overtime on weekdays.

To address different types of occupancy schedules used in energy models during normal (deterministic schedules) and overtime (stochastic schedules) work periods, a hybrid approach to energy model calibration is proposed, shown in Fig. 12. First, the whole cooling simulation period is divided into three parts: the normal working hours with a deterministic occupancy schedule, the overtime on weekdays with a detailed stochastic occupancy model, and the overtime on weekends and holidays with a simplified deterministic occupancy schedule. Different criteria are then used to calibrate energy models for the three types of schedule. For the normal working hours, the hourly calibration criteria in ASHRAE Guideline 14 are used as the occupant schedule is deterministic. For overtime on weekdays, weekends and holidays, the two-sample KS test is adopted as the calibration criterion. The two samples to be tested are the simulated and measured hourly cooling energy consumption during overtime. In statistical significance testing, the p-value is the probability of obtaining a test result at least as extreme as the one that was actually observed, assuming that the null hypothesis is true [34]. Usually, the null hypothesis will be rejected (h = 1) when the p-value turns out to be less than a certain significance level, often at 0.05 or 0.01 [35]. If a more stringent requirement for overtime calibration is needed, a significance level of 0.05 can be used. In this study the significance level of 0.05 is used. In other words, if the p-value is greater than 0.05 (i.e., the KS test fails to reject the null hypothesis at the 5% significance level (h = 0)) the overtime model in the building energy model can be regarded as calibrated and verified as accurate.

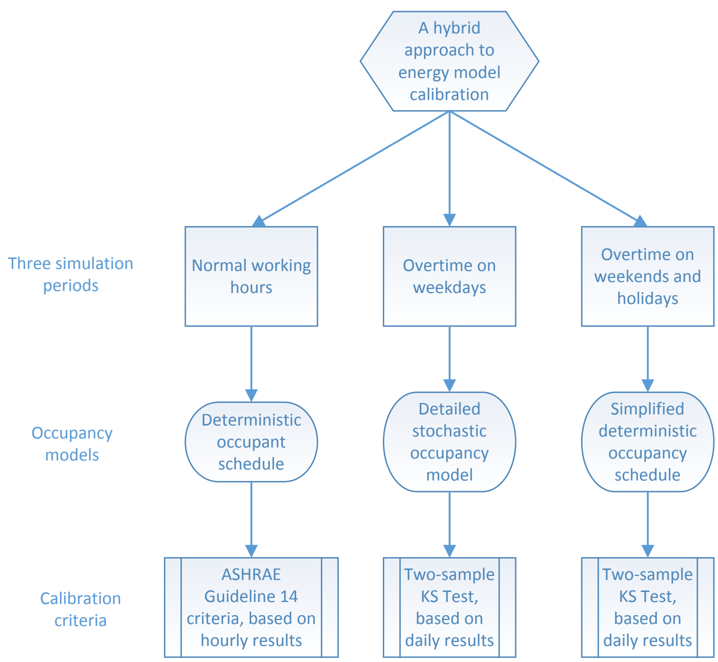


Fig. 12. Overview of the hybrid approach to energy model calibration

3.4. Application of the stochastic overtime models in building energy simulation

In order to demonstrate the use of the stochastic overtime models and verify their accuracy, a second office building (Building B) is selected for the study. The overtime models developed in this study are applicable to other office buildings, since the parameters in the models have taken into consideration the different characteristics of different types of office buildings. Therefore, though their occupants might have different overtime characteristics, it is reasonable to use another office building to verify the accuracy of the overtime models.

3.4.1. Simulation results from the energy model without considering overtime

An energy model of Building B (Fig. 13) is developed using DeST based on survey results described in Section 2.3. Through the use of questionnaires, the occupant schedule during normal working hours is determined to be 9:00-18:00, Monday to Friday. When overtime is not considered in the model, it is assumed that there are no occupants in the building during after-work hours on weekdays, weekends or holidays. Note that lighting and appliance (plug-loads) schedules in Building B come from measured electricity consumption, so they do not change with how overtime is considered in this study. From the survey of Building B, the AHUs are operated during 8:00-19:00 on weekdays, so HVAC systems will be switched off after 19:00 on weekdays, all weekends and holidays. The hourly measured and simulated cooling energy use of Building B are compared, as shown in Table 2, Figures 14 and 15, which demonstrate that the energy model without considering overtime can't be calibrated to meet the acceptance criteria defined in ASHRAE Guideline 14. From the hourly consumption profile in Fig. 14 and the interquartile profile in Fig. 15, it can be seen that cooling energy is consumed after 19:00 on weekdays in the measured data, while there is none in the simulation results. When normal working hours are considered independently, the simulated results can meet ASHRAE Guideline 14's acceptance criteria. Therefore, it is necessary to consider overtime in the energy simulation of office buildings where occupants conduct work during overtime hours.

