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HVAC terminal hourly end-use disaggregation in commercial buildings with Fourier series model

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ABSTRACT

One major obstacle encountered in building energy conservation and retrofit is the lack of detailed energy submetering data. Direct submetering is expensive and sometime very difficult to be installed in real practice. For example, the HVAC terminal end-use electricity consumption is extremely difficult to measure, because its data is always mixed together with lighting-plug or power submeter. This paper presents a new approach to solve this problem, which is based on a Fourier series model (FSM) for calculating the lighting-plug and power submeters in commercial buildings, and then disaggregate the HVAC terminal end-use hourly electricity consumption from them. Compared with black-box models, such as ANN, SVM and so on, FSM as a grey-box model has two key advantages (1) the application is convenient because of its simple model structure and (2) once a model is developed, it can be used in other same type commercial buildings directly. Measured data from two office buildings and two shopping malls located in Shanghai are analyzed in this paper. The disaggregation results demonstrate that the method is accuracy within a reasonable degree. The calculated hourly HVAC terminal end-use electricial consumption is close to the real measured data. The MRE (mean relative error) and CV (coefficient of variability) both can be controlled within 10%, and in some special cases they are almost within 1%.

1. Introduction

Building sector consumes more than 30% of the global energy consumption [1]. In the United States, building energy use accounted for 39.9% of total energy use in 2008 and 41.3% in 2010 and commercial buildings amounted to approximately 18% of the total U.S. energy consumption [2,3]. In China, building sector accounted for 23.4% and 28% of total energy use in 2011 and 2012, respectively. The energy consumption density of public buildings is the highest, while HVAC energy consumption accounts for 60% of total building energy [4,5]. One major obstacle encountered in commercial building energy conservation and retrofit is the lack of a detailed energy consumption submetering data and without the data it is hard to pinpoint the design and operations problem in HVAC systems.

In 1992, Hart formally proposed a concept "energy submetering" [6]. Generally speaking, total building energy consumption is classified into four main submeters and several secondary submeters, as shown in Fig. 1 [6,7]. Lighting-plug refers to the circuits content both lighting and plug load. In many commercial buildings, these two items are mixed together and impossible to be metered separately. Direct submetering each end-use is expensive and sometime impossible. Power circuits in this paper are mainly for heavy equipment in buildings, such as elevators, none-HVAC water pumps, and air compressors. HVAC terminal end-use energy consumption is referring to the electricity consumption by the terminal units such as fan coils, air handling units, and VAV boxes. The measurement of terminal unit energy consumption is difficult, as shown in Fig. 1, because terminal electrical circuits are always mixed together with lighting-plug or power circuits. Indirect measurement methods may offer some opportunities to solve this problem. In this paper, HVAC terminals mixed with lighting—plug circuits is called "scenario I". Terminals mixed with building power circuits is called "scenario II". In Fig. 1, except for HVAC terminal end-use, almost all other electricity data can be measured independently. Knowing HVAC terminal end-use data has several benefits, (1) to calibrate building energy simulation models, (2) to explore building energy-saving potentials and calculate energy retrofit savings, and (3) to optimize operation and minimize energy consumption through fault detection and diagnosis at building, system, and equipment levels. So, accurate energy consumption prediction of HVAC terminal end-use is very important.

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Nomenclature

CV	coefficient of variability (%)
RE	relative error (%)
MRE	mean relative error (%)
E_{EL}	HVAC terminal end-use energy use mixed in lighting-plug submeter (kW h)
E_{EP}	HVAC terminal end-use energy use mixed in power submeter (kW h)
E_{LM}	mixed lighting-plug submeter energy use including HVAC terminal end-use (kW h)
E_L	lighting-plug submeter energy use (kW h)
E_{PM}	mixed power submeter energy use including HVAC terminal end-use (kW h)
E_P	power submeter energy use (kW h)
E_{L_Office}	lighting-plug submeter energy use in office building (kW h)
$E_{L\_Shopping}$	lighting-plug submeter energy use in shopping mall (kW h)
$E_{P\_Shopping}$	power submeter energy use in shopping mall (kW h)
α_m, β_m, δ_n, η_n, γ_m, λ_m, μ_n, κ_n	coefficients of Fourier series model frequencies
ω_m	Fourier frequency for day
ω_n	Fourier frequency for hour
d	day of year
h	hour of day
SD_m	mth sine frequency of day
CD_m	mth cosine frequency of day
SH_n	nth sine frequency of hour
CH_n	nth cosine frequency of hour
E_{Mi}	measured energy use data of ith data point (kW h)
E_{Pi}	calculated energy use data of ith data point (kW h)
N	total number of data points
P_i	instantaneous power (W or kW)

2. Literature review

Non-intrusive Load Monitoring (NILM) is an indirect submetering method. It identifies the equipment by the on/off signal and marks the time and power data through monitoring the real time building energy. Then the equipment energy consumption can be calculated according to the on/off time and power data. Some researchers such as Hart, Schweppe and Hart, Marceau and Zmeureanu, Pihala, Murata and Onoda, etc have conducted a lot of studies on NILM method, but those studies are only limited to simple residential buildings [6,8–11]. Following above researches, Norford, Mabey, Leeb, etc attempted to use NILM method in commercial buildings, but the results were relatively poor because of equipment complexity in commercial building [12–14].

Akbari, Konopacki and Heinemeier [15–20] studied terminal end-use disaggregation algorithm (EDA), and they disaggregated hourly total building energy consumption with piecewise linear regression method. Their methods are not proved very accurate, because of the lack of long time end-use data to verify their methods under various operation conditions by these previous researches.

In recent years, with the efforts of many researchers and development of computer technology, many innovative and meaningful studies emerge on building total energy demand modeling, HVAC system energy consumption prediction and building terminal end-use energy disaggregation. These methods include traditional regression methods [21,22], artificial neural networks (ANN) methods [23–26], building simulation methods [27,28], and decision tree method [29–31], etc. The regression method is comparatively simple and efficient, but its accuracy is relatively poor. Compared with regression method, ANN and decision tree models are just the opposite. Especially, the black box model, such as ANN, is difficult to interpret and hard to extrapolate from one operation condition to another.

Pandit and Wu [32] found that the pattern of hourly energy use in almost all commercial buildings was periodic. They used sine and cosine basis functions to describe nonlinear, periodic behavior of hourly energy use with respect to time. It is a miniature of Fourier series model. Seem and Braun [33] put forward a trigonometric form assuming a weekly periodic behavior of hourly energy use. The predicted ability of this model was relatively poor. Dhar et al. [34–37] made further developments and pointed out that weather independent and weather dependent energy consumption should be modeling separately, and weekdays and weekend should be modeling separately. They used Fourier series approach to model hourly energy use of some university campus buildings in Texas with a reasonable degree of accuracy. But the model was not tested in other types of commercial buildings and other parts of the world.

Although all these nonlinear techniques provide good approximations, the Fourier series functional form maybe the most suitable because its periodic pattern of variation in hourly energy use. This viewpoint is further confirmed later in this paper, after we compare the calculated data to the measured energy consumption data. Fourier model has two key advantages, (1) the model is simple, people can understand and use it easily even if non-professionals, and (2) once the model is established, it can be used in other same type commercial buildings directly.

