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Energy performance model development and occupancy number identification of institutional buildings

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ABSTRACT

This paper presents a detailed investigation and analysis of the energy consumption characteristics of three institutional buildings in Singapore. Building information, energy consumption data of the air-conditioning system, and energy consumption data of the plug loads were collected separately. Identification models are developed to predict the real daily energy consumption data. Developed models involve three specific functions to represent the variability of the daily occupancy, the additional occupancy due to visitors and the variation of outdoor air temperature. The performance of the developed identification model is very satisfactory and fits very well with the real energy consumption data. Based on the identification model, key factors which are influencing the energy consumption in institutional buildings are identified as the variability of the daily occupancy, hence a methodology is developed to calculate the occupancy in the building. The identified parameters are used as inputs into deterministic energy simulation programs, like Energy Plus, to perform detailed energy analysis. The whole methodology developed has improved significantly the accuracy of the energy simulation modeling of institutional buildings and has permitted to understand and evaluate the major energy characteristics of these buildings.

1. Introduction

Institutional buildings focus on the creation or expansion of institutions and enduring features of social life [1]. As early as back to the 15th century, institutional buildings emerged in the form of buildings for educational institutions. The importance of looking at the institutional buildings has been addressed as early as in 1972 during the Stockholm Conference on the Human Environment [2]. Typically, in order to accomplish a general or specific purpose of the institutional building, occupant interaction is an important factor [3]. The function of the building also varies significantly according to the different needs of the occupant interacting of the building [4].

Due to the large number of people using these buildings and their different functions, institutional buildings are classified amongst buildings which presents with the highest energy consumption [5,6]. It is reported that commercial and educational buildings consume more than 19% of all energy annually in USA [7]. By looking at previous studies about the energy consumption in institutional/educational buildings, the typical annual heating consumption in Ireland is recorded as 96 kW h/m^2 [8], 192 kW h/m^2 for Slovenia [9] and 157 kW h/m^2 in the UK [10]. The specific energy consumption reported in Serbia [11] is even 3–4 times higher compared with European countries. The mean annual heating consumption of educational buildings in Greece was reported to be 31 kW h/m^2 and 46 kW h/m^2 for the coldest climatic area [12]. A higher value of 84 kW h/m^2 was also reported in 77 northern Greece educational buildings [13], the100 kW h/m^2 average annual consumption for space heating are derived from 117 educational buildings in the Province of Torino [14].

Considering the function of rooms in institutional buildings such as lecture rooms, seminar rooms, conference/meeting rooms etc., there is always more occupancy in a relatively higher density [15]. Questionnaire studies demonstrated that 92% of the institutional building users were visitors, with only 8% of the users claiming to have a permanent office in the building [16]. This shows a huge variability potential of occupancy number from day to day. Another study [17] shows that with a wide variety of building functions and operation characteristics, the number of people that enter and exit in one hour period in an institutional building is equal to the maximum occupancy of the building. This kind of occupancy variation comes from two points. First is that

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the presence possibility of people in a space is highly related to the occupant's complex behavior, which is a collection of random variables over time. Second is difficulty in characterize the stochastic nature of occupant behavior both in time and space aspect [18].

Study [19] has demonstrated that energy consumption, especially the large electricity consumption variation, can only be explained by reference to some kind of occupant-related features. Proper intervention of occupant behavior has been demonstrated a potential of 24.7% energy reduction changes in commercial and residential buildings [20,21]. Occupancy based controls have also been used in the field of air-conditioning energy consumption reduction [22], ventilation [23], and lighting [24] in buildings. However, it is difficult to apply intervention techniques to institutional buildings because the occupants of institutional buildings are not responsible for their electricity usage and bill, thus making the process of modifying behavior through bill feedback challenging.

Occupancy is the basic input of building simulation tools such as Energy Plus [25] and DeST [26]. Traditionally, the occupancy can be taken according to ASHRAE standard or Energy Plus typical schedule according to the space type for a corresponding type of building. However, according to the study by Duarte et al. [27], the collected long-term data shows variations of occupancy diversity factors are as much as 46% different from those currently recommended by ASHRAE Standard90.1.

Above researches has proved that occupancy is important for building energy consumption, building energy savings and energy performance simulation, thus it is important to collect the building occupancy data. There are a few methods used for building occupancy detection, tracking and estimation.

The most frequently used method is using sensors, which respond to occupants' presence/absence within their field-of-view. PIR occupancy sensors for lighting control applications was used in [28] but they are not able to detect stationary occupant [29]. Video camera or networks of cameras are also used for building occupancy monitoring by [30]. However, privacy may be a key concern. There are other types of seonsors, such as a typical microwave sensor [31] and acoustic sensor [32], but both have their disadvantages, such as false alarms. Another method of building occupancy sensing is the use of biometric sensors which takes measurements of human physiognomy for identification [33]. However, this is not suitable for institutional buildings as most of the occupants are visitors. Timers and ambient sensors such as carbon dioxide sensors and light sensors were also an option [34,35]. However, these occupancy-detection approaches have some limitations, such as time delay, high cost etc. A relatively new option is the GPS location and Wi-Fi connection [36], which is suitable for institutional buildings with multiple overlapping access points for Wi-Fi network However, the total number of Wi-Fi connections may not be accurate with the large building scale and a large number of occupants in institutional buildings.

In this study, we collected and analysed data from three institutional buildings in Singapore. To overcome the main uncertainties regarding the high daily variation of energy consumption and the impact of temperature variation on the energy consumption of the buildings, identification tools have been developed, which is able to calculate the variability of the occupancy without the tracking and monitoring process and also identify the main input uncertainties to deterministic simulation models in order to evaluate the retrofitting potential of the buildings. Instead of smooth trend simulation, the proposed methodogy in this study looks at the daily energy consumption variation, which is a big progress for energy forecasting and hence providing information to the facility management of a building. The simple inputs approach makes the methodology be easily applied to other buildings. In addition, this research will show approaches with regards to the improvement of ENERGY PLUS simulation accuracy. Therefore, this paper provides insights for both the industry practitioners and researchers who are keen on the energy consumption characteristics of institutional buildings as well as bringing about energy efficiency improvements in institutional buildings.

2. Approaches

2.1. Approaches to understand the energy consumption pattern

Energy consumption pattern is highly dependent on the different functions of building spaces and the categories of buildings [37]. Previous research has investigated the energy consumption in residential buildings, office buildings and commercial buildings [38–40]. However, institutional buildings, with much more complex functions and high occupancy variations, are not sufficiently investigated. Although historical data is the typical way to develop mathematical model to understand the energy consumption pattern [41–43], the rationale behind these past energy consumption data is not easy to found. Li and Wen [44] reviewed the three energy models: White-box (Physics-based), black-box (data-driven) and gray-box (combination of physics based and data-driven model). In order to understand the high energy consumption patterns of the institutional buildings, a black-box model is an option since it uses the data-driven method so that the interrelationship and rationale inside the data can be found out. The major challenging of the black-box model is the input data. On one hand, more inputs can provide valuable insight into general physical mechanism to the output, but are often limited to specific building due to the possible representative input data required; on the other hand, less input data can be easily generalized to other buildings but may suffer the accuracy issue. In a typical application, the input data in many models fall between these two extremes [45].

The work presented in this paper aims to develop a model using limited available data without the scarifies in daily variation accuracy in predicting the building cooling load consumption. The HVAC energy consumption, plug load consumption as well as the outdoor air temperature data, which are commonly available information are the three inputs required for the model, so that the model can be easily applied to other institutional buildings.

2.2. Approaches to calculate the large scale and variation of occupants' number

The above approach with its black-box nature is able to tell the mechanism behind the high energy consumption phenomenon in institutional buildings. The next step is to use the white box method to find out the whole building behaviors which results from the same mechanism as stated above. ENERGY PLUS [7], as one of the most comprehensive white-box model, have been successfully used in developing satisfied building simulation in previous studies [46–50]. With sufficient and accurate building details such as design plan, manufacture catalog and on-site measurement, the building components and sub-systems can be modeled to predict the energy consumption. As regard to prediction of the HVAC system, extensive research work [51–53] have reported the validation by using ENERGY PLUS. However, the main challenging in using ENERGY PLUS is that the large amount of data and schedule input as well as the accuracy of the input data. The higher accurate the input is, the higher levels of accuracy can be achieved [54,55]. Occupancy input is one of the most difficult parts of the inputs and will have an impact on the simulation accuracy as discussed previously. On one hand, the heat generated by occupancy will in turn affect the building's HVAC loads [56]; On the other hand, the occupancy number and habits are predominantly affected by the ambient temperature and humidity created by the HVAC load pattern [57]. Hence, the importance of occupancy information is critical in joint optimization of energy consumption and thermal comfort [58–60]. Although there are some typical occupancy schedule developed such as the library in open studio [61] to help with the energy plus occupancy input, it is not suitable for institutional buildings with huge variations of occupancy number.

