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Methodology of comprehensive building energy performance diagnosis for large commercial buildings at multiple levels

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HIGHLIGHTS

- A methodology of building energy performance diagnosis at multiple levels is developed.
- Proposed approach is based on the building and key equipment power data rather than complicated and unreliable BA data.
- Different benchmarking methods are adopted according to respective power use feature by automatic selection algorithm.
- Faulty operation and corresponding energy saving measures of different systems are identified.

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ABSTRACT

The proposed energy performance diagnosis is intended to identify poor energy performance in a building and pinpoint the causes to provide suggestions for building operators to implement timely repair and maintenance. Many previous studies have probed the complicated problem of building energy performance diagnosis to achieve energy conservation and better performance. However, few of them have been successful because most of these methods rely on a large amount of data from an Energy Management and Control System (EMCS), and these data are unreliable. A detailed description of the methodology based on energy consumption data is presented in this paper along with the development of a prototype integrated toolkit. Weekly, daily and hourly diagnoses are developed at the whole building level, system level and component level, respectively. To validate the feasibility and applicability of the method, a case study on an office building demonstrating the proposed method was completed and was able to detect underperformance operation and energy waste.

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1. Introduction

The building sector is widely recognized as a major consumer of both energy and resources [1]. Currently, the building sector takes up 41.3% of the total primary energy in the United States and approximately 40% in the EU (European Union) [2,3]. Experience has demonstrated that 20% of this energy is wasted due to unnoticed faults and underperformance occurring at different levels of the building [4]. Building energy performance diagnosis has gradually become a useful tool that can track, detect and handle abnormal systematic behavior and help operation personnel to identify energy waste and inefficient operation. In many buildings, approximately 15% of the building energy can be saved using the results of an energy performance diagnosis [5].

Energy benchmarking plays a significant role in the process of an energy performance diagnosis. To build a benchmark, models are needed and better benchmarks need more precise models. The methods of energy benchmark modeling can be universally categorized into white box methods, black box methods and gray box methods [6,7]. The black box methods, such as the artificial neural network (ANN), supports vector machine (SVM) and regression method, are used when detailed building information is not available but sufficient historical data can be provided. Especially, ANN and SVM methods are capable of solving nonlinear problems to predict building energy consumption, and the latter is even effective with limited training data [8,9]. If the benchmarks have a stringent requirement on modeling transient behavior, the RC (Resistance-Capacitance) Network method [10,11], a gray box method, is an ideal alternative. The white box method, also termed as a first-principle based method, as it uses physical principles to calculate the energy performance, requires a large amount of specific building data. Some sophisticated simulation software packages, such as DOE-2, EnergyPlus, BLAST, ESP-r, are often used

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Nomenclature

CV_σ	coefficient of variation
ρ	correlation coefficient
EPI	energy performance indices
HDHs	heating degree hours
CDHs	cooling degree hours
DAY	working days in one week
T_b	benchmark temperature
T_m	daily mean temperature
Y	weekly power consumption kW h
T	daily average ambient temperature
WW	day type
E_{AC}	HVAC terminal power consumption kW h
C_0, C_1, C_2	regression coefficients
UL	upper limit value
LL	lower limit value
Q_1	the first quartile
Q_3	the third quartile
IQR	interquartile range
α	constant mean hourly submeter
h	hour of day
ω_n	Fourier frequency for hour
ε	residual
CV(RMSE)	rooted mean squared error
$\hat{x}_i$	the ith prediction energy use data
x_i	the ith measured energy data
$\bar{x}$	mean value of the training data
n	data number of the dataset
m	variable number in the regression model
CAM	characteristic average method
CULLM	characteristic upper-lower limit method
SRM	specific regression method
AE	absolute error
RE	relative error
COP	coefficient of performance
WTF	water transportation factor
EER	energy efficiency ratio
CL	cooling load

to predict the energy consumption [12]. Proactive system identification models can also be used because they are high fidelity models and computationally efficient [13]. To summarize, different models are used for different benchmark and diagnostic purposes.