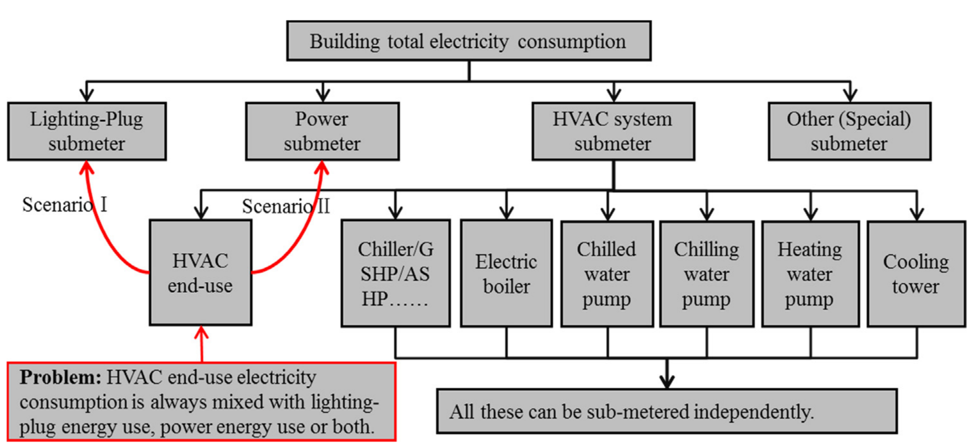


Fig. 1. Submetering structure and existing problems.

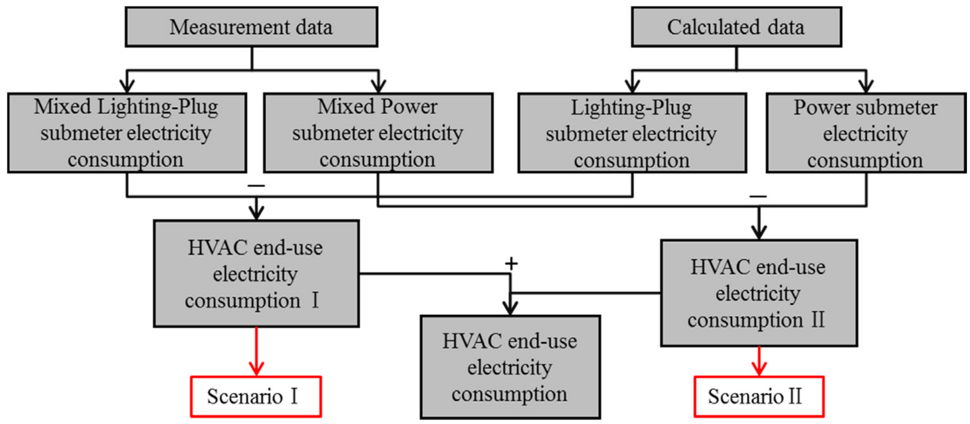


Fig. 2. HVAC terminal end-use energy consumption disaggregation algorithm flow chart.

3. Disaggregation algorithm

We surveyed a total of 287 large public buildings that more than 20,000 square meters and equipped with submetering system in Shanghai in 2013 to understand how HVAC terminal units are electrical circuited and submetered. Only four buildings have directly independent measurement on HVAC terminal units. The rest of the other buildings can be classified into three groups, (1) HVAC terminal circuits is mixed with lighting-plug circuits (scenario I), (2) HVAC terminal circuits is mixed with power circuits such as elevators and non-HVAC water pump (scenario II), and (3) Part of HVAC terminal circuits is mixed with lighting-plug and the remaining part is mixed with power lines (scenario I + scenario II). Therefore, a disaggregation approach designed to handle this situation is proposed as shown in Fig. 2. The first step is to collect hourly submeter data that include lighting-plug, power, and HVAC terminal energy use. The hourly lighting-plug and power data can then be calculated from the algorithm which will be presented in detail later. HVAC terminal energy consumption is obtained through subtraction lighting-plug or power submeter from the total. We used the four buildings with direct HVAC terminal energy consumption data to verify the accuracy of the methods.

3.1. General Fourier series model

Previous researches [10,37,38] have proved that lighting and equipment energy use vary periodically in daily and annual cycles and not depend on ambient temperature and other weather variables. In other words, among all the equipment in building, just the HVAC equipment energy use is sensitive to the outdoor weather variable. According to this theory a weather independent and time dependent general Fourier series model is built for the research in this paper as following equations:

$$E_{\mathrm{EL}} = E_{\mathrm{LM}} - E_L \tag{1-1}$$

$$E_{\mathrm{EP}} = E_{\mathrm{PM}} - E_P \tag{1-2}$$

$$E_L(\text{or}\quad E_P) = a + f(d) + \varphi(h) + \phi(d,h) + \varepsilon \tag{2}$$

$$f(d) = \sum_{m=1}^{m_{\max}} \left[\alpha_m \sin(2\pi\omega_m)\mathrm{d} + \beta_m \cos(2\pi\omega_m)d\right] \tag{2-1}$$

$$\varphi(h) = \sum_{n=1}^{n_{\max}} \left[\delta_n \sin(2\pi\omega_n)h + \eta_n \cos(2\pi\omega_n)h\right] \tag{2-2}$$

$$\phi(d,h) = \sum_{m=1}^{n_n}\sum_{n=1}^{n_{\max}} [\gamma_m \sin(2\pi\omega_m)d + \lambda_m \cos(2\pi\omega_m)d] \times [\mu_n \sin(2\pi\omega_n)h + \kappa_n \cos(2\pi\omega_n)h] \tag{2-3}$$

$$\omega_m = \frac{m}{365},\quad m = 1-182,\quad \omega_n = \frac{n}{24},\quad n = 1-12 \tag{2-4}$$

where a is the constant mean hourly submeter; $f(d)$ represents the seasonal hourly submeter amplitude with the day frequency and year cycle; $\varphi(h)$ represents the diurnal hourly submeter amplitude with the hour frequency and day cycle; addition of $\phi(d,h)$ enables the model to represent submeter shape amplitude with combined effect of day and hour; ε is the residual.

Some criteria are selected to evaluate the model and the definitions as follow Eqs. (3)–(5).

The coefficient of variability (CV) CV

$$= \frac{\sqrt{\left(\sum_{i=1}^{N}(E_{Mi} - E_{Pi})^2\right)/N}}{\left(\sum_{i=1}^{N} E_{Mi}\right)/N} \tag{3}$$

Relative error (RE) $\mathrm{RE} = \dfrac{E_{Mi} - E_{Pi}}{E_{Mi}}$ (4)

Mean relative error (MRE) $\mathrm{MRE} = \dfrac{\sum_{i=1}^{N}\left|E_{Mi} - E_{Pi}\right|}{\sum_{i=1}^{N} E_{Mi}}$ (5)

3.2. Specific Fourier series model

Specific models are fine tuned to deal with four commercial buildings mentioned above with independent hourly HVAC terminal submeter. The detailed information of the four buildings is summarized in Appendix A, Table A1. Building A is an office building. Building B is a mixed-used building, its shopping mall area is very small and its energy use characteristic is very similar to office building A. Therefore building B is regarded as an office building in this research. Building C and D are both shopping malls. The first step to fine tune the Fourier series models for those four buildings is to decide how many day types are included in different buildings.