2.3. Approaches to increase the energy consumption simulation accuracy through the occupancy number calculation

The final objective of this study is to develop and use a hybrid gray box method to identify uncertain characteristics of institutional buildings like the variability of the occupancy and then use them in deterministic models to achieve higher simulation accuracy [62]. Section 2.1 introduced the data driven model, Section 2.2 introduced the ENERGY PLUS simulation and the requirement of input from the identification tool model, which is a typical process to develop and train the gray models [63]. The outcome of these steps are the identification of the parameter that plays a key part in minimizing errors between model prediction and real measurements. Hence the last step is to find out and then apply the identified coefficients or parameters through black-box model into the forward white-box model to simulate the building operation.

Different parameters have been stuied as input for the developments of building environment gray box models [64–66]. In this study, the occupancy number would be the input and the solution for improving the accuracy of ENERGY PLUS simulation. The final gray box model would be a very useful and accurant tool in order to quantify the real effect of a specific energy saving solution in a specific building. It makes possible to compare two different scenarios such as before and after retrofitting work, hence identifying the best energy renovation practices for defining optimal long term strategies.

3. Data collection and pre-process

3.1. Characteristic of the three studied institutional buildings

The three institutional buildings studied are located in Singapore. As shown in Fig. 1, The outdoor temperature and relative humidity ratio is constantly high through-out the year due to the physical location of tropics. Although there is no heating load generated in these three buildings, in order to achieve cool and dehumidified indoor environment, high cooling and dehumidification capacity are required for these three buildings. The rooms of the three buildings A, B and C are mainly offices, lecture rooms, labs, studios, with typical functions for institutional buildings. Buildings A and C have five storeys while building B only has three floors. Building C has a much larger floor areas and more lecture rooms, studios and seminar rooms. Hence the occupancy number in Building C is much more than that in B and A. The present air conditioning system (i.e., cooling tower) for the three buildings is a combination of centralized chilled water system (2 plant locations) and DX units. Plant 1 located at Building B comprises of 1 water-cooler chillers serving Building A and B and carries a total cooling capacity of 320 RT. Plant 2 located at Building C comprises of 3 water-cooled chillers serving Buildings A and C and carries a total cooling capacity of 810RT. Water loop system in both plants runs through independent sets of cooling towers located on the rooftop of Building B and C, respectively. Based on previous energy audit, COP of Chiller in Building A,B and C are 3.3, 2.7 and 3, respectively.

3.2. Data collection

Energy data for three institutional buildings in Singapore is obtained over one year (year 2013). The data is divided into Air-conditioning and Non Air-conditioning loads (Plug-load). Both of them are obtained through the University's facility management office which collects energy data for all buildings in the campus at every 30 min interval. The data is available daily for 365 days for the three institutional buildings mentioned in Section 3.1.

Outdoor climatic condition data, average outdoor temperature, relatively humidity ratio and radiation are obtained from the National University of Singapore (NUS) weather station maintained by the Department of Geography, NUS. The station is located on the rooftop of building E2 (Faculty of Engineering) of the NUS Kent Ridge campus. The location is at the highest point of the surrounding region with an altitude of about 90 m. In order to be consistent with the building energy consumption data, average value are taken from 6am to 6pm for each day. Before utilization of these data for

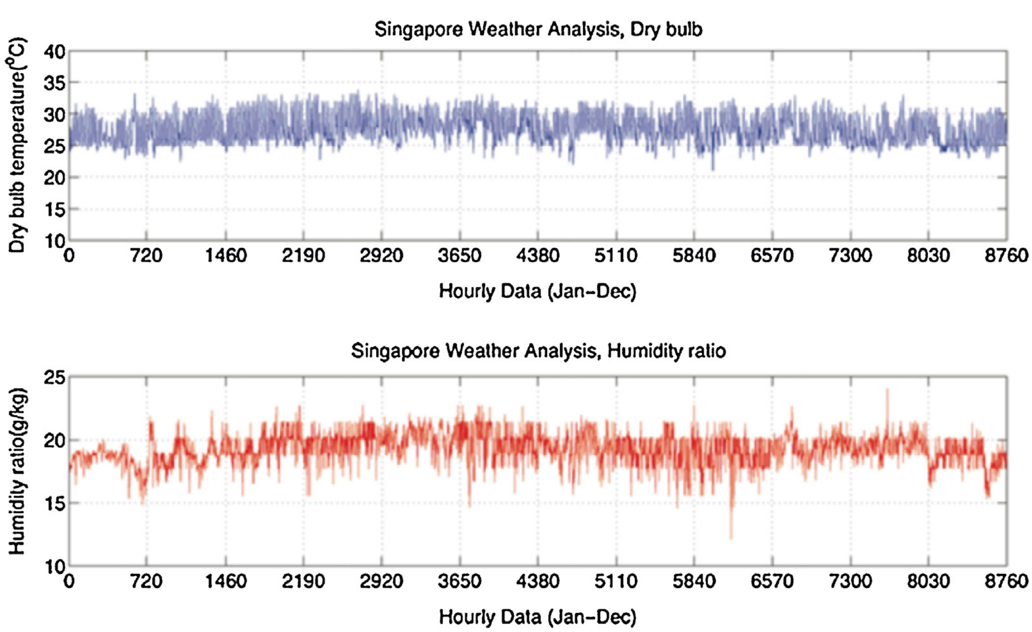

Fig. 1. Weather data for Singapore.

Table 1
University estimated average occupancy number for each building.

Occupancy No.	Jan to May (Semester 2 of academic year 2012–2013)					Aug to Dec (Semester 1 of academic year 2013–2014)				
	Mon	Tue	Wed	Thu	Fri	Mon	Tue	Wed	Thu	Fri
Building A	288	278	260	275	264	241	283	268	195	242
Building B	203	199	233	181	146	231	273	268	199	244
Building C	1651	1328	1604	1456	1015	1662	1378	1340	1670	1530

Table 2
Construction characteristics.

Glass door and window	6 mm clear glass
Interior wall	25 mm gypsum board + wall insulation + 25 mm gypsum board
Floor	100 mm lightweight concrete + 150 mm concrete
External wall	50 mm gypsum + concrete + 25 mm gypsum board
False ceiling	Acoustic tile

Table 4
Correlation of the HVAC data and three climatic variables.

R^2	Correlation with outdoor temperature	Correlation with relative humidity	Correlation with radiation
Building A	0.26	0.1	0.19
Building B	0.4	0.02	0.02
Building C	0.11	0.02	0

analysis, K-means clustering approach and data imputation using linear regression with past five hour input are used to detect the data outliers. The size of the resulting clusters is further analyzed into key factor to identify groups of energy consumption so as to observe the outlier that are distinct from the majority of the data. Therefore, cleaning data set is used for research in this study.

The daily module registered occupancy number for all the available venues were obtained from Information Technology Unit of the School. The occupancy number refers to all the students including undergraduates, postgraduates, and exchange students. The permanent staff number was also given at an average estimated level. Table 1 listed the occupancy number for the three buildings. It shows that the occupancy number in Building C is much more than that in Building A and Building B.

It is found that the centralized air-conditioning system is on from 6 am to 6 pm for Building A and Building B, and it is from 6 am to 10 pm for most parts of Building C. Table 2 lists some of the construction characteristics for all of the three buildings.

3.3. Data pre-process

First, the whole year HVAC energy consumption data and plug load data are plotted as shown in Fig. 2. The figures show that the daily variation of energy consumption is huge.