The current methods of building energy performance diagnoses can be grouped into three categories according to the scope of their diagnosis: whole building level diagnosis, system and component level diagnosis and multi-level diagnosis [14].

A whole building level diagnosis normally does not need a massive amount of information on the building operation [15]. This type of diagnosis typically requires electricity, gas or chilled water energy consumption data at the building level and then identifies operation problems by calculating the building energy consumption deviations from that of the design intent [16]. The idea of whole building level diagnosis has been embedded into some automated whole building diagnostic (AWBD) software, such as the Automated Building Commissioning Analysis Tool (ABCAT) and the Whole Building Diagnostician (WBD) [17]. ABCAT, of which input parameters are building power consumption, cooling load, heating load and weather data, uses first principle models to predict whole building energy consumption [18]. Many further researches make a headway regarding the application and optimization of ABCAT [16,19,20]. Unlike ABCAT, WBD uses a multi-variable bin method that can be categorized as a black box method for building level diagnosis. The WBE (Whole-building Energy Diagnostician) module, one of the diagnostic modules in WBD, classifies the loads into different variable bins and uses bin medians to gauge the expected energy consumption from each bin [21].

A whole building diagnosis only addresses the overall consumption of the building. To identify and locate exactly which component or subsystem leads to underperformance issues, a more targeted investigation of the system or component is needed [22,23]. John proposed an intelligent data analysis method using the modified z-score to identify abnormal power consumption in HVAC systems [24]. Wang et al. presented an approach that detects different kinds of faulty operations of HVAC components through trend data analysis and functional testing [25]. Khan et al. employed pattern recognition techniques and ANN Ensembling approaches to diagnose the anomalies for lighting systems and whole building power consumption [26].

By comparison, multi-level diagnosis has the most comprehensive scope and largest coverage, expanding the inspection of energy performance from whole building level to system and component levels. A prototype EARM-OAM (Energy Assessment and Reporting Method's -Office Assessment Method) enables us to have a hierarchical diagnosis for an office building at multiple levels [27,28]. Yan et al. proposed a novel diagnosis method for energy information in poor buildings with limited energy use data and some building automation data. The monthly energy performance of a whole building and system level is examined by general rules, such as the energy use intensity (EUI), and then the energy-conservation potential of the HVAC components is calculated [15].

In a nutshell, previous studies of multi-level diagnoses merely stick to the building energy performance in a fixed time span, e.g., monthly diagnosis [15]. On the other hand, multi-level diagnosis requires detailed information and often relies on trend data from Building Automation Systems (BAS). It is nonetheless the case that the measured data from BAS is inaccurate and sensor-bias errors frequently occur due to the encompassing nature of sophisticated systems [29,30]. For example, temperature measurements are vulnerable to ambient environmental fluctuations and pressure signals are often obtained by intrusive measurements. Additionally, the placement of flow and temperature sensors in large ducts or pipes is another factor to consider. Besides, there are also the issues of missing, mislabeled and distorted data from the transmission of large amounts of BAS data. By contrast, building power measurements are more reliable and practical. Norford et al. proposed two techniques for using electrical power data for FDD in HVAC equipment. One was based on gray-box correlations of electrical power with flow or other variables, and the second one relied on physical models of the electromechanical dynamics with sub-metered data for a pump or a fan [31,32]. The authors stated that both methods are potentially more robust than FDD methods that rely on temperature and flow sensors in the sense that they do not require estimations of small temperature differences with sensors that are subject to errors [32]. Armstrong et al. [33] developed a device called the Non-Intrusive Load Monitor (NILM) that detects various faults in rooftop cooling units by observing variations in high-frequency sampled electrical data. Hence, it can be seen that the power measurement based FDD is forging its way as a new approach for identifying faults.