3.2.1. Day type

The lighting-plug submeter data of a typical office building in Shanghai from Apr. 10 to Jul. 18 in 2013 is shown in Fig. 3. The two days with low energy consumption is weekend (see red circles in Fig. 3). The low energy consumption time over the second two

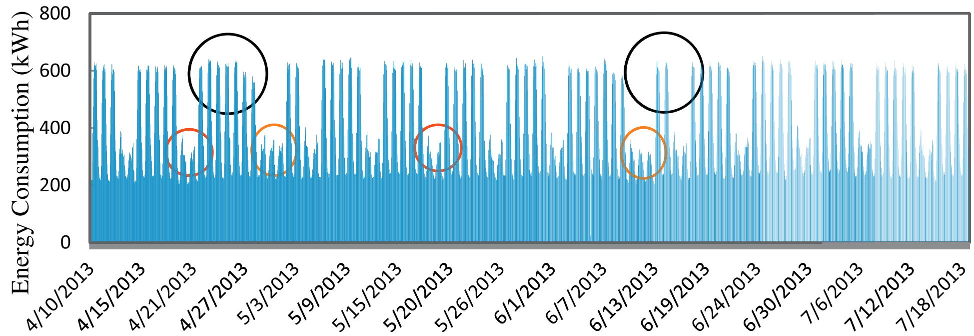


Fig. 3. Period hourly lighting-plug submeter of an office building in Shanghai. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

days is holiday (see orange circles in Fig. 3). Generally, there are five weekdays in one week, while some times it is less or more than five days due to holidays or shifting work (see black circles in Fig. 3). From Fig. 3 it is concluded that energy use characteristic in all working days are nearly the same and in different non-working days are also very similar, but characteristic difference between working days and non-working days is very large. This finding is consistent with the observation from A. Dhar et al.'s. The mean daily lighting-plug power usages in different day types of the four commercial buildings are listed in Table 1. Based on this table, it can be concluded that there are two day types in building A and B 'Weekday (0)' and 'Weekend + Holiday (1,2,3)', and building C and D only have one day type 'Full year (0,1,2,3)'. In other words there are two day types in office buildings and only one day type in shopping mall.

Unfortunately, the power submeter of office building A and B are not measured completely, so just power submeter of shopping mall C and D are analyzed in Section 5. Energy use characteristic and day types of power submeter are analyzed with the same method as above paragraph and not discussed in detail here. As the lighting-plug submeter of shopping mall, power submeter of shopping mall also has one day type 'Full year'.

3.2.2. *Specific Fourier series model for scenario I (HVAC terminals mixed with lighting-plug)*

On the basis of the general model illustrated in Section 3.1, specific Fourier series models to calculate hourly lighting-plug submeter are set up in this section by using stepwise regression with full year cycle, and using hourly measured data as the training data. Stepwise regression includes regression models in which the choice of predictive variables is carried out by an automatic procedure. The stepwise regression processes of the two office buildings and two shopping malls are shown in Appendix B, Tables B1 and B2, respectively. In the tables, items with R^2 larger than 0.001 are marked with bold red font. As shown in table B1 and B2, it is undoubtedly the fact that the most important variable is 'h' and the influence of 'd' is small enough to be ignored. The important frequencies are those which have large partial R^2 and appear consistently in particular building types. In this research, for office building A and B the following frequencies are important CH1, SH1, SH3, CH2, SH4 and SH5 and for shopping mall C and D the important frequencies are SH1, CH1, CH3, CH5 and SH7. The important frequencies whose partial R^2 are larger than 0.001 are summarized from high to low in Appendix C, Table C1, and a conclusion can be drawn that the most important frequency of office building lighting-plug submeter calculating model is CH1, on the contrary, for shopping mall model it is SH1.

To improve the accuracy of HVAC terminal energy use disaggregation model, the lighting-plug power consumption calculating model needs to be as accurate as possible. In other words, the lighting-plug submeter calculating model should cover all frequencies as much as possible. However, if the model is too complex, the method cannot be easily used. Considering the regression results of two office buildings, lighting-plug submeter calculating model for office buildings is established (see Eq. (6)). This model nearly covers all possible items whose partial R^2 larger than 0.001 and keeps simple structure because only variable 'h' is chosen. This model is suitable for both working days and non-working days. The training model R^2 of the two office buildings are 0.967 and 0.986 and CV values (calculated by Eq. (3)) are not larger than 8% and 5%, respectively. It can be seen that some frequencies in Eq. (6), such as SH2, CH3 and CH4, are not important and they still not be removed, which are kept mainly for the purpose of maintaining a simple model structure and improving the accuracy of the model to some extents.

$$E_{L\_\text{Office}} = a + \sum_{n=1}^{6} \left[\delta_n \sin(2\pi\omega_n)h + \eta_n \cos(2\pi\omega_n)h\right] + \varepsilon \tag{6}$$

Similarly, considering the regression results of two shopping malls, lighting-plug submeter calculating model for shopping mall is shown as Eq. (7). The training model R^2 of the two shopping malls

Table 1
Lighting-plug submeter data from four buildings analyzed in this study.

Day type		Average daily lighting-plug submeter data points			
No.	Name	A	B	C	D
0	Weekday	11,737	10,304	22,359	14,410
1	Weekend	7537	6927	22,602	14,652
2	Holiday	6853	6719	22,031	14,714
3	Spring festival	5913	6594	21,501	14,095

are 0.983 and 0.993 and the CV values are controlled within 8% and 7%, respectively.

$$E_{L\_Shopping} = a + \sum_{n=1}^{11} \left[\delta_n \sin(2\pi\omega_n)h + \eta_n \cos(2\pi\omega_n)h\right] + \varepsilon \quad (7)$$

3.2.3. Specific Fourier series model for scenario II (HVAC terminals mixed with power)

Similar to Section 3.2.2, stepwise regression using full year measured data as the training data is completed. Stepwise regression processes of the two shopping malls are shown in Appendix B, Table B3. In table B3 partial R^2 items larger than 0.001 are also marked with bold red font as table B1 and B2. The most important variable is still '*h*' and the influence of '*d*' is still small and '*d*' can be ignored. For shopping mall C and D, in scenario II the important frequencies are SH1, CH1, CH3, SH5, CH5, SH2 and SH7. Likewise, the important frequencies whose partial R^2 are larger than 0.001 are summarized in Appendix C, Table C1. A conclusion can be drawn that the most important frequency of shopping mall power submeter calculating model is SH1. It is the same as shopping mall lighting-plug submeter calculating model.

Considering the regression results of two shopping malls, power submeter calculating model for shopping mall is built as Eq. (8). The training model R^2 of the two shopping malls are 0.992 and 0.977 and CV values are not larger than 7% and 9%, respectively. It is not difficult to find that Eqs. (7) and (8) are identical.

$$E_{P\_Shopping} = a + \sum_{n=1}^{11} \left[\delta_n \sin(2\pi\omega_n)h + \eta_n \cos(2\pi\omega_n)h\right] + \varepsilon \quad (8)$$

4. Scenario I case analysis

This section describes a case study under scenarios I, where HVAC terminal hourly energy consumption are mixed with lighting-plug submeter (referring to Fig. 2). Section 4.1 introduces the data information including the measurement of submeter data and the selection of model training data and calculating data. Section 4.2 summarizes the results of hourly lighting-plug submeter calculation of the four commercial buildings. And Section 4.3 presents the HVAC terminal end-use hourly energy consumption disaggregation results and a comparison with what was measured directly.

4.1. Data

4.1.1. Data measurement

As mentioned above, four commercial buildings (two office buildings and two shopping malls) in Shanghai are chosen as study cases in this research. Complete submetering systems are installed in the four buildings and the monitored data is classified according to Fig. 1. In a very rare occasion, the HVAC terminal end-use energy consumption, lighting-plug submeter and power submeter in the four commercial buildings are measured separately. Data measurement starting time of building A and C is October 2013, while building B and D's is December 2012. And all the data collection periods are more than one year. Data frequency is 5 min and the recorded data is instantaneous power. The hourly energy consumption is calculated by following equation:

$$E = \sum_{i=1}^{12} \left(P_i \times \frac{1}{12}\right) \quad (9)$$

Data period of building A and C is from Nov. 1, 2013 to Oct. 31, 2014, while in building B and D is 2013 full year.