It is clear from the graphs that the energy consumption amount and dynamics during semester is quite different from that during vacation time for both plug load part and HVAC energy consumption part. As compared in Table 3, the energy consumption varies a lot between semester time and non-semester time in Building C. The percentage difference is up to 50.1% for plug load, and 22% for air-conditioning load. Meanwhile, the percentage difference for Building B is very small, just 13.3% for plug load and 4.9% for HVAC energy consumption

Under data preliminary analytics, the HVAC energy consumption data is initially correlated with the three climatic variables as listed in Table 4. The results show a very low correlation between the HVAC energy consumption and outdoor climatic variables except the outdoor temperature.

4. Identification model (black-box model) development

It is clear that building energy consumption characteristics play an important role in getting the knowledge of dynamic energy budget interrelationship. For the vision to be realized, an identification model (Knowledge of Dynamic Energy Budget Interrelationships) is developed using the available limiated data For each of the building, we have the energy consumption data from HVAC system and the energy consumption data from the plug load system. It is well known that for the building energy consumption, there are certain constant loads, such as lighting, fan and some plug loads, which do not change with occupancy number, especially the landlord energy consumption, typically comprising: (a) mechanical ventilation central plant system which supply air-conditioning inside the building; (b) artificial lighting system in the common area, i.e. corridor or public common service areas such as toilets and lifts; (c) ventilation system such as exhaust fan and ventilator. Therefore, it seems more meaningful to start the energy consumption analysis by dividing it into two parts: occupancy dependent part and occupancy independent part, rather than analyzing the whole building energy consumption data. Hence, it is motivated to make an exploration of two parts of building energy consumption performance. If we take N as the number of occupancy for a day, for the energy consumption data from HVAC system Q_{HVAC}, there is a parameter (b) related to the presence of number of occupancy and another parameter (a) independent of the occupancy, as expressed as Eq. (1). Similarly, for plug load, c is assumed to be the occupancy dependent parameter while d is assumed to be the independent parameter as shown in Eq. (2).

$$Q_{\mathrm{HVAC}} = a + bN \tag{1}$$

$$Q_{\mathrm{plug}} = cN + d \tag{2}$$

Table 3
Comparison of energy consumption between semester time and vacation time.

		Semester time	Vacation time	Difference percentage
Building A	Plug load (kw h/m^2)	0.14	0.10	24.1
	Air-con (kw h/m^2)	141.4	130.5	7.8
Building B	Plug load(kw h/m^2)	0.46	0.40	13.3
	Air-con (kw h/m^2)	161.1	153.2	4.9
Building C	Plug load(kw h/m^2)	0.59	0.29	50.1
	Air-con (kw h/m^2)	288.4	224.9	22

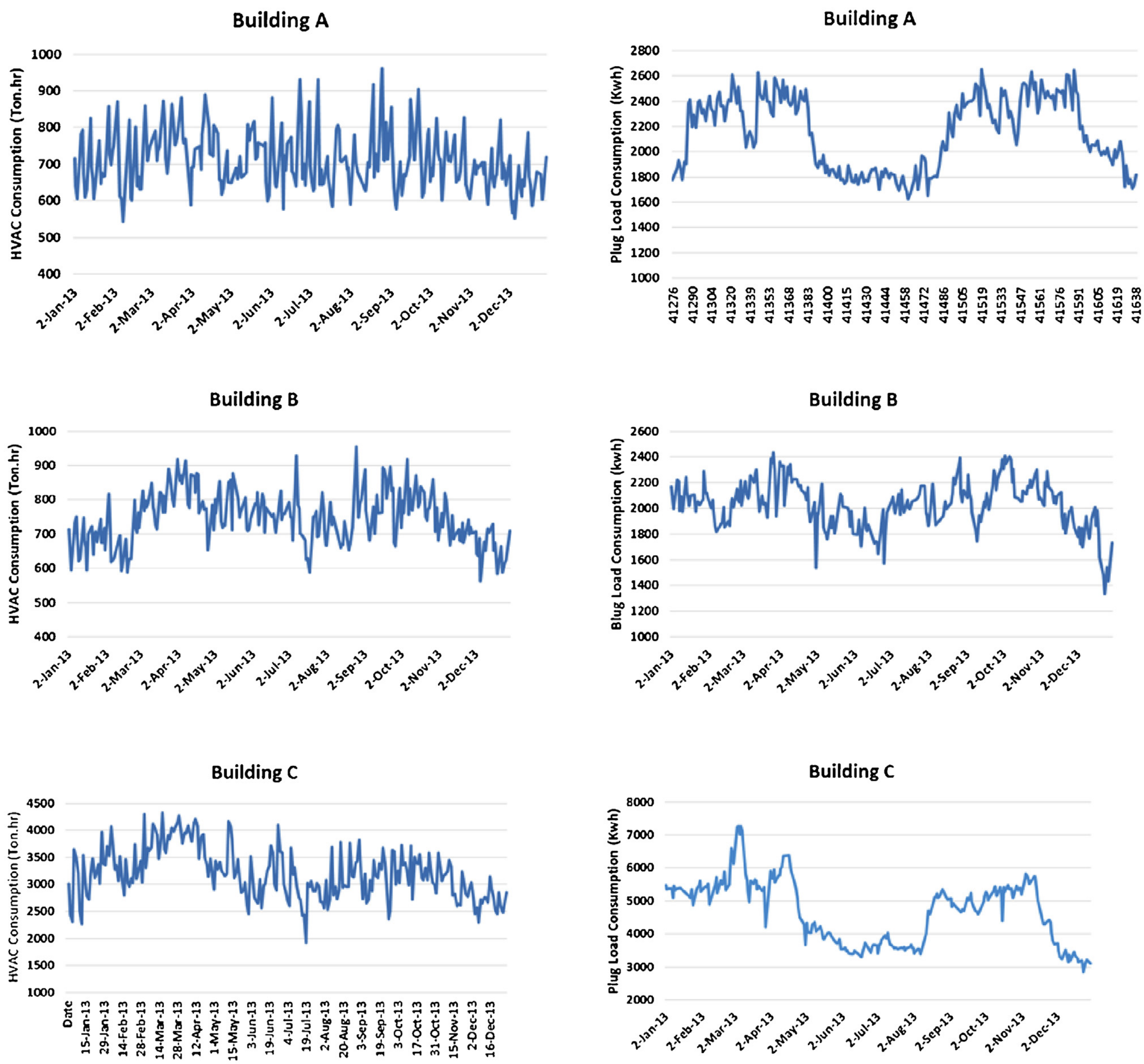

Fig. 2. Whole year HVAC load and plug load data for the three buildings.

Hence, Q_{HVAC} and Q_{plug} are interrelated by the occupancy number N and Q_{HVAC} can be expressed as the following equation:

$$Q_{HVAC} = a + \frac{\left(Q_{plug} - d\right) b}{c} \tag{3}$$

4.1. Transfer function

The HVAC energy consumption and plug load consumption are estimated using the "black-box" modeling. The MATLAB system identification toolbox provides several different model structures. Previous work [67] has summarized different system identification approaches for building energy modeling as time domain models and frequency domain models. In this study the data is considered as a time-domain data consisting of input and output variables recorded at a uniform interval as 1 s over a period of time [68].

For linear and time-invariant systems impulse response function f_k is used to describe the relationship between the input signal U_{t-k} and the output signal y_t. In our study, causal single-input–single-output (SISO) system is used and described as:

$$y_t = \sum_{k=0}^{\infty} f_k U_{t-k} \tag{4}$$

Using the back-shift operator, defined by $q^{-1}yt = y_{t-1}$, and a transfer function $f(q)$ is defined:

$$f(q) = h_0 + f_1 q^{-1} + f_2 q^{-2} + f_3 q^{-3} + \cdots \tag{5}$$

Hence, the relationship between input and output can be written as

$$y_t = f_{(q)} U_t \tag{6}$$

4.2. Model 1

As described above, non-parametric model called time domain is used to build the inputs and outputs. As expressed in Eq. (6), plug load is used as input and HVAC load is used as output. Because the

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identification model uses past input values to calculate the next output values, the less the past values the less the accuracy. Therefore, the first 80 data predicted by the model would have a lower accuracy. In order to predict the first 3 months energy consumption value with a higher accuracy, a data set with a series of data starting from September using 16 months' data is created. It includes all values from September, October, November, and December and followed by the whole year from January to December. For each month, the data starting from 4 months before is used to stabilize the identification model 1 and improve its convergence. For example, data from September until end of January is created to develop the model for January. The data from September to December is just for model stabilization.