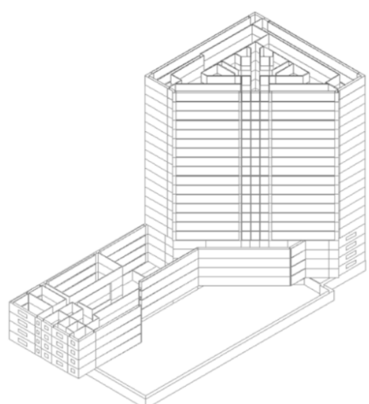


Fig. 13. An illustration of the Building B model in DeST

Table 2. Comparison of measured and simulated results using ASHRAE Guideline 14 criteria (hourly), for Building B without considering overtime

	All time (normal + overtime) (%)	**Normal working hours (%)**
NMBE	-0.66	6.4
CVRMSE	36.4	23.3

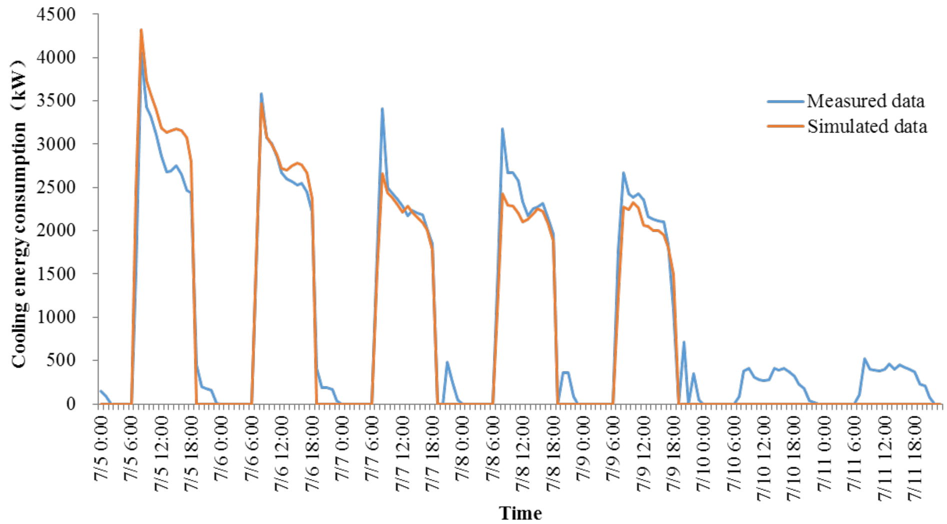
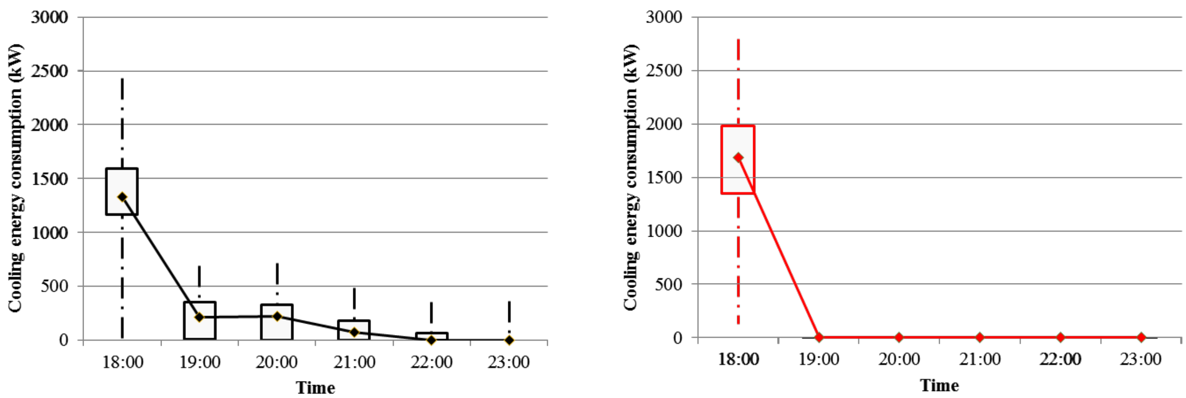


Fig. 14. Comparison of hourly simulated and measured cooling energy consumption in a typical week (model without overtime)



(a) Measured Data

(b) Simulated Results

Fig. 15. The interquartile profile of hourly cooling energy consumption during overtime on weekdays for the whole cooling season: (a) Measured data; (b) Simulated results without overtime.

Note: the upper and lower limits of the boxes are quartiles of each column (75% and 25%, respectively); the upper and lower limits of the dashed lines are maximum and minimum value. The center dots are the medians and the connecting line between the dots shows the time-series trend in order to compare the measured and simulated results visually.