4.1.2. Training data and calculating data

One section of lighting-plug submeter data is used as training data to train the models described in Eqs. (6) and (7). After training, all the constant items and coefficients have been obtained. The trained models were then used to calculate remaining hourly lighting-plug power consumption. After that HVAC terminal end-use energy use certainly can be calculated by subtracting calculated lighting-plug power consumption from measured mixed submeter data.

The selection of training data and predicted data are important because the existence of transition seasons. Transition season refers to the period in which HVAC system is not operating, and so that the mixed submeter data in this period does not include HVAC terminal energy use. Generally speaking, April, May, October and November are considered to be transition seasons in Shanghai, but it does not mean that HVAC systems are off at all times in those four months. So some engineering judgments were made when choosing training data. It has been illustrated in Fig. 1 that the power of all the equipment in HVAC system except for terminal end-use are measured independently. Thus, those hourly lighting-plug submeter data in transition season were selected as training data when the electricity use of boiler, chiller, heating pump, chilled pump and chilling pump are all 0 kW h or at a very low standby level.

Before determining data of which period can be used as calculating data, some attentions were paid to Fig. 4 to exam the data. Two weeks' HVAC terminal end-use energy use disaggregation results of building A are illustrated in Fig. 4(a) and (b). By observing the two figures, the following conclusions can be drawn: (1) HVAC system running time is the same as people's working time, and (2) the distributions of measured data and calculated data are almost identical and the residuals are very small, indicating that the modeling result is very good, (3) the distribution of the relative error fluctuate between day and night. During day time when HVAC terminal were on, energy consumption is high and the relative error is very small. While at night HVAC terminal end-use is in standby mode and energy consumption is extremely low. Although the relative errors are very large at night, the residuals are still very small. Since the purpose of this study is 'HVAC terminal hourly energy consumption disaggregation', so model residuals and relative errors in HVAC terminal running time both are concerned. But for non-operating time relative error is unimportance. However, this is not to say that the disaggregation of HVAC terminal energy use in non-operating time is meaningless, because sometime this information is important for fault detection and diagnosis. For example, the data in red circles in Fig. 4 explains HVAC terminal end-use was running on Saturday. If no occupants work on Saturdays, the system scheduling may have problems.

Electricity consumption data when HVAC systems are on during heating and cooling periods is used as calculating data. Heating period was from Dec. 1 to Mar. 31 in the next year and cooling period was from Jun. 1 to Sep. 30. For office building A and B, HVAC system running time is same as occupants working time. Tenants work hours are not always same and some people may arrival at earlier or leave later. Taking this situation, the HVAC running time in office building is defined from 8:00 am to 6:00 pm. For shopping mall C and D, the opening time is from 9:00 am to 10:00 pm, but the HVAC system is turned off at 9:00 pm. So the HVAC running time in shopping mall is defined from 9:00 am to 9:00 pm.

4.2. Lighting-plug submeter calculation

The results of hourly lighting-plug submeter training models and calculating models of the four commercial buildings analyzed in this paper are summarized in Table 2. To evaluate the results, two evaluation criteria R^2 and CV are calculated in each model. The R^2 values of all four training models are larger than 0.95 and CV

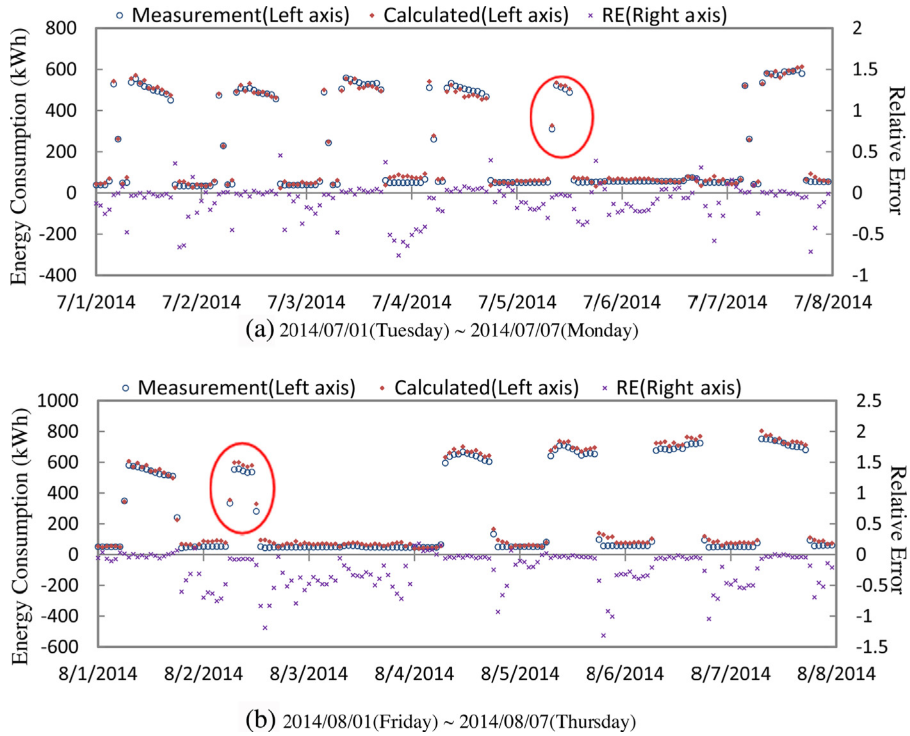


Fig. 4. Weekly results of HVAC terminal end-use disaggregation from lighting-plug submeter of building A. (a) 2014/07/01(Tuesday)–2014/07/07(Monday), (b) 2014/08/01(Friday)–2014/08/07(Thursday)

values are smaller than 8% except for 'Weekend + Holiday' of building B. The result of building D is the best with a R^2 of 0.995 and a CV of 5.38%. Calculating model results are also very good. The CV values of the four calculating models in HVAC system working time are 6.6%, 4.8%, 8.2% and 4.5%, respectively. Although the results of 'Weekend + Holiday' models of building A and B are not so satisfying, they are still acceptable on account of they are not the focus of this study.

4.3. HVAC terminal energy consumption disaggregation

The measured data and calculated data of hourly HVAC terminal-units energy use of the four buildings are illustrated in the top part of pictures (a)–(d) in Fig. 5. The hourly HVAC terminal end-use energy use disaggregation results are presented in Table 3. To evaluate the results, two evaluation criteria CV and MRE are calculated in each model. From Table 3 combined and Fig. 5, it can be seen that the disaggregation results are satisfying. The best result is that of building B. The CV value is 7.38% and MRE is just 5.56%. Building D's disaggregation result is the worst, but its CV and MRE are still within 10%.

The relative errors of hourly HVAC terminal energy use disaggregation models of the four buildings are distributed in the bottom part of pictures (a)–(d) in Fig. 5. And the proportions of data points within particular error range are listed in Table 4. For the disaggregation results of the four buildings, the proportions of data points whose relative error is within 10% are 80%, 81%, 90% and 70%, respectively. If the relative error range is extended to 20%, the proportions even reach 92%, 97%, 97% and 95%, respectively.

From Fig. 5, Tables 3 and 4, it is also can be concluded that disaggregation results in cooling period are better than those in heating period. For this phenomenon two reasons are obtained through investigation and analysis. (1) The intermittent operation of HVAC terminal end-use is more frequent in heating period than cooling period. (2) Other kinds of electric heating equipment are used sometimes in heating period.

Table 2
Results of lighting-plug submeter training model and calculating model of the four commercial buildings analyzed in this study.