In 1992, Hart formally proposed a concept of 'energy sub-metering'; since then, more and more large commercial buildings are sub-metered [34]. For example, the California Public Utilities

Commission (CPUC) issued a decision on sub-metering of electricity in multi-story commercial buildings [35]. By knowing where power is used or wasted, sub-metering can not only help building owners and tenants solve the split incentive issue, but also to know which building equipment and system needs upgrades or better management and scheduling. Also, to promote sub-metering, the U.S. Department of Energy's Buildings Technologies Program announced one of its latest challenges: an initiative to develop a $100 wireless sub-meter [36]. In 2008, the Ministry of Housing and Urban-Rural Development of China (MOHURD) put forward a new policy and offered subsidies to promote sub-metering [37]. To date thousands of large commercial buildings in China have installed sub-metering systems. With the establishment of the energy consumption monitoring platform in nearly all major cities, an overwhelming amount of power consumption data is accumulated in databases.

So far there are quite a few papers utilizing the sub-metering data in building applications. Jain et al. explored the use of power-metering-based energy forecasting in residential buildings [38]. Fan et al. used power consumption data and meteorological variables to develop ensemble models to predict next-day energy consumption and peak power demand [39]. Ji et al. disaggregated HVAC terminal end-use from the lighting-plug or power sub-meters in commercial buildings using a Fourier series model by analyzing the pattern of the sub-metering data [40]. Ji et al. also developed a new bottom-up model calibration procedure with sub-metering data and cooling/heating loads during the building operation phase [41]. However, studies pertaining to the subject of building performance assessment and diagnosis are to a lesser extent limited. Henze et al. demonstrated an energy signal tool that estimates energy use at different sub-metered levels for commercial buildings [42]. Xiao et al. used data mining (DM) techniques to mine sub-metering data retrieved from a real building and detected several fault conditions, such as the problem of deficit flow and abnormal operation of the pumps [43]. Later, a framework for building diagnostics using DM was proposed by Fan et al. to discover and apply knowledge hidden in the massive amount of power data. Changes in building operation strategies and some non-typical building operation conditions can be identified. Under that framework, domain knowledge and DM expertise are requisite [44].

To more effectively use sub-metering data in the scope of building energy performance diagnoses, a methodology is proposed in this paper that makes substantial improvements from prior researches. The originality of the method lies in the following features:

- A comprehensive energy performance diagnosis at different levels and time spans is used. The energy performance diagnosis is more thorough and detailed than in previous studies.
- Robust power data from sub-metering instead of BAS is used, which makes the energy performance diagnosis more practical in the near term and rely less on data quality improvement of BAS.
- The diagnostic procedure is automated and less dependent on the domain knowledge, making it possible to develop into a prototype toolkit.
- The diagnostic results have adequate consistency and accuracy, which makes possible to detect abnormal operations at multiple levels in real buildings.
- The abnormalities are in the form of a three-tier output that can be easily comprehended by the building operators or users.

In the methodology, as shown in Fig. 1, weekly, daily and hourly diagnostic modes are presented at different temporal levels. Weekly diagnoses, as the most macroscopic time level, allows us to have a quick and broad perception of the building energy performance. Daily diagnoses, which evaluate different energy uses in a whole day, are the most useful and practical. Hourly diagnoses are rather detailed and can supplement daily diagnoses to figure out faults when abnormal operation is detected. On the other hand, total power consumption, four main sub-meters and several secondary sub items are diagnosed at different system levels. Different system levels are matched with corresponding temporal levels. For building total energy consumption, we mainly focus on weekly energy use. For energy performance in devices such as chillers, we pay more attention to daily and hourly energy performance.