Transfer function is used to estimate the model. After having tried different numbers of poles and zeros, the 'best fit' model is chosen as function $f1$ of Eq. (7) to estimate the HVAC load.

$$Q_{\mathrm{HVAC}}(i) = \sum f(1)\, Q_{\mathrm{plug}}(i) \tag{7}$$

Eq. (7) expresses the cooling load dynamics based on the dynamics of plug load. Although the two energy consumptions have quite different dynamics, the basic occupancy number in a building is able to correlate them to learn the building energy consumption patterns. This is because the number of basic occupancy in each building will influence the pattern of plug load consumption as well as the cooling load demand.

Fig. 3 shows the predicted value by model 1 and the measured value with the data of a complete year from January to December for the three buildings. It is found the R^2 are 0.14, 0.25 and 0.33 for building A, B and C, respectively. Since model 1 considers the influence of daily basic occupancy number on the cooling load dynamics, the results shows the daily occupancy dominant Building C energy consumption more than Buildings A and B, which agrees with the fact that building C consists of most of the lecture rooms and seminar rooms with much more occupancy variation while Building A consists more office rooms with much smaller occupancy variation.

4.3. Model 2

Fig. 3 shows although the predicted value from model 1 can follow the trend of the measured value, it is not enough to explain the dynamics of cooling load only based on the consideration of the basic occupancy. This happens because there is always occupancy variation that affects the cooling load much more than the way it affects the plug load. Therefore function 2 is developed to take into account of the additional occupancy variation by defining the difference of plug load and HVAC load. Eqs. (8) and (9) are developed to interrelate the plug load and HVAC load. Hence, the transfer function in identification tool box is applied by using $\Delta QL(i)$ as inputs and ΔQ_{HVAC} (i) as outputs to estimate $f2$ in Eq. (10), where Q_{HVAC} (i) is the value as predicted by Model 1.

$$\Delta Q_{\mathrm{HVAC}}(i) = Q_{\mathrm{HVAC\,measured}}(i) - Q_{\mathrm{HVAC}}(i) \tag{8}$$

$$\Delta QL(i) = Q_{\mathrm{HVAC\ \ measured}}(i) - Q_{\mathrm{plug\ \ measured}}(i) \tag{9}$$

$$\Delta Q_{\mathrm{HVAC}}(i) = \sum f2(i)\, \Delta QL(i) \tag{10}$$

Although 5 months' data is available from model 1 for each month, the first 30 sets of data estimated by $f1$ and model 1 have a quite low accuracy. Therefore, the first month's data and results from model 1 are erased and hence 4 months data is used in model 2. Again, the first 3 month's data is just used for stabilizing and getting convergence. Then the predicted HVAC energy consumption can be obtained through the following equation:

$$Q_{\mathrm{model2}}(i) = Q_{\mathrm{HVAC}}(i) + \Delta Q_{\mathrm{HVAC}}(i) \tag{11}$$

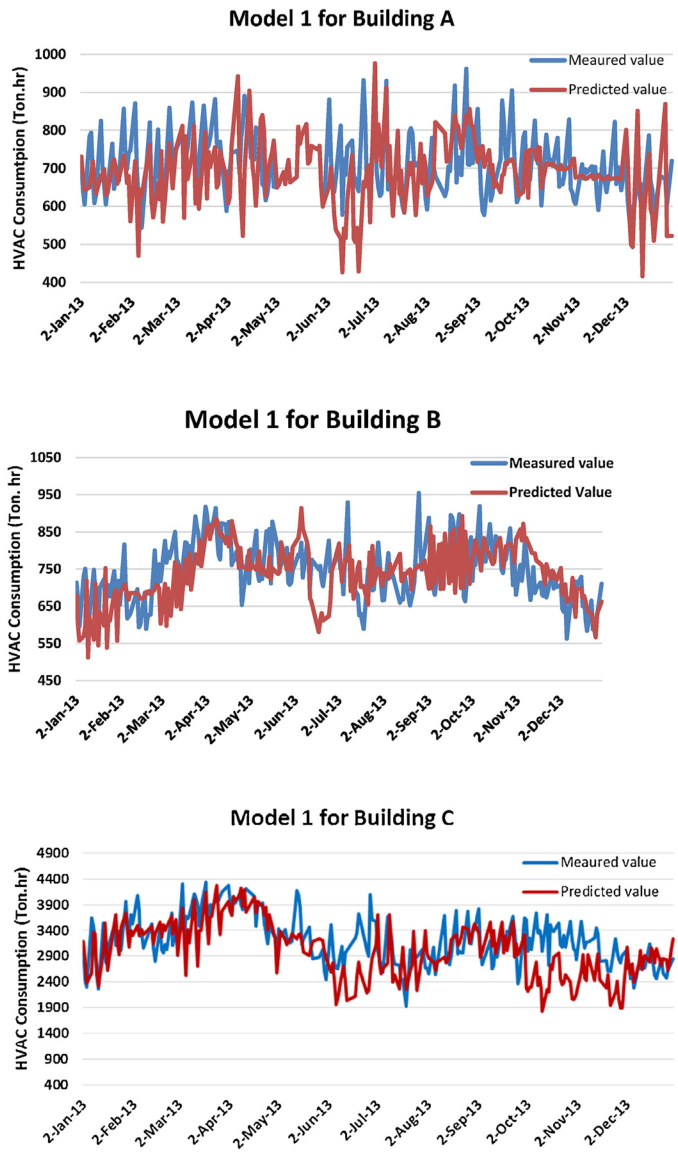

Fig. 3. Predicted value by model 1 and the measured value for the three buildings.

Comparison of the predicted results by model 2 and the measured results is shown as Fig. 4. The R^2 are 0.35, 0.46 and 0.49 for building Buildings A, B and C, respectively.

The figures show that with additional occupancy variation taken into account, the prediction is much better. The increase of R^2 are 0.21, 0.21 and 0.05 for Buildings A, B and C, respectively. This agrees with the fact that there are more additional occupancy variations in Buildings A and B since more visitors going to the school and department offices so that the influence of additional occupancy variation on the HVAC consumption is much higher. However in Building C, the large number of basic occupancy dominates the cooling load dynamics.

4.4. Final model

The value predicted by the second model follows the trend of measured data much better but still cannot predict the peak value. This happens because the two identification models do not consider the impact of the outdoor temperature variation. In addition to occupancy pattern, weather input is hence included. This is not only because of the impact of outdoor temperature

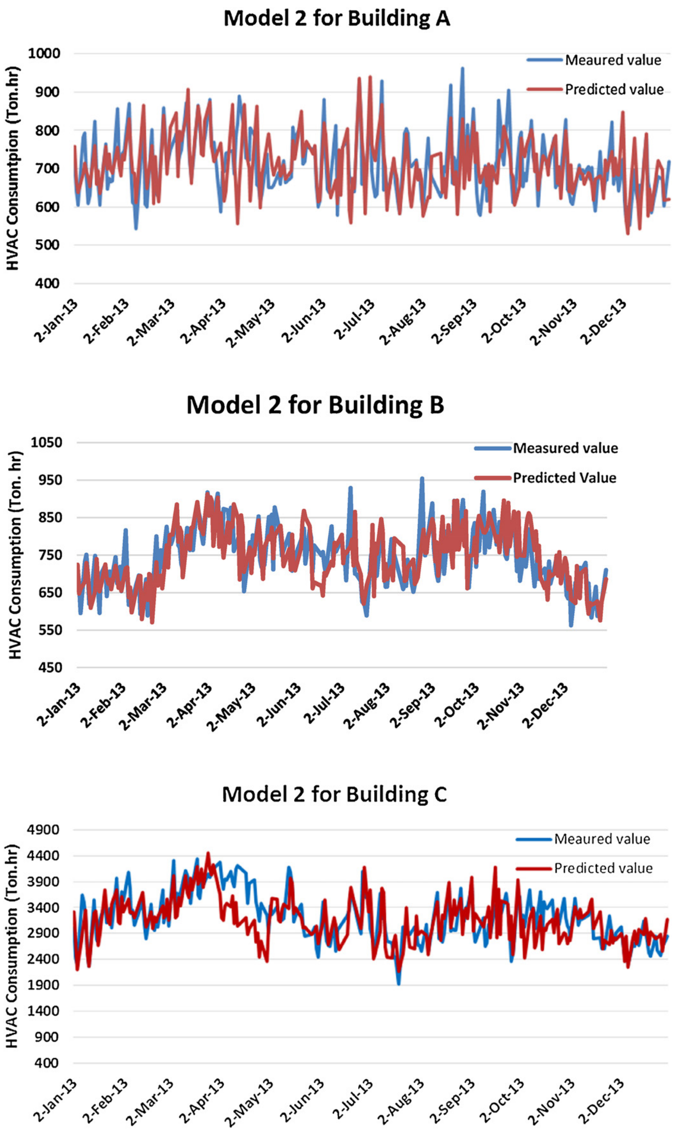

Fig. 4. Predicted value by model 2 and the measured value for the three buildings.