Building name	Period	Training data	Calculating data	Day type	Training model R^2	Training model CV (%)	Calculating model CV (%)
A	2013.11.01–2014.10.31	Lighting-plug submeter data without HVAC terminal end-use in transition season	Lighting-plug submeter data in heating season (12/01–03/31) and cooling season (06/01–09/30)	Weekday	0.9550	7.48	6.62
				Weekend + Holiday	0.7453	7.47	9.29
B	2013.01.01–2013.12.31			Weekday	0.9879	4.25	4.84
				Weekend + Holiday	0.7663	10.52	10.65
C	2013.11.01–2014.10.31 (09.19–09.30 no data)			Full year	0.9847	7.27	8.22
D	2013.01.01–2013.12.31			Full year	0.9950	5.38	4.50

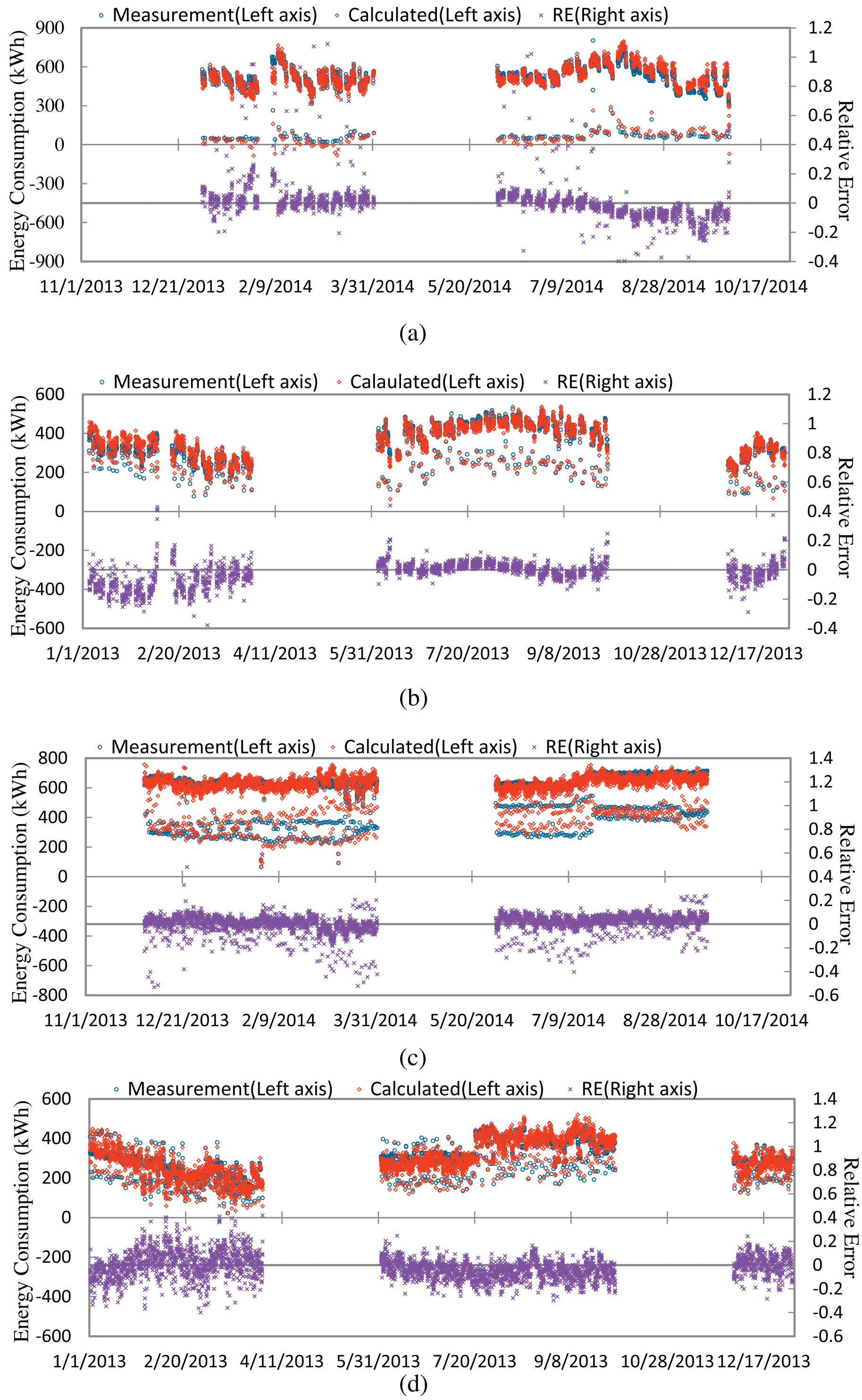


Fig. 5. Results of HVAC terminal end-use disaggregation from lighting-plug submeter.

5. Scenario II case analysis

This section presents the results of HVAC terminal hourly energy consumption disaggregated from mixed power submeter (referring to scenario II in Fig. 2).

5.1. Training data & calculating data

As the training data and calculating data selection method presented in Section 4.1.2, power submeter data during transition seasons is used to train the models referring to Eq. (8) and calculate

Table 3
Results of HVAC terminal energy consumption disaggregation of the four commercial buildings analyzed in this study.

Building name	Period	Time	Terminal end-use disaggregation (%)					
			Total		Heating period		Cooling period	
			CV	MRE	CV	MRE	CV	MRE
A	2013.12.01–2014.03.31; 2014.06.01–2014.09.30	Weekday: 8:00–18:00	7.98	5.95	8.17	5.44	7.81	6.29
B	2013.01.01–2013.03.31; 2013.06.01–2013.09.31; 2013.12.01–2013.12.31	Weekday: 8:00–18:00	7.38	5.56	11.33	8.89	4.2	3.32
C	2013.12.01–2014.03.31 2014.06.01–2014.09.18	Full year: 9:00–21:00	8.95	5.2	11.31	5.48	5.86	4.91
D	2013.01.01–2013.03.31; 2013.06.01–2013.09.31; 2013.12.01–2013.12.31	Full year: 9:00–21:00	9.81	7.81	10.9	8.53	8.99	7.29

the constant items and coefficients in this section. Then the models are used to calculate heating and cooling period hourly power submeter. Since the mixed power submeter data has been measured, the HVAC terminal end-use energy use certainly can be calculated through subtraction. Because of the incomplete measurement of building A and B, just building C and D are studied in scenario II. The same as scenario I, the HVAC running time in building C and D is still from 9:00 am to 9:00 pm.

5.2. Power submeter calculation

The results of hourly power submeter training models and calculating models of the two buildings are listed in Table 5. The R^2 values of training models are 0.972 and 0.993 and CV values are 9.9% and 6.5%, respectively. The CV values of calculating models are 8.0% and 5.6%.

5.3. HVAC terminal end-use energy use disaggregation

The measured data and calculated data of hourly HVAC terminal energy use of building C and D are illustrated in the top part of pictures (a)–(b) in Fig. 6. The hourly HVAC terminal electricity use disaggregation results are presented in Table 6. From Table 6 and Fig. 6, it can be seen that the disaggregation results are excellent. The model's CV and MRE of building D are 5.2% and 1.1%, respectively. And building D's are 1.5% and 3.9%.

The relative errors of hourly HVAC terminal end-use energy use disaggregation models of the two buildings are shown in the bottom part of pictures (a)–(b) in Fig. 6. And the proportions of data points within particular error range are listed in Table 7. For the disaggregation results of the two buildings, the proportions of data points whose relative error is within 5% are 94% and 73%, respectively. If the relative error range is extended to 10%, the proportions even reach 99% and 89%, respectively.

Similarly, the disaggregation results in cooling period are better than those in heating period. The reasons have been analyzed in Section 4.3.