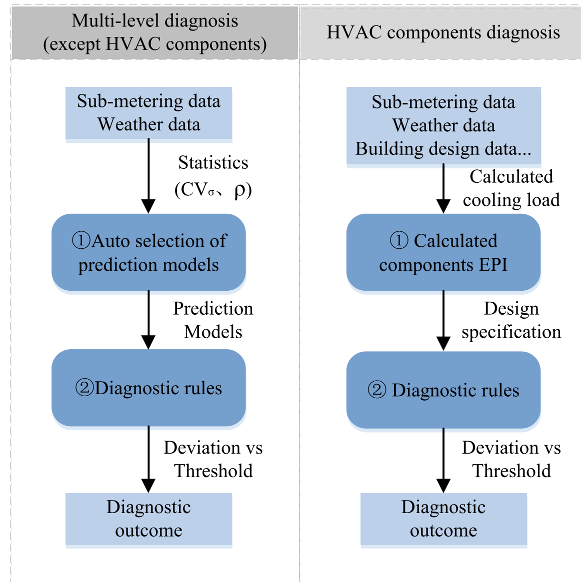

Fig. 1. Proposed diagnostic methodology from temporal level and content level.

The rest of the paper is organized as follows. Section 2 gives a brief description of the basic idea and schematics of the proposed methodology. Sections 3 and 4 gradually elaborate the methodology. Section 5 presents a case study to verify the validity and feasibility of the method. The method successfully pinpointed poor building energy performance and identified the underlying causes.

2. The outline of the methodology

The kernel outline of the building energy performance diagnostic methodology is depicted in Fig. 2.

The power consumption of the sub-meters, weather data, building design data and some in-situ data are the basic required inputs in the method. Some power consumption models serve as the foundation of the method. The detailed diagnostic procedure includes automatic selection of the prediction models and the rules for the multi-level building energy performance diagnosis. The prediction models are chosen by an automatic selection algorithm to calculate the forecasted baseline, which is then compared with the sub-metering data. Relevant diagnostic results are obtained by analyzing the deviation with diagnostic rules. Various energy performance indices (EPI) for the consumption of the HVAC components are used to assess energy performance.

3. Energy benchmarking methods

The prediction models are set up to provide benchmark energy consumption data for the building energy efficiency diagnosis. Energy consumption models rather than component performance models are used here not only because energy is the most important issue, but also because they are applicable to data from sub-metering monitoring systems. A physics-based model of building energy consumption is difficult to be built due to the lack of detailed input information. A model established with simulation tools aimed at one specific single building and is unlikely to be useful for other buildings. Black-box models, which are accurate and extendable, can be used, but they often require a long training period. Despite the fact they are generally acknowledged as being less accurate, regression methods are relatively easy to develop. The results in our previous studies demonstrates that regression models have a sufficient precision for energy efficiency diagnoses using suitable influence factors [40,45].

So in this paper, the following prediction methods are adopted for the building performance diagnoses with consideration of both the feasibility and precision: (1) Regression method, (2) Characteristic average method, (3) Characteristic upper-lower limit method, (4) Fourier series method.

3.1. Data classification

By analyzing the monitoring data, it was found that the data from different building functional areas need to be treated differently. Office and commercial buildings have very different cooling load patterns because of their different occupants and equipment. Besides, scheduling and meteorological conditions have a partial impact on energy use. This study only targets three building types: office buildings, shopping and retail buildings and mixed-use buildings. A mixed-use building refers to a high-rise tower with a retail area in the lower portion of the building. These types of buildings are very popular in many parts of Asia. Normally, office buildings operate on weekdays and close on weekends and holidays, so lighting and HVAC energy consumption in office buildings is different than in shopping malls. As a result, the datasets were divided into two temporal partitions: workdays and non-working days. The HVAC energy consumption patterns also change with the seasons, and so a season division based on the climatic parameter was also required to predict the total and HVAC power consumption.

3.2. Season division

The season division presented here is mainly based on a correlation analysis between the building energy consumption and outdoor climate parameter rather than the conventional four seasons defined in meteorology. The daily average temperature was selected as the metric to determine the season division on that day. The reference temperature, also known as the base temperature, is a balance point temperature at which the HVAC systems do not need to operate to maintain comfortable conditions. The base temperature does not vary very much for a certain type of building and can be calculated from historical data. A whole-year of historical power consumption data in distinct building types was selected and the base temperature was then determined through the relationship between the consumption and outdoor temperature. In this way, the whole year can be divided into a cooling season, heating season and transition season.