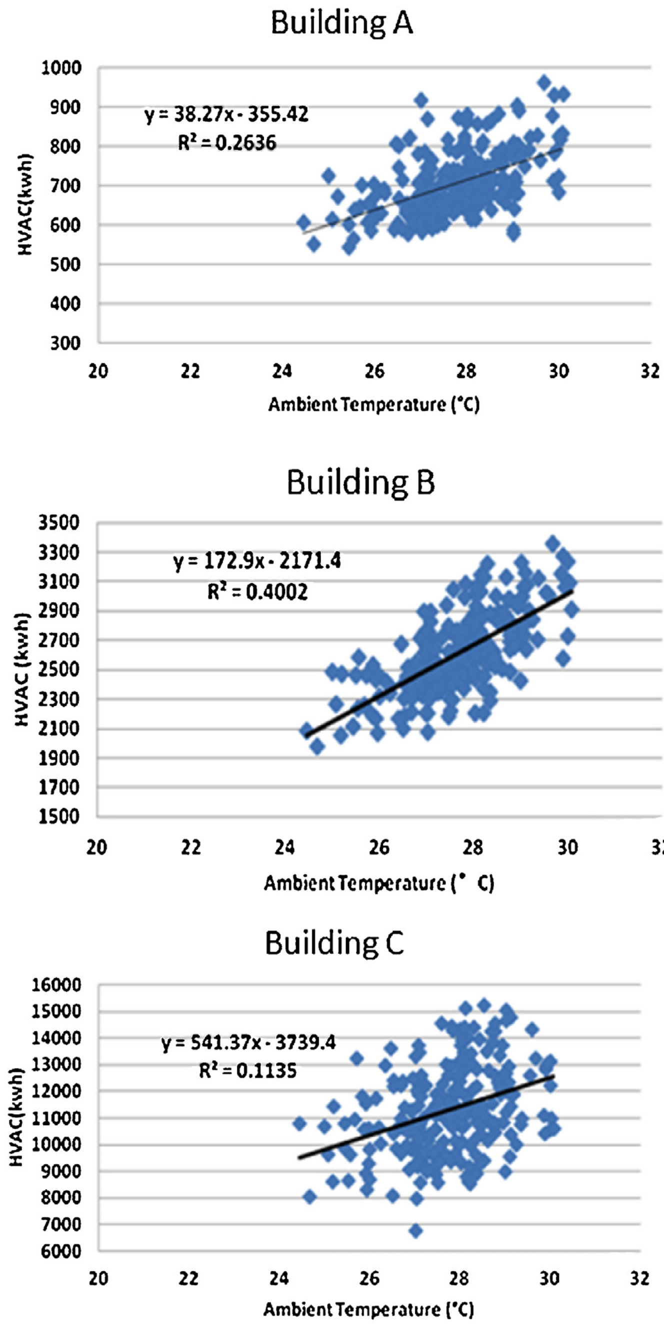

Fig. 5. Strong function between HVAC consumption and ambient temperature.

on HVAC consumption, but also due to the fact that weather and occupancy patterns are correlated [69,70].

Fig. 5 shows that the HVAC consumption has a strong function of ambient temperature. Therefore, the ambient temperature is introduced to improve the model. The coefficient by the regression plot of temperature and HVAC consumption is used to multiply the daily temperature variation so that the Q temperautre correction term is developed, which is defined in Eq. (12). Coefficient β can be obtained by regression plot of cooling load and ambient temperature as Eq. (13):

$$Q_{\text{tempcrct}}(i) = \beta(T_{\text{amb}}(i) - T_{\text{aveamb}}) \tag{12}$$

$$Q_{\text{HVAC measured}}(i) = \beta T_{\text{amb}} - \mu \tag{13}$$

In order to get the β for each month, the correlation is performed month by month so as to get a higher accuracy. The results of β for each building are listed in Table 5.

Therefore, Eq. (14) can represent the final model which includes three functions. Fig. 6 shows that the final identification model follows the trend of the energy consumption and also predicts most of the peaks

$$Q_{\text{HVAC final}}(i) = Q_{\text{HVAC}}(i) + DQ_{\text{HVAC}}(i) + Q_{\text{tempcrct}}(i) \tag{14}$$

Table 5
Value of β for three buildings month by month.

Building	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
A	64.9	50.5	13.7	76.7	70.6	36.5	53.2	74.5	58.4	43.6	40.8	15.5
B	31.3	47.1	26.3	44.2	43.7	15.0	46.0	60.8	43.8	35.1	19.9	24.1
C	1220.5	444.7	1003.8	295.3	861.3	494.1	824.6	248.8	576.6	281.9	449.3	430.1

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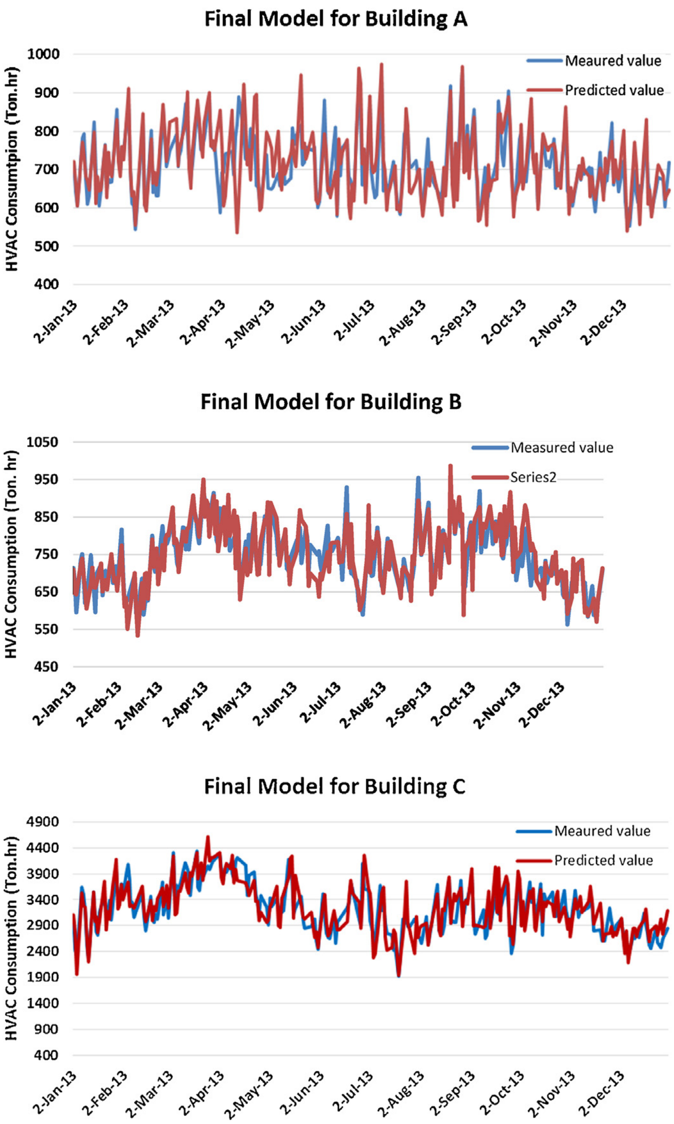

Fig. 6. Predicted value by final model and the measured value for the three buildings.

In order to evaluate the degree of agreement between the numerical and experimental results, root-mean-square deviation (RMSD) is used to measure of the differences between the values predicted by each model and the measured values. Table 6 listed the RMSD for each model of each building. It is found that with the additional occupancy variation and temperature variation taken into account, the RMSD reduced from Model 1 to Model 2 and to the Final Model for all three buildings, which means the standard deviation of the differences between predicted values and observed values are reduced.