Compared with the disaggregation results of building C and D in Section 4.3, the results in this section are much better. In other words, for the same shopping mall, the result of hourly HVAC terminal end-use electricity disaggregated from power submeter is more accurate than that disaggregated from lighting-plug submeter. In these two scenarios, for the same shopping mall hourly HVAC terminal end-use energy consumption is the same, while hourly lighting-plug submeter is significantly greater than power submeter. So when the CV values of submeter calculating models in two scenarios are similar, the residuals in scenario II are far smaller than those in scenario I. This is the reason why disaggregation results of building C and D in scenario II are better than those in scenario I.

6. Special scenario—Building electricity with significant tenants change

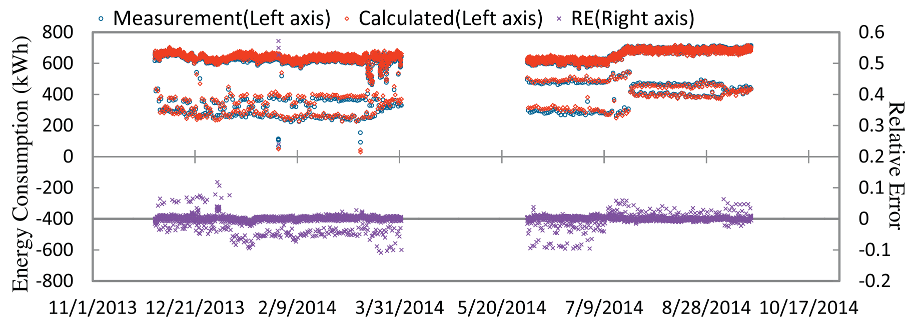
In the early Section 4, two questions still have not been answered. First, in the stepwise regression process variable '*d*' has very little impact on models of the analyzed buildings in addition to building A (see Tables B1 and B2). Different from other models, four frequencies SD1, CD1, SD2 and CD2 have some influence on the model accuracy of building A. Second, the models' relative errors of building B, C and D distribute around zero graduation line evenly and symmetrically. However, building A's relative errors decline from positive to negative gradually. To solve these problems, we analyzed lighting-plug power curve of building A, and conducted an interview to the building management staff. It is found that office

Table 4
Relative error proportion analysis of HVAC terminal end-use energy consumption disaggregation of the four commercial buildings analyzed in this study.

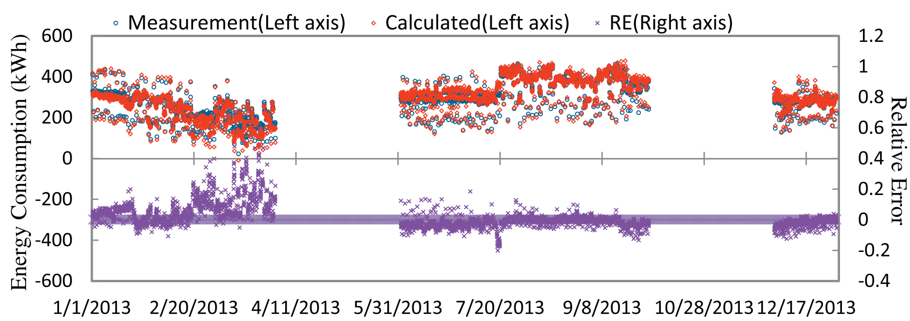
Building name	Data points		Proportion (%)					
			RE ≤ 5%	RE ≤ 10%	RE ≤ 15%	RE ≤ 20%	RE ≤ 25%	RE ≤ 30%
A	Total	1606	55.73	80.07	87.8	91.84	94.15	94.89
	Cooling period	946	56.77	79.18	88.48	92.39	94.93	95.67
	Heating period	660	54.24	81.36	86.82	91.06	93.03	93.79
B	Total	1837	60.32	81.11	91.51	97.22	99.29	99.46
	Cooling period	935	82.78	97.65	99.14	99.57	99.89	99.89
	Heating period	902	37.03	63.97	83.59	94.79	98.67	99
C	Total	3003	63.87	89.84	94.71	96.87	98.1	98.57
	Cooling period	1430	63.01	91.89	95.94	97.9	99.37	99.79
	Heating period	1573	64.65	87.98	93.58	95.93	96.95	97.46
D	Total	3159	45.43	70.09	87.18	94.65	95.25	99.08
	Cooling period	1586	48.36	73.96	90.86	97.23	99.68	100
	Heating period	1573	42.47	66.18	93.58	92.05	90.78	98.16

Table 5
Results of power submeter energy consumption training model and calculating model of the two shopping malls analyzed in this study.

Building name	Period	Training data	Calculating data	Day type	Training model R^2	Training model CV (%)	Calculating model CV (%)
C	2013.11.01–2014.10.31 (09.19–09.30 no data)	Power submeter data without HVAC terminal end-use in transition season	Power submeter data in heating season (12/01–03/31) and cooling season (06/01–09/30)	Full year	0.9716	9.94	8.02
D	2013.01.01–2013.12.31			Full year	0.9929	6.51	5.57



(a)



(b)

Fig. 6. Results of HVAC terminal end-use disaggregation from power submeter.

Table 6
Results of HVAC terminal end-use energy consumption disaggregation of the two shopping malls analyzed in this study.

Building name	Period	Time	Terminal end-use disaggregation					
			Total		Heating period		Cooling period	
			CV	MRE	CV	MRE	CV	MRE
C	2013.12.01–2014.03.31; 2014.06.01–2014.09.18	Full year: 9:00–21:00	1.53	1.09	1.88	1.42	1.09	0.75
D	2013.01.01–2013.03.31; 2013.06.01–2013.09.31; 2013.12.01–2013.12.31		5.16	3.9	7.22	5.73	3.52	2.6

Table 7
Relative error proportion analysis of HVAC terminal end-use energy consumption disaggregation of the two shopping malls analyzed in this study.

Building name	Data points		Proportion (%)					
		RE ≤ 5%	RE ≤ 10%	RE ≤ 15%	RE ≤ 20%	RE ≤ 25%	RE ≤ 30%	
C	Total	3003	94.14	99.2	99.8	99.83	99.83	99.83
	Cooling period	1430	97.83	99.79	100	100	100	100
	Heating period	1573	90.78	98.66	99.62	99.68	99.68	99.68
D	Total	3159	73.12	89.08	93.83	97.25	98.07	98.96
	Cooling period	1586	88.84	97.79	99.31	100	100	100
	Heating period	1573	57.28	80.29	88.3	94.47	96.12	97.9

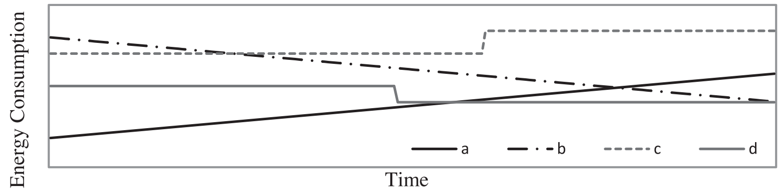


Fig. 7. Energy consumption trend diagram. *Note*: (1) The figure just represents the energy consumption trends and do not represent the specific values. (2) Line 'a' represents that energy consumption increases gradually. For example, users settle in the building gradually. (3) Line 'b' represents that energy consumption decreases gradually. For example, users move out from the building gradually. (4) Line 'c' represents that energy consumption rises suddenly. For example, purchase some new high-power devices. (5) Line 'd' represents that energy consumption falls suddenly. For example, remove some high-power equipment or carry out retrofit.