From Fig. 3, it can be found that office buildings and mixed-use buildings begin cooling when the daily mean temperature (T_m) is over 20 °C and begin heating when T_m is below 12 °C. Similarly, for commercial buildings, cooling starts when the outdoor air temperature is over 15 °C, and heating starts when the outdoor temperature is below 10 °C. In other words, for office buildings and mixed-use buildings, the day is defined as a cooling day when T_m is above 20 °C. The day is defined as a heating day when T_m is lower than 12 °C, otherwise it is deemed a transition day. Likewise, for commercial buildings, the day is defined as a cooling day when T_m is above 15 °C and as a heating day when T_m is below 10 °C, and the rest are transition days. The detailed season division approach of a day based on T_m is tabulated in Table 1. The season division of a week depends on which day type is most prevalent in the week. That is to say, if there are five cooling days and two transition days in a week, then the week is treated as the cooling season for the weekly diagnosis.

3.3. Specific regression method

The multi-variable regression model is well applied in the presented diagnosis algorithm, of which the scope ranged from the weekly and daily prediction for total energy consumptions with four main sub-meters, as well as several secondary sub items except for the HVAC components. This section proposes specific forms of the weekly and daily prediction models for different building types.

The weekly prediction model uses the concept of the cooling/heating degree hour. Just as with the degree days, degree hours represent a versatile climatic indicator in the analysis of building energy performance that require less data and can be used to estimate how energy consumption may be influenced by major design factors (e.g. insulation level, glazing area rate of the building, assumptions about infiltration, etc.). Heating degree hours (HDHs) are defined as the deviation from the outdoor mean temperature in that hour from a heating reference temperature, accounting only for the positive values. Likewise, cooling degree hours (CDHs) are calculated from the temperatures above the base temperature. For a short period of time (daily, weekly, etc.), the accumulated cooling/heating degree hours (ACDHs/AHDHs) are calculated using the following Eqs. (1) and (2):

$$\mathrm{ACDH} = \sum_{j=1}^{N} (\mathrm{CDH}_j) \begin{cases} \textit{if } T_j > T_b & \textit{then } \mathrm{CDH}_j = T_j - T_b \\ & \textit{else } \mathrm{CDH}_j = 0 \end{cases} \tag{1}$$

$$\mathrm{AHDH} = \sum_{j=1}^{N} (\mathrm{HDH}_j) \begin{cases} \textit{if } T_j < T_b & \textit{then } \mathrm{HDH}_j = T_b - T_j \\ & \textit{else } \mathrm{HDH} = 0 \end{cases} \tag{2}$$

where N is the period of time i.e. number of hours in the week. The corresponding number of hours for the accumulated degree-hours for any period of time is determined by summing the hours with the difference between T_j and T_b.

In daily prediction models, because of the relatively strong correlation between HVAC power consumption and T_m, a cubic polynomial was used to reflect their relationship.

3.3.1. Weekly prediction models

The specific functions of the weekly prediction models are summarized in Table 2. Weekly prediction model I was used for weekly predictions of the building total power consumption and HVAC power consumption. Weekly prediction model II was applied in the weekly prediction of the four main sub-meters except for HVAC sub-meters, in which case HVAC terminal end-use was mixed with the lighting-plug or power sub-meter. To avoid of the difficulty of isolating HVAC terminal energy consumption, the HVAC consumption was added as an influence factor to characterize the feature that the lighting, power and special sub-meters change over the ambient temperature.

Where Y represents the weekly power consumption in kW h, DAY represents the number of working days in a whole week, ACDH/AHDH are the accumulated cooling/heating degree hours with the base temperature, E_{ACT} is the HVAC terminal power consumption in kW h, and C_0, C_1, C_2 are the regression coefficients.