5. Calculation of occupancy variation ratio

From the above identification model development process in Section 4, it has identified that occupancy number is a key influencing parameter for the HVAC energy consumption. Hence, if the daily occupancy variation and occupancy number can be identified as part of the knowledge of the building operational characteristics, it will contribute to the building energy consumption management system to a large extent.

Table 6
Root-mean-square deviation (RMSD) between the values predicted by each model and the measured values.

RMSD	Building A	Building B	Building C
Model 1	93.9	76.9	676.0
Model 2	66.1	54.8	356.6
Final model	58.8	44.2	252.8

As described earlier in Eq. (3), Q_{HVAC} and Q_{plug} are interrelated by the occupancy number N and Q_{HVAC} can be expressed as Eq. (3).

For both cooling load and plug load, there is one part dependent of occupancy number and another part independent of occupancy number. In order to find out the part of plug load consumption that dependent of occupancies, the occupancy independent part should be subtracted from the overall plug load. For each month, the occupancy independent part 'd' is taken as the averaged Sunday plug load of the corresponding month which is listed in Table 7. This is because the plug load consumption in institutional buildings on Sunday represents the situation when no occupancy presents. The daily plug load was plotted in over a whole year with two parts Fig. 7.

Similarly, for HVAC load, there is an occupancy independent part 'a', which can be found out by plotting the occupancy dependent part of plug load against the HVAC load according to Eq. (3). For each month, the occupancy independent part 'a' plotted and calculated of the corresponding month is listed in Table 8.

After finding out the occupancy depend part for both plug load and cooling load, a series of occupancy ratio based on day i and day $i+1$ can be found out.

The total energy consumption is the sum of energy consumption of HVAC and the energy consumption of plug load. Hence the total energy consumption for day i and day $i+1$ can be expressed as Eqs. (15) and (16). After get the ratio from Eq. (17), the number of occupancy is normalized by assuming the first day's occupancy as 1.

$$Q\text{tot}(i) = Q\text{hvac}(i) + Q\text{plug}(i) = a + d + (b + c)N(i) \tag{15}$$

$$\begin{aligned} Q\text{tot}(i+1) &= Q\text{hvac}(i+1) + Q\text{plug}(i+1) \\ &= a + d + (b + c)N(i+1) \end{aligned} \tag{16}$$

$$\frac{N(i+1)}{N(i)} = \frac{[Q\text{tot}(i+1) - a - d]}{[Q\text{tot}(i) - a - d]} \tag{17}$$

By applying the data in Tables 6 and 7 and Eq. (17), the monthly occupancy ratio could be obtained.

6. Coupling the indentification with a white box model for better prediction (gray-box model)

According to the development of identification model in Sections 4 and 5, the black-box methods (data-driven model) have identified some of the main energy consumption influencing factors.

In this section, white-box method will be utilized to simulate the building energy consumption. The basic idea is to use detailed physics based equations to simulate different building sub-systems so that the whole building performance such as weather and solar impact, enclosure thermal behaviors, HVAC system capacity and energy consumption can be achieved.

In this study, the performance evaluation was accomplished by the use of the building energy simulation programme "EnergyPlus" which is a component based system simulation program. The cooling load consumption can be modeled by a specific occupancy number and schedule which may be defined or altered by the user to suit the particular occupancy numbers and variation in a building. The result generated by EnergyPlus allows the user to

Table 7
Occupancy independent part of plug load for three buildings.

kw h	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
A	356	388	461	384	341	358	365	414	405	404	399	387
B	1130	998	1180	980	818	790	860	1000	940	1015	830	830
C	2862	3452	4044	4096	2462	1938	2080	2517	3223	3666	3692	2077

Table 8
Occupancy independent part of cooling load for three buildings.

kw h	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
A	1900	1800	2300	2100	1700	1200	2000	1620	1500	1500	2000	1880
B	1440	682	2175	1420	2120	1920	1300	1400	2300	2400	1880	1870
C	6859	11625	13934	10753	6242	2446	5196	8729	4958	7355	8278	6553

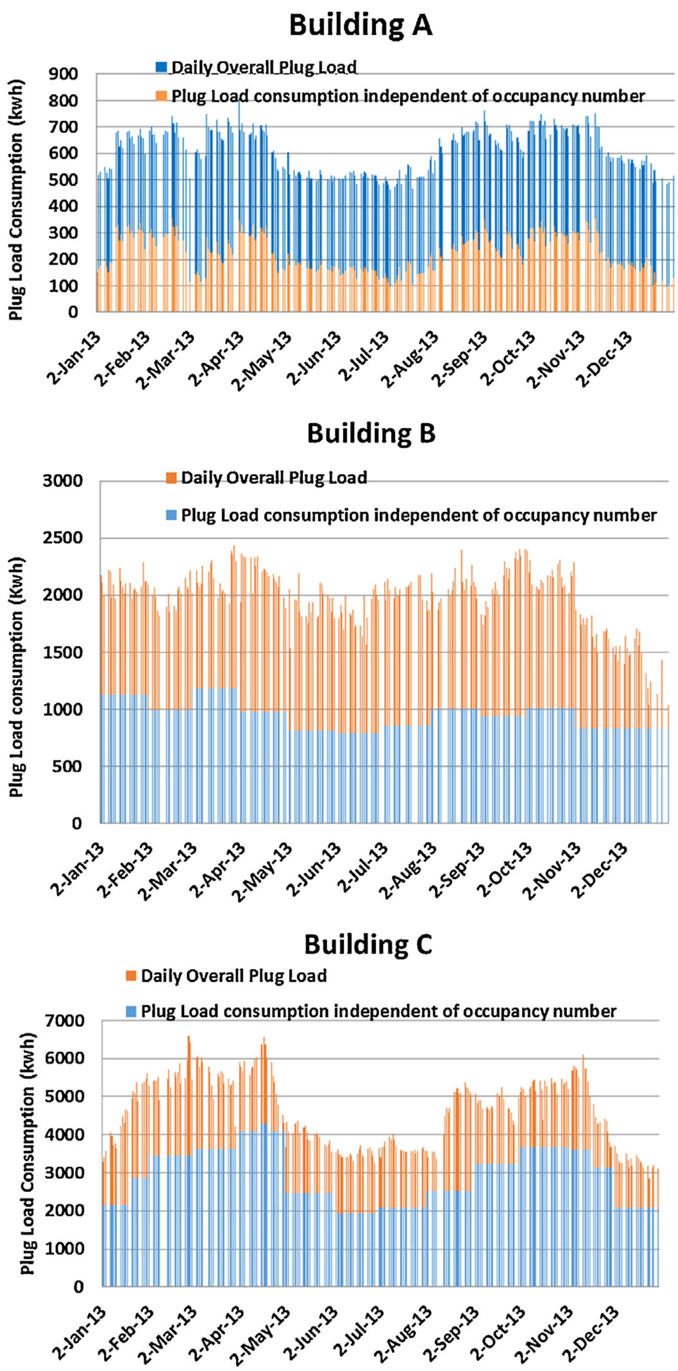

Fig. 7. Daily plug load value with two parts over a whole year.

Table 9
Basic physical characteristics and design parameters of the three buildings.

Indoor design temperature	23 °C
Indoor design humidity	40%
Air conditioning open time	6am to 6pm for Building A, B 6am to 10pm for Building C
Method of heat rejection Air-cooled	Air-cooled
Pump efficiency	0.6
Fan efficiency	0.5
Condenser loop design temperature difference	5.6 K
Chilled water loop design temperature difference	6.67 K

extract the required data, which is the cooling load consumption in this study.

6.1. Cooling load

To simulate the thermal behavior of the building, Sketch Up is used to build the building geometry and Openstudio 15.3 is used to define the sub-systems and components of the HVAC sytem. EnergyPlus version 8.2 is used to calculate the cooling load. As Singapore are now available in the EnergyPlus weather files, the outdoor temperature and relative humidity data needed for the study are obtained from the EnergyPlus weather file. Table 9 lists the parameters used in the cooling load calculation.

6.2. Loads

Lighting, electric equipment and occupancy loads are obtained from previous audit report. The electric equipment only considers computer desktop equipment, laptops, electrical fans, and other office appliances such as printers and facsimile machines. Other electrical loads such as lifts and lights and fans in toilets are not included in the simulation since they are considered to only contribute to a minute portion of the total loads and are therefore negligible. Lights density is calculated based on the total number of

Table 10
Typical load assumptions for Building A.