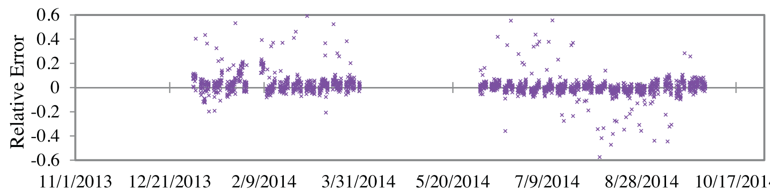


Fig. 8. Relative error of HVAC terminal end-use energy consumption disaggregation of A.

building A is new and most tenants have settled in 2013, while still a few tenants moved into this building in 2014 gradually. So the lighting-plug submeter data shows the tendency of increasing gradually like line 'a' in Fig. 7. This results in disaggregated HVAC terminal end-use energy consumption changes from smaller than the measured data to larger than the measured data, so the relative errors decrease from positive to negative.

Frequencies SD1, CD1, SD2 and CD2 are added to Eq. (6) and a new Eq. (10) is achieved, which is used to do disaggregation of building A once more and new relative distribution is illustrated in Fig. 8. Compared with Fig. 5(a), this result is better.

In conclusion, if the annual data of lighting-plug submeter or power submeter changes like line 'a' or 'b' in Fig. 6, Eq. (10) should be chosen rather than Eq. (6). Additionally, if the changes like line 'a' or 'b' in Fig. 6, there is no need to change equation, but piecewise calculation should be used before and after the energy change point.

$$E'_{L\_Office} = a + \sum_{m=1}^{2} \left[\alpha_m \sin(2\pi\omega_m) d + \beta_m \cos(2\pi\omega_m) d\right] + \sum_{n=1}^{6} \left[\delta_n \sin(2\pi\omega_n) h + \eta_n \cos(2\pi\omega_n) h\right] + \varepsilon \qquad (10)$$

7. Conclusion

This paper explores the feasibility of using a set of specific Fourier series models to calculate light-plug and power submeters energy use of some office buildings and shopping malls. In a rare occasion four buildings with direct measurement of HVAC terminal electricity use provide us the opportunity to verify the accuracy of the models. The models are six frequencies, eleven frequencies and eleven frequencies standard Fourier series models with variable '*h*', respectively (see Eqs. (6)–(8)). On the basis of which hourly HVAC terminal end-use energy consumption can be calculated through indirect measurement (see Eqs. (1-1) and (1-2)). The method with physically meaningful day types and stepwise regression model training is able to disaggregate the electrical data with a good accuracy. The simple model structure proposed in this paper works both in shopping malls and office buildings.

The disaggregation results are within reasonable accurate. MRE values of all case are within 10% and the best one is within 1%. The most important frequency of office building models is CH1, on the contrary, for shopping mall models it is SH1. But disaggregation results in cooling period are better than those in heating period because of the intermitted operation in winter. In shopping mall, hourly HVAC terminal end-use electricity disaggregated from power submeters is more accurate than that disaggregated from lighting-plug submeters.

For buildings with significant tenants changes and gradual increase or decrease of submetering energy consumption in lighting-plug and power, we recommended to add in SD1, CD1, SD2, CD2 four new parameters to the models. This ensures a wide range of applicability of Fourier series models in disaggregating hourly HVAC terminal end-use energy use in different application scenarios.

The models used for same shopping mall in scenario I and scenario II are identical. Due to the incomplete measurement of power submeter in office building A and B, it is still not confirmed that whether the models used for same office building in scenario I and scenario II are also identical or not. To expand the application range of the models developed in this paper, more buildings of office type and shopping mall type and more other building types in Shanghai and other parts of the world should be studied in the future research.

Acknowledgements

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Appendix A.

Table A1.

Table A1
Key descriptions of Shanghai commercial buildings whose monitored data were used in this paper.

Information	Building name			
	A	B	C	D
Location	Shanghai	Shanghai	Shanghai	Shanghai
Type of building	Office building	Complex building (similar to office building)	Shopping mall	Shopping mall
Floor	30	Shopping mall (1–4) Office (5–34)	7	9
High (m)	140	150	43	52
Area (m^2)	70,795	68,330	60,287	40,000
Opening time	Weekday: 9:00–17:00	Weekday: 9:00–17:00	Full year: 10:00–22:00	Full year: 10:00–22:00
Type of HVAC	Chiller + Boiler	Chiller + Boiler	Chiller + Boiler	Chiller + ASHP
Type of terminal end-use	AHU + FAU	AHU (1–4) FCU + DOAS (5–34)	AHU + FAU	AHU
Type of energy use	Electric Boiler: oil/gas	Electric	Electric Boiler: oil/gas	Electric

Appendix B.

Tables B1–B3.

Table B1
Stepwise regression result of lighting-plug submeter in office building.

No.	Variable	A (Weekday)			B (Weekday)		
		R^2	Partial R^2	CV (%)	R^2	Partial R^2	CV (%)
1	*a*	–	–		–	–	
2	SH1	0.2660	**0.2660**	32.73	0.3199	**0.3199**	32.75
3	CH1	0.9135	**0.6475**	11.24	0.9468	**0.6269**	9.16
4	SH2	0.9137	0.0002	11.23	0.9469	0.0001	9.15
5	CH2	0.9211	**0.0074**	10.74	0.9521	**0.0052**	8.69
6	SH3	0.9557	**0.0346**	8.04	0.9799	**0.0278**	5.63
7	CH3	0.9560	0.0003	8.02	0.9803	0.0004	5.58
8	SH4	0.9625	**0.0065**	7.42	0.9834	**0.0031**	5.12
9	CH4	0.9627	0.0002	7.39	0.9836	0.0002	5.09
10	SH5	0.9639	**0.0012**	7.16	0.9851	**0.0015**	4.84
11	CH5	0.9644	0.0005	7.12	0.9854	0.0003	4.81
12	SH6	0.9651	0.0007	7.02	0.9854	0.0000	4.81
13	CH6	0.9665	**0.0014**	6.77	0.9859	0.0005	4.71
14	SH12	0.9665	0.0000	6.77	0.9859	0.0000	4.71
15	CH12	0.9670	0.0005	6.77	0.9860	0.0001	4.71
16	SD1	0.9720	**0.0050**	6.40	0.9860	0.0000	4.70
17	CD1	0.9754	**0.0034**	6.00	0.9863	0.0003	4.65
18	SD2	0.9777	**0.0023**	5.71	0.9869	0.0006	4.55
19	CD2	0.9788	**0.0011**	5.57	0.9869	0.0000	4.55
20	SD3	0.9788	0.0000	5.57	0.9878	0.0009	4.39
21	CD3	0.9789	0.0001	5.95	0.9878	0.0000	4.38
22	SD4	0.9789	0.0000	5.55	0.9878	0.0000	4.39
23	CD4	0.9793	0.0004	5.50	0.9878	0.0000	4.38
24	SD12	0.9795	0.0002	5.48	0.9878	0.0000	4.38
25	CD12	0.9795	0.0000	5.47	0.9879	0.0001	4.38
26	SH1 × SD1	0.9796	0.0001	5.47	0.9882	0.0003	4.38
27	SH1 × CD1	0.9796	0.0000	5.47	0.9890	0.0008	4.17
28	CH1 × SD1	0.9797	0.0001	5.45	0.9890	0.0000	4.17
29	CH1 × CD1	0.9797	0.0000	5.45	0.9897	0.0007	4.03

Table B2
Stepwise regression result of lighting-plug submeter in shopping mall.