3.4.2. Calibrated simulation results from the energy model considering overtime

Based on the probability of overtime, tenants can be categorized into two types: (1) occupants with a higher probability of overtime, and (2) occupants with a lower probability of overtime. Among the four surveyed tenants, one tenant has higher overtime probabilities (0.367 on weekdays and 0.322 on weekends and holidays), while the other three tenants have lower overtime probabilities (0.202 on weekdays, and 0.044 on weekends and holidays). Table 3 shows the rented floor areas of the four tenants, based on which the proportion of the two types of tenants in Building B can be calculated. About 90% of the tenants are the second type, while the remaining 10% are the first type. Assume each floor is rented by a single tenant, there are 18 floors of the second type and 2 floors of the first type in Building B.

Table 3. Floor Area of the surveyed tenants (in m^2).

Tenant 1	Tenant 2	Tenant 3	Tenant 4
950	950	243.5	250

According to the stochastic overtime models in Section 3.2.1, the number of overtime occupants and the overtime duration of each occupant can be generated. Thus the occupancy schedule during overtime on weekdays on each floor can be calculated. As for weekends and holidays, it is assumed that no overtime is worked because the second type of tenant has a very low overtime probability. For the first type of tenant, the simplified model is used (Section 3.2.2).

According to the interview results of the building operators, the tenants make a request to the operators and pay a certain additional fee if cooling services need to be extended for their overtime work. In this study a tenant is assumed to work overtime if at least 25% of its employees work overtime during the first hour immediately after normal working hours. HVAC systems will be shut down for tenants not working overtime. Approximately half of the overtime tenants request continuous HVAC operation immediately after the normal working hours, while the other half choose to restart cooling two hours after the HVAC systems are shut down in order to save the cost of cooling, under the assumption that the room temperature won't increase too much due to the cooling thermal mass storage in the building structure. For overtime tenants, the HVAC schedules on weekends and holidays were assumed to be the same as that of normal operating hours on weekdays. It should be noted that the calibration term used in this study refers to the addition of the occupant schedule and systems operation during overtime to the energy models. None of other model inputs were adjusted during the calibration process.

When the ASHRAE Guideline 14 calibration criteria is applied to all time periods, the simulated results barely meet the acceptance criteria, as shown in Table 4, although a better match to the measured data is illustrated in Figures 16 and 17. To better address the deterministic occupant schedule during normal working hours and the stochastic occupant schedule during overtime, a hybrid approach to model calibration is proposed. First the whole cooling season is divided into three parts: the normal working hours, the overtime on weekdays, and the overtime on weekends and holidays. Secondly the ASHRAE Guideline 14 criteria are applied to the measured and simulated results for the normal working hours, as shown in Table 4. Thirdly the KS test is applied to the measured and simulated daily cooling energy use during overtime on weekdays, as shown in Table 5. The KS test is also applied to the results during overtime on weekends and holidays, as shown in Table 5.

Table 4. Calibration results of the Building B energy model with overtime using ASHRAE Guideline 14 criteria (hourly)

	All time (normal + overtime) (%)	**Normal working hours (%)**
NMBE	-1.5	2.8
CVRMSE	28.5	19.3