Space type	Equipment density (W/m^2)	Lighting (W/m^2)
Computer room	23.47	16.65
Circulation spaces		11.54
General offices	6.45	15.01
Seminar rooms		12.88
Research labs	13.99	8.34
Staff room	6.74	22.13
Research room	11.013.99	5.95
Staff offices	6.74	22.13
Multimedia lab	23.47	6.03

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Table 11
Typical load assumptions for Building B.

Space type	Equipment density (W/m^2)	Lighting (W/m^2)
Building labs	39.01	11.76
Circulation spaces		9.23
E-studio	23.47	14.84
Executive room		17.77
Staff room	6.74	26.38
Research room	13.99	13.72

Table 12
Typical load assumptions for Building C.

Space type	Equipment density (W/m^2)	Lighting (W/m^2)
Crit room		15.91
Circulation spaces		4.51
DDS	45.74	11.69
DTS studio	18.44	16.13
Lecture theatres	13.99	9.9
Staff room	6.74	22.13
Research room	13.99	16.01
Staff offices	6.74	12.68
Workshop	115.62	11.22

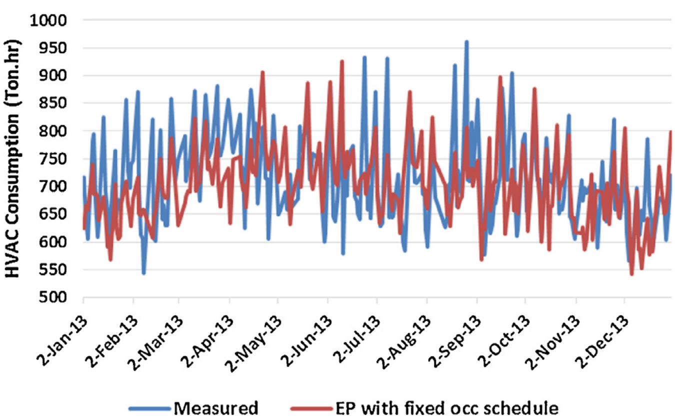

Fig. 8. Comparison of the simulated value and the measured value using fixed occupancy schedule for Building A.

light fixtures used and nominal power output per light tube. There are three types of light fixtures in these three buildings: 3 × 18 W short fluorescent tubes, 2 × 36 W long fluorescent tubes and 18 W compact fluorescent. Some of the typical load assumptions based on previous audit report and observation are listed in Table 10 for Building A, Table 11 for Building B and Table 12 for Building C.

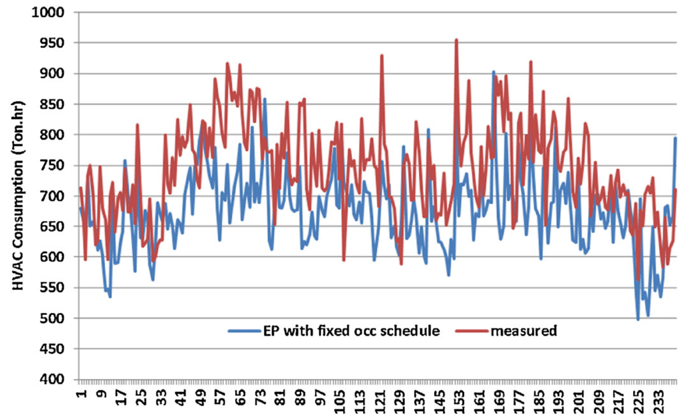

Fig. 9. Comparison of the simulated value and the measured value using fixed occupancy schedule for Building B.

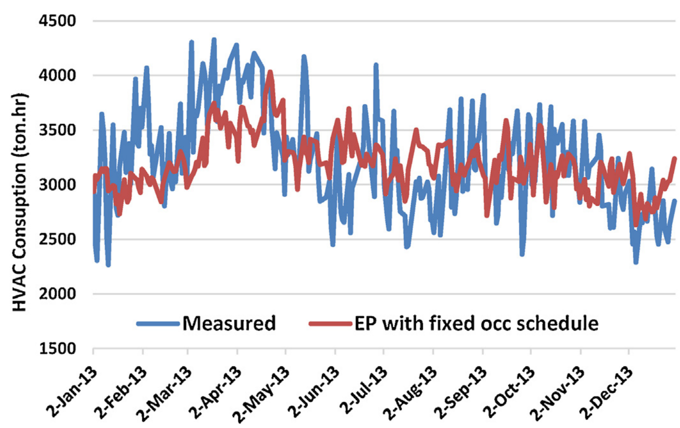

Fig. 10. Comparison of the simulated value and the measured value using fixed occupancy schedule for Building C.

6.3. Occupancy input

Previous black-box model has identified occupancy number as an important factor in the institutional building HVAC energy consumption field, therefore the occupancy input will be critical for the building energy consumption simulation.

First, fixed daily occupancy schedule is used as input into ENERGY PLUS for comparison reason. The occupancy fraction schedule is obtained by observation and counting for every 2 h during working hours and every 3 h during non-working hours.

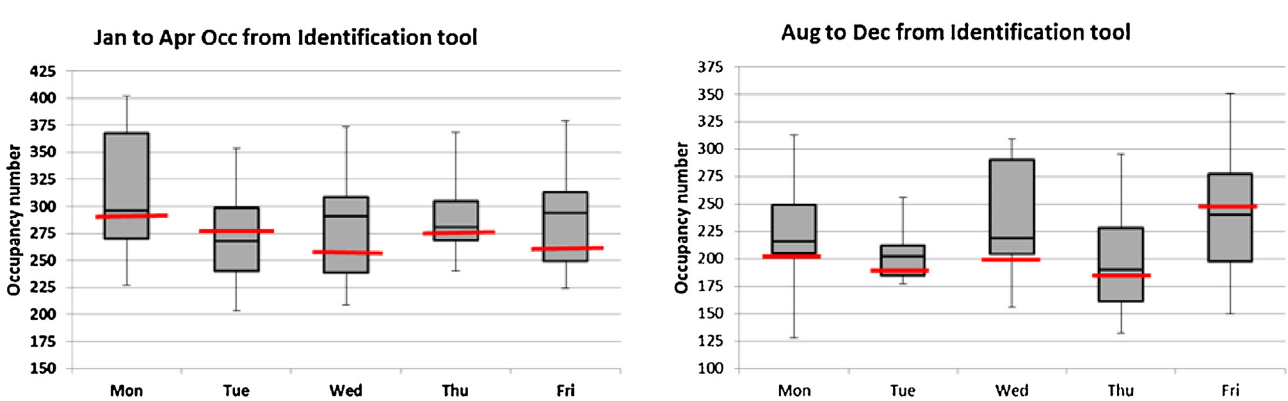

Fig. 11. Box plot of occupancy number calculated from Identification tool ratio for Building A. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

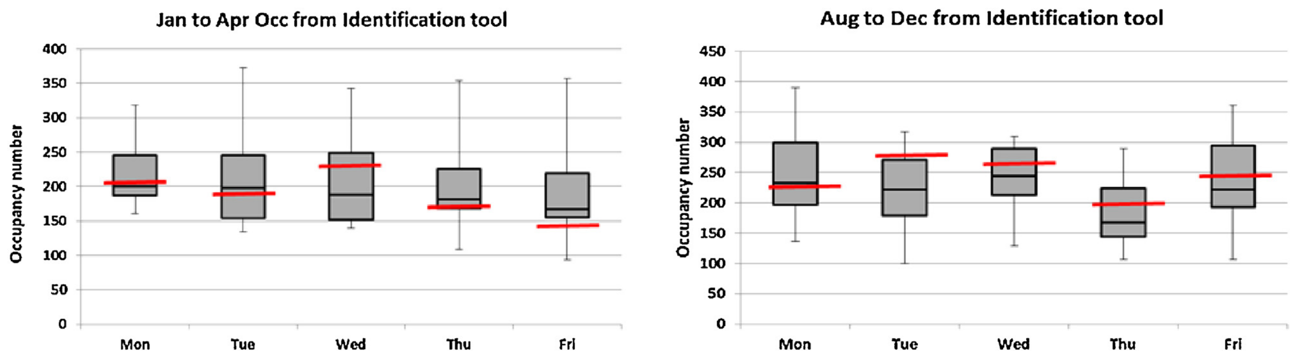

Fig. 12. Box plot of occupancy number calculated from Identification tool ratio for Building B. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