3.3.2. Daily prediction models

The specific functions of the daily prediction models are summarized in Table 3. Daily prediction model I is applicable to the daily prediction of building total power consumption and HVAC power consumption. The data were divided into six datasets according to the day type and season partition before the regression, though model I has the single formation. Daily prediction models II and III were applied in the daily prediction of the four main sub-meters except for HVAC sub-meters, in which case the HVAC terminal end-use is mixed with a lighting-plug or power sub-meter. The difference between the two models lies in whether the day type partition is accounted for.

Where Y represents the daily power consumption, kW h, T_m is the daily average ambient temperature in K, WW reflects the day type and equals 1 on workdays and 0 on non-working days, E_{ACT} is the HVAC terminal power consumption in kW h, and C_0, C_1, C_2 are the regression coefficients.

3.4. Characteristic average method

The method is used in weekly and daily prediction of total energy consumption, four main sub-meters, both for daily and hourly prediction of secondary sub items except for the HVAC components. The characteristic average model fundamentally follows the idea of the moving average approach and the classification in data mining. The historical data were sorted into categories mainly according to its characteristics. In the building sub-metering data, the total and HVAC power consumption changed noticeably with the ambient temperature. However, power consumption is still not fully correlated to the meteorological parameters, for instance, unmixed lighting-plug sub-meters and power sub-meters. A three-year statistical analysis of the lighting-plug and power sub-meters in Shanghai is tabulated in Table 4. The coefficient of variance (CV) indicates the discreteness of the same characteristic dataset. From Table 4, it can be inferred that certain power consumptions, like from a lighting-plug, power plug or special sub-meters, can be predicted by the characteristic average model in the same time period and characteristic, as long as they are not mixed with the HVAC terminal consumption.

The factors considered during data splitting were different due to various energy consumption features. In the weekly prediction model, the factor considered was just the season. In the daily prediction model, the season, month and day type were taken into account. In the hourly prediction, the factors that mattered were month, day type and hour. The specific function and applicable situation of the characteristic average models are listed in Table 5.

3.5. Characteristic upper-lower limit method

The model employs a box-whisker-mean plot and gives reasonable upper-lower limit values using the following Eqs. (3) and (4). This plot type provides a threshold band by eliminating the outliers and can be used in circumstances that other prediction approaches are unable to be used in line with the diagnostic algorithm.

$$UL = Q_3 + 1.5 \times IQR \tag{3}$$

$$LL = Q_1 - 1.5 \times IQR \tag{4}$$

where UL and LL means the upper and lower limit value, Q_1 and Q_3 is the first quartile and the third quartile, respectively, and IQR is interquartile range, that is, IQR = $Q_3 - Q_1$.

3.6. Specific Fourier series method

Our previous studies proved that the Fourier series model can be well tuned to predict the energy use that varies periodically in daily cycles (i.e. hourly lighting-plug and power sub-meters) [38]. The specific Fourier series models for office and shopping buildings are listed in Table 6. Note that the method could not work provided that the HVAC terminal circuits are mixed with lighting or power circuits.

Where α represents the constant mean hourly sub-meter, the middle term indicates the diurnal hourly amplitude, h is the hour of day, ω_n is Fourier frequency for the hour, and ε is the residual.

4. Diagnostic algorithm

The algorithm is in a top-down time sequence: weekly, daily and hourly. The general procedure of the multi-level diagnosis algorithm can be divided into two steps. The first step is to automatically select prediction methods, which is presented in Section 4.1. The second step is to compare the deviation with certain allowable tolerances and eventually calculate the outcome, which is detailed in Section 4.2. Particularly, for the HVAC components, an index-based diagnostic algorithm is proposed in this study due to the sophisticated nature of energy use in the HVAC components.