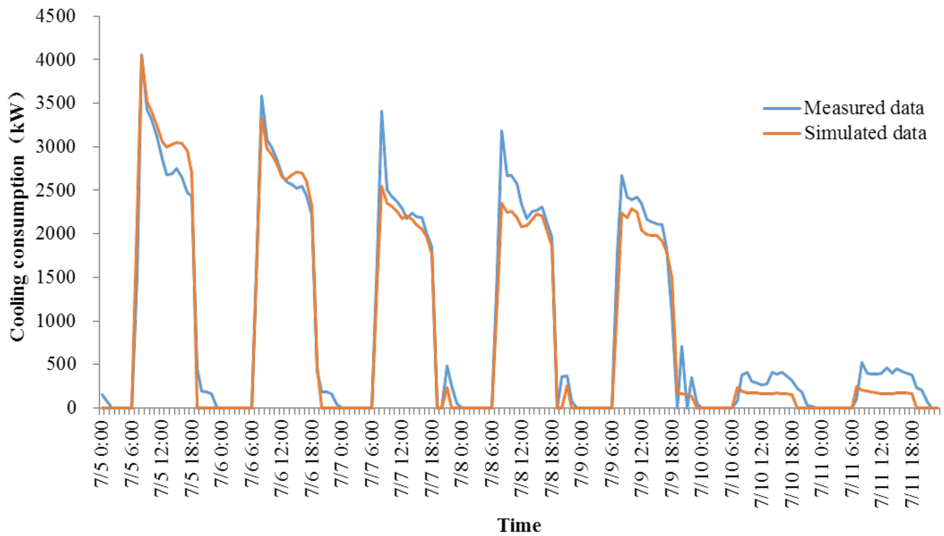
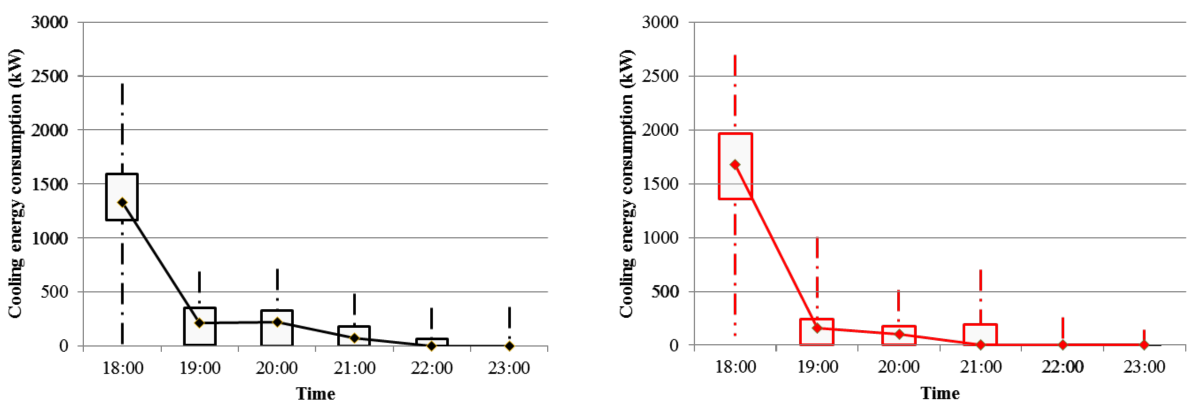


Fig. 16. Comparison of the hourly simulated and measured cooling energy consumption in a typical week (model with overtime)



(a) Measured Data

(b) Simulated Results

Fig. 17. The interquartile profile of the hourly cooling energy consumption during overtime on weekdays for the whole cooling season: (a) Measured data; (b) Simulated results from the model with overtime.

Table 5. Calibration results of the Building B energy model for overtime using the KS test

	Total cooling energy consumption (kWh)		**Results using ASHRAE Guideline 14 criteria (hourly)**		**Results using the KS test**	
	Measured	Simulated	NMBE (%)	CVRMSE (%)	h	p-value
Overtime on weekdays	162479	175259	7.9	82.3	0	0.257
Overtime on weekends and holidays	125341	96049	-23.4	70.3	1	4.74×10^{-4}

Note: h is the null hypothesis that the simulated results and the measured data are from the same distribution. h will be 0 if the KS test fails to reject the null hypothesis at the 5% significance level, otherwise h will be 1.

It can be seen that the simulated results during the normal working hours and overtime on weekdays pass the calibration criteria respectively. The results during overtime on weekends and holidays failed the test mainly due to the inadequate overtime data and the simplified assumption made in the occupancy model. This is an area for future research.

The calibration results for the overtime model during weekdays demonstrated that: (1) the stochastic overtime model for weekdays worked well to capture the random characteristics of overtime, and (2) the KS test is a valid approach to model calibration considering the stochastic nature of overtime occupancy schedules.

4. Conclusions

This study developed a stochastic model for overtime occupancy based on measured occupancy data from an office building. The overtime model was then applied to another office building for validation. A hybrid approach to energy model calibration is proposed to address the different occupancy schedules used for normal working hours and for overtime. The main findings from this study are: (1) Overtime occurs stochastically, both on weekdays and on weekends and holidays because the probability of overtime for different occupants on different days varies significantly; (2) For overtime on weekdays, the number of occupants working overtime follows a binomial distribution, which has two parameters that can be obtained by surveying occupants - the number of total occupants and the average probability of overtime for each occupant. The duration an occupant works overtime follows an exponential distribution, which has a single parameter - the occupants' average overtime duration; (3) Occupant schedules and HVAC schedules during overtime hours can be determined according to the stochastic overtime model; and (4) A hybrid approach to energy model calibration is proposed and tested, which combines ASHRAE

Guideline 14 for normal working hours on a deterministic basis, and the KS test for overtime on a probabilistic basis. These findings help to understand and describe characteristics of overtime in office buildings, and the stochastic overtime model can be used to generate occupant schedules during overtime as an input to building energy simulations to improve the accuracy of their results.

Future work will continue to investigate overtime on weekends and holidays, and develop an appropriate stochastic overtime model. If recorded occupant overtime data for more buildings are made available, the stochastic overtime models could be verified directly using the recorded overtime data instead of other measured building data, and necessary enhancements to the overtime model can be implemented to improve its accuracy.

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