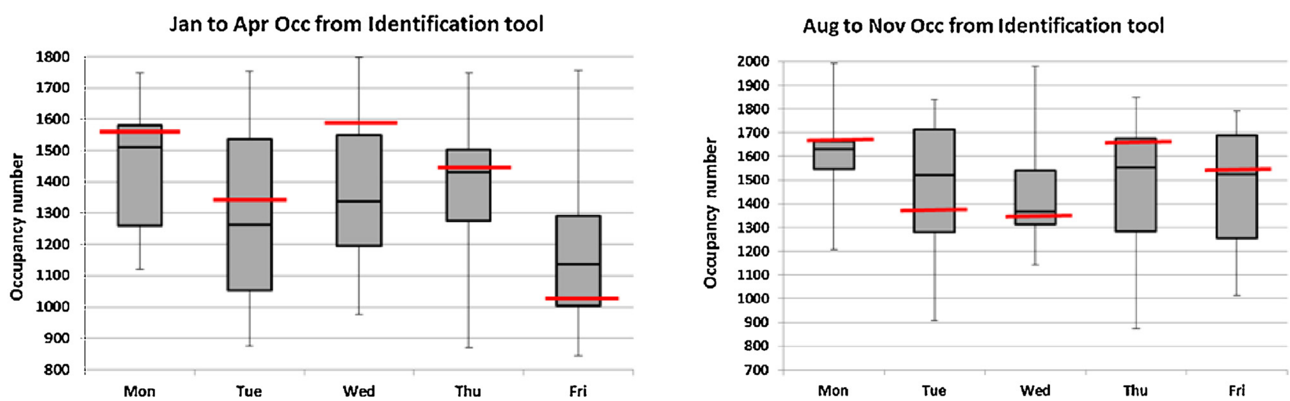

Fig. 13. Box plot of occupancy number calculated from Identification tool ratio for Building C. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

6.4. Preliminary simulation results

Figs. 8–10 show the daily comparison of the simulated HVAC energy consumption and the measured value when fixed occupancy fraction schedule is applied for Buildings A,B,C, respectively. A significant difference between the predicted value and the measured one is observed when normal fixed occupancy schedule is used as an input into energy plus. For Building A, the simulated one is more smooth than the measured. For Building B, especially for some months during semester time, the gap between the measured one and the simulated one is significant. The daily difference of the simulated value and the measured in Building C is even worse although generally the two lines follow the similar trend.

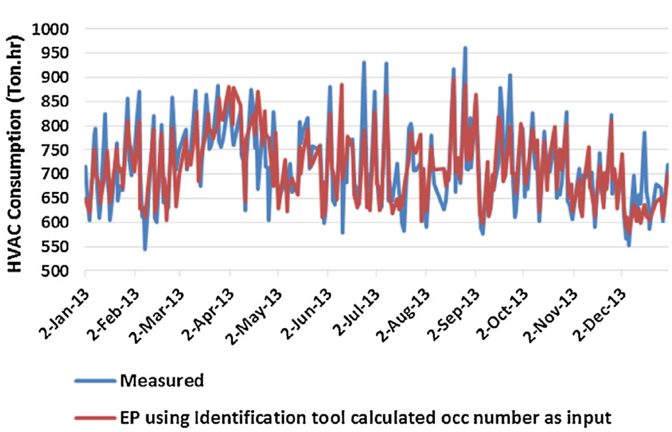

Fig. 14. Comparison of the simulated value and the measured value using identification tool calculated occupancy number schedule for Building A.

6.5. Identification tool calculated occupancy number

Since the occupancy variation ratio for the three buildings has already been calculated, ENERGY PLUS is then applied to simulate the building until the simulated value is the same as the measured one just only for the first day of each month. Then the occupancy number for the whole month can be obtained. The calculated occupancy number from the identification tool ratio is box plotted in Figs. 11–13for Buildings A,B and C, respectively. The red line in each box plot is the estimated averaged occupancy number obtained from the University as described in Table 1. The figures show that the calculated occupancy from the identification tool ratio is quite close to the real data, which means the identification tool model can also be trusted.

6.6. Calibration of ENERGY PLUS by using identification tool calculated occupancy number

According to Section 6.4, by using the fixed occupancy schedule as input into ENERGY PLUS, there is a huge gap between the daily simulated value and the measured one. Section 6.5 shows it is possible to get the reasonable and trustable occupancy number through the identification tool ratio. Therefore, the identification tool calculated occupancy number can be used as an input into ENERGY PLUS for higher prediction accuracy. Figs. 14–16 show the daily comparison of the simulated cooling load energy consumption using the identification tool calculated occupancy number as input and the measured value for Buildings A, B, C, respectively.

Above three figures show that with the input of occupancy number calculated from the identification tool, a higher accurancy of predicted value from ENERGY PLUS can be achieved. This means

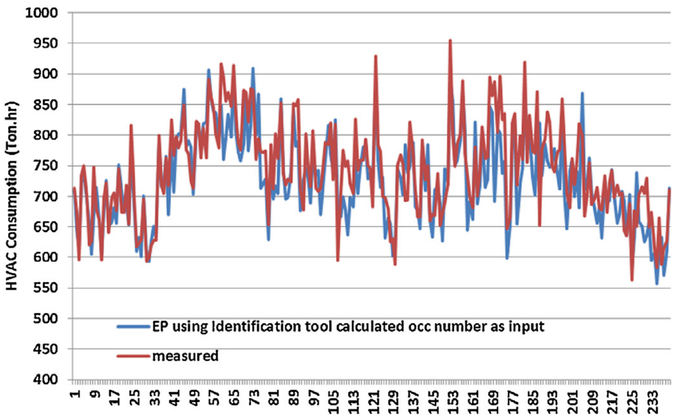

Fig. 15. Comparison of the simulated value and the measured value using identification tool calculated occupancy number schedule for Building B.

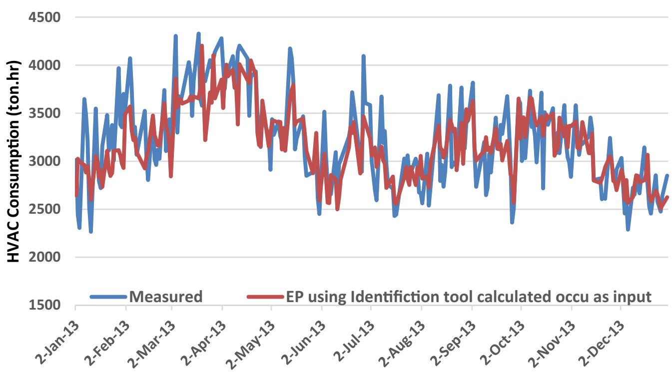

Fig. 16. Comparison of the simulated value and the measured value using identification tool calculated occupancy number schedule for Building C.

the ENERGY PLUS model is calibrated and the gray-box model is achieved.

7. Discussion of the methodology and conclusion

This study presents an investigation and discussion on a newly developed methodology for institutional building cooling load consumption modeling and simulation. A great progress has been made in applying building energy model for institutional building operation and energy saving potential analysis, such as achieving the daily energy consumption variation prediction with limited input parameter; achieving higher accuract for ENERGY PLUS stimulation. A few conclusions are summarized as follows:

Detailed black-box model is developed to simulate daily energy performance for institutional buildings. Critical factors for cooling load consumption for institutional buildings were identified as daily permanent occupancy number, occupancy number variation and the outdoor temperature during the model development. Daily variation of the cooling load consumption in the model is achieved instead of traditional smooth simulation method.

White box model, ENERGY PLUS, is being used. However, it requires large number of accurate available information as input to achieve high accuracy. Occupancy numbers, as one of the most difficult input to be determined, will influence the accuracy of ENERGY PLUS simulation significantly for institutional buildings.

Gray-box model is developed by using the new occupancy number from identification model as input for ENERGY PLUS. Much higher simulation accuracy can be achieved.

This article is an elaborate extension of the paper presented in 'ISHVAC-COBEE' Conference in Tianjin between July 12th and 15th (2015) and published in Procedia Engineering [ref. 71].

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