4.1. Automatic selection of benchmarking methods

The first step of the algorithm is to choose the appropriate prediction model for the kind of power consumption according to its energy use feature. To determine and quantify the energy use

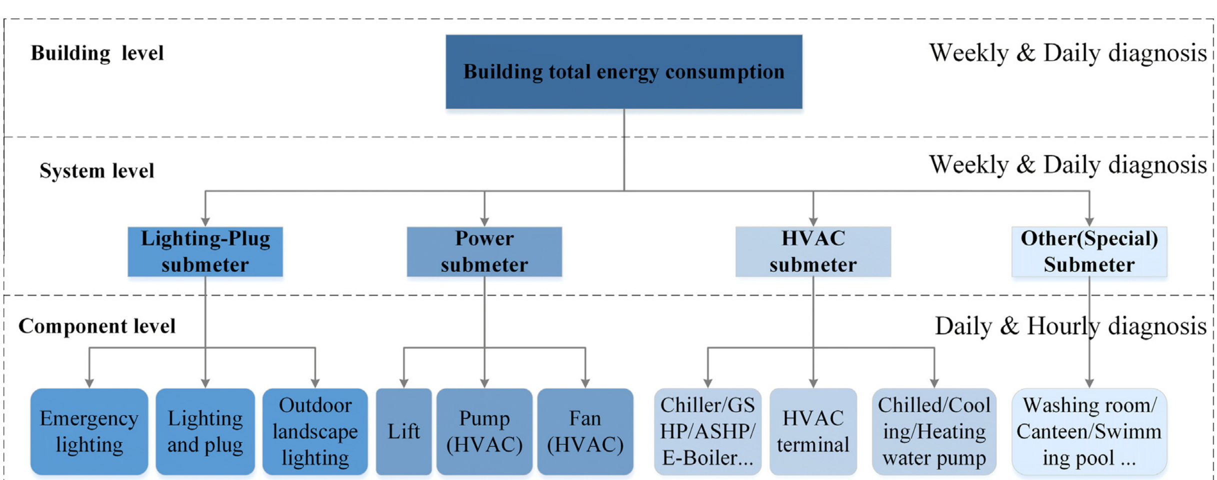

Fig. 2. General outline of the multi-level building energy performance diagnostic method.

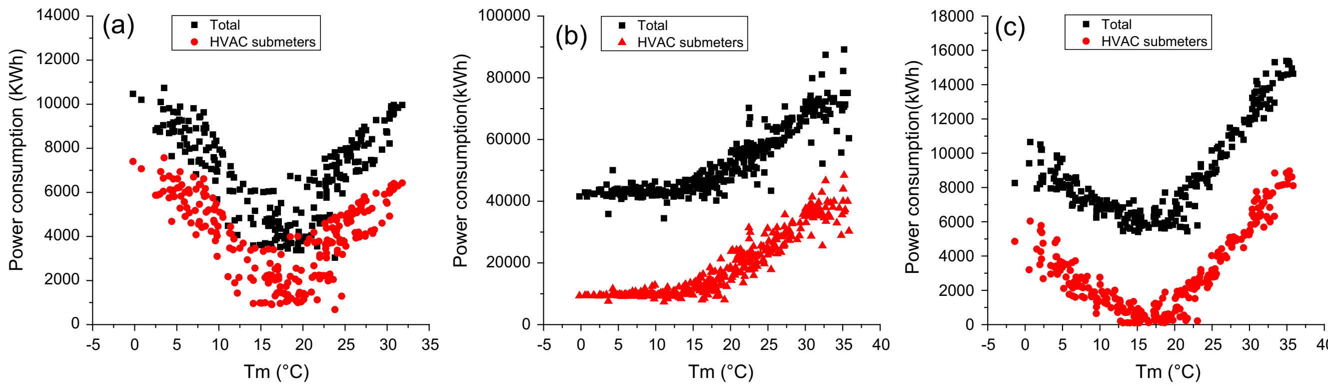

Fig. 3. Scatter diagram of total power consumption corresponding to T_m in a year of (a) an office building (b) a commercial building (c) a mixed-use building.

Table 1
Season division approach based on daily mean temperature (T_m).