No.	Variable	C (full year)			D (full year)		
		R^2	Partial R^2	CV (%)	R^2	Partial R^2	CV (%)
1	*a*	–		–	–		–
2	SH1	0.6693	**0.6693**	34.83	0.7337	**0.7337**	39.65
3	CH1	0.8363	**0.1670**	24.51	0.8559	**0.1222**	29.16
4	SH2	0.8364	0.0001	24.50	0.8634	**0.0075**	28.40
5	CH2	0.8386	**0.0022**	24.34	0.8643	0.0009	28.31
6	SH3	0.8391	0.0005	24.30	0.8735	**0.0092**	27.34
7	CH3	0.9485	**0.1094**	13.75	0.9489	**0.0754**	17.37
8	SH4	0.9487	0.0002	13.72	0.9493	0.0004	17.31
9	CH4	0.9490	0.0003	13.68	0.9493	0.0000	17.31
10	SH5	0.9660	**0.0170**	11.17	0.9543	**0.0050**	16.44
11	CH5	0.9712	**0.0052**	10.29	0.9708	**0.0165**	13.13
12	SH6	0.9712	0.0000	10.28	0.9711	0.0003	13.06
13	CH6	0.9724	**0.0012**	10.06	0.9719	0.0008	12.89
14	SH7	0.9787	**0.0063**	8.81	0.9808	**0.0089**	10.65
15	CH7	0.9806	**0.0019**	8.45	0.9816	0.0008	10.42
16	SH8	0.9809	0.0003	8.39	0.9819	0.0003	10.35
17	CH8	0.9809	0.0000	8.37	0.9821	0.0002	10.28
18	SH9	0.9811	0.0002	8.34	0.9870	**0.0049**	8.76
19	CH9	0.9829	**0.0018**	7.92	0.9882	**0.0012**	8.35
20	SH10	0.9831	0.0002	7.88	0.9884	0.0002	8.27
21	CH10	0.9832	0.0001	7.87	0.9884	0.0000	8.27
22	SH11	0.9832	0.0000	7.87	0.9890	0.0006	8.07
23	CH11	0.9836	0.0004	7.76	0.9931	**0.0041**	6.38
24	SH12	0.9836	0.0000	7.76	0.9931	0.0000	6.38
25	CH12	0.9837	0.0001	7.74	0.9932	0.0001	6.33
26	SD1	0.9837	0.0000	7.74	0.9939	0.0007	6.02
27	CD1	0.9840	0.0003	7.69	0.9945	0.0006	5.73
28	SD2	0.9840	0.0000	7.69	0.9945	0.0000	5.73
29	CD2	0.9841	0.0001	7.67	0.9945	0.0000	5.71
30	SD3	0.9845	0.0004	7.60	0.9945	0.0000	5.70
31	CD3	0.9845	0.0000	7.59	0.9945	0.0000	5.70
32	SD4	0.9847	0.0002	7.57	0.9945	0.0000	5.70
33	CD4	0.9847	0.0000	7.56	0.9945	0.0000	5.70
34	SH1 × SD1	0.9848	0.0001	7.54	0.9946	0.0001	5.68
35	SH1 × CD1	0.9861	**0.0013**	7.30	0.9946	0.0000	5.67
36	CH1 × SD1	0.9862	0.0001	7.29	0.9946	0.0000	5.67
37	CH1 × CD1	0.9873	**0.0011**	7.07	0.9946	0.0000	5.67

Table B3
Stepwise regression result of power submeter in shopping mall.

No.	Variable	C (full year)			D (full year)		
		R^2	Partial R^2	CV (%)	R^2	Partial R^2	CV (%)
1	*a*	–		–	–		–
2	SH1	0.6311	**0.6311**	46.48	0.6623	**0.6623**	34.02
3	CH1	0.8723	**0.2412**	27.35	0.8526	**0.1903**	22.48
4	SH2	0.8753	**0.0030**	27.03	0.8582	**0.0056**	22.04
5	CH2	0.8768	**0.0015**	26.87	0.8597	**0.0015**	21.93
6	SH3	0.8789	**0.0021**	26.64	0.8602	0.0005	21.90
7	CH3	0.9615	**0.0826**	15.02	0.9347	**0.0745**	14.96
8	SH4	0.9631	**0.0016**	14.71	0.9352	0.0005	14.91
9	CH4	0.9639	0.0008	14.55	0.9372	**0.0020**	14.67
10	SH5	0.9776	**0.0137**	11.46	0.9473	**0.0101**	13.44
11	CH5	0.9811	**0.0035**	10.53	0.9554	**0.0081**	12.37
12	SH6	0.9811	0.0000	10.53	0.9555	0.0001	12.36
13	CH6	0.9826	**0.0015**	10.10	0.9582	**0.0027**	11.97
14	SH7	0.9852	**0.0026**	9.33	0.9658	**0.0076**	10.89
15	CH7	0.9873	**0.0021**	8.62	0.9667	0.0009	10.48
16	SH8	0.9880	0.0007	8.38	0.9689	**0.0022**	10.37
17	CH8	0.9881	0.0001	8.36	0.9702	**0.0013**	10.08
18	SH9	0.9883	0.0002	8.30	0.9711	0.0009	9.96
19	CH9	0.9903	**0.0020**	7.54	0.9744	**0.0033**	9.38
20	SH10	0.9908	0.0005	7.34	0.9753	0.0009	9.30
21	CH10	0.9912	0.0004	7.19	0.9759	0.0006	9.23
22	SH11	0.9915	0.0003	7.05	0.9759	0.0000	9.23
23	CH11	0.9915	0.0000	7.05	0.9773	**0.0014**	8.71
24	SH12	0.9915	0.0000	7.05	0.9773	0.0000	8.71
25	CH12	0.9919	0.0004	6.90	0.9782	0.0009	8.45
26	SD1	0.9926	0.0007	6.70	0.9791	0.0009	8.28

Table B3 (*Continued*)

No.	Variable	C (full year)			D (full year)		
		R^2	Partial R^2	CV (%)	R^2	Partial R^2	CV (%)
27	CD1	0.9928	0.0002	6.50	0.9808	**0.0017**	8.12
28	SD2	0.9929	0.0001	6.47	0.9812	0.0004	8.10
29	CD2	0.9930	0.0001	6.43	0.9823	**0.0011**	7.80
30	SD3	0.9930	0.0000	6.42	0.9832	0.0009	7.60
31	CD3	0.9930	0.0000	6.42	0.9837	0.0005	7.49
32	SD4	0.9930	0.0000	6.42	0.9838	0.0001	7.47
33	CD4	0.9930	0.0000	6.41	0.9839	0.0001	7.44
34	SH1 × SD1	0.9933	0.0003	6.27	0.9839	0.0000	7.44
35	SH1 × CD1	0.9933	0.0000	6.27	0.9847	0.0008	7.26
36	CH1 × SD1	0.9934	0.0001	6.23	0.9849	0.0002	7.21
37	CH1 × CD1	0.9934	0.0000	6.22	0.9851	0.0002	7.16

Appendix C.

Table C1.

Table C1
Influence of different variables on the model according to partial R^2 ($\geq$0.001) from highest to lowest.

Variable	No.	Disaggregation from Lighting-plug submeter				Disaggregation from Power submeter	
		A	B	C	D	C	D
H	1	CH1	CH1	SH1	SH1	SH1	SH1
	2	SH1	SH1	CH1	CH1	CH1	CH1
	3	SH3	SH3	CH3	CH3	CH3	CH3
	4	CH2	CH2	SH5	CH5	SH5	SH5
	5	SH4	SH4	SH7	SH3	CH5	CH5
	6	CH6	SH5	CH5	SH7	SH2	SH7
	7	SH5		CH2	SH2	SH7	SH2
	8			CH7	SH5	SH3	CH9
	9			CH9	SH9	CH7	CH6
	10			CH6	CH11	CH9	SH8
	11				CH9		CH4
	12						CH2
	13						CH11
	14						CH8
D	1	SD1					CD1
	2	CD1					CD2
	3	SD2					
	4	CD2					
H, D	1			SH1 × CD1			
	2			CH1 × CD1			

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