Building type	Cooling day	Heating day	Transition day
Office	>20	<12	12–20
Commercial	>15	<10	10–15
Mixed-use	>20	<12	12–20

feature of the training dataset, several statistical parameters are introduced. The coefficient of variation (CV_σ), as defined in Eq. (5), indicates the discreteness of the dataset, which is regarded as the threshold for deciding whether or not to adopt the characteristic average model. The correlation coefficient (ρ) represents the correlation degree of two datasets. In this paper we use it to demonstrate whether the dataset is related to the day type. The determination coefficient (R^2) reflects how well the regression model fits. The coefficient of variation of the rooted mean squared error (CV(RMSE)) expresses the uncertainty of the regression model, denoted by Eq. (6). The regression model in Section 3.3 is thought to be applicable if the following conditions are met: $R^2 > 0.6$, $CV(RMSE) < 0.2$. It is worth noting that outliers should be eliminated to obtain a better fit, and the regression model is not available if the outlier surpasses 20% of the original training data.

$$CV_\sigma = \frac{\sqrt{\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n-1}}}{\bar{x}} \times 100\% \tag{5}$$

where CV_σ is the coefficient of variation, $\bar{x}$ is the mean value of the dataset, and n is the data number in the dataset.

$$CV(RMSE) = \frac{\sqrt{\frac{\sum_{i=1}^{n}(x_i-\widehat{x_i})^2}{n-m}}}{\bar{x}} \times 100\% \tag{6}$$

where CV(RMSE) is the coefficient of variation of the rooted mean squared error, $\widehat{x_i}$ is the ith prediction energy use data while x_i represents the ith measured energy data, $\bar{x}$ is the mean value of the training data, n is the data number of the dataset, and m is the variable number in the regression model.

The detailed methods are described in the time sequence as follows.

4.1.1. Weekly diagnosis

As shown the flow chart depicted in Fig. 4, the weekly power consumption E should be longer than one year to ensure the training data cover all four seasons. CV of the dataset is calculated to judge whether the weekly power consumption changes with the season. After testing the algorithm and studying the energy use feature of many large commercial buildings, we set the baseline of CV to 20%. That is to say, if the CV value is less than 20%, the characteristic average model is selected. On the contrary, the weekly power consumption E is thought to be relative to the season and have a HVAC component. The next step is to see whether the power consumption E is total or just HVAC power consumption. If so, the season division is needed and CV values are calculated with respect to the divided dataset. If not, we need to calculate the correlation coefficient (ρ) between the dataset E and HVAC terminal consumption to determine whether the power consumption E is mixed with the HVAC terminal. Specific regression method (1) is used under the condition that the CV value is more than 20% and model prediction is met. Specific regression method (3) will be adopted provided that ρ is more than 0.3 and model prediction is met. Otherwise, the algorithm will jump to the characteristic upper-lower-limit model.

4.1.2. Daily diagnosis

The flow chart of the daily diagnosis is shown at length in Fig. 5. It follows the same idea as the weekly algorithm but is more sophisticated. To avoid repetition, it is not described in this paper.

4.2. Diagnostic rules

The general diagnostic rules after automatically selecting prediction methods are elaborately illustrated in Fig. 6.

Table 2
Separate weekly regression prediction model for different building types.

Model	Building type	Season division	Specific function
(1)	Office, Mixed-use	Cooling	$Y = C_0 + C_1 \times DAY + C_2 \times ACDH20$
		Heating	$Y = C_0 + C_1 \times DAY + C_2 \times AHDH12$
		Transition	$Y = C_0 + C_1 \times DAY + C_2 \times ACDH20 + C_3 \times AHDH12$
	Commercial	Cooling	$Y = C_0 + C_1 \times ACDH15$
		Heating	$Y = C_0 + C_1 \times AHDH10$
		Transition	$Y = C_0 + C_1 \times ACDH15 + C_2 \times AHDH10$
(2)	Office, Mixed-use	–	$Y = C_0 + C_1 \times DAY + C_2 \times E_{ACT}$
	Commercial		$Y = C_0 + C_1 \times E_{ACT}$

Table 3
Separate daily regression prediction models.

Model	Specific function
(1)	$Y = C_0 + C_1 \times T_m + C_2 \times T_m^2 + C_3 \times T_m^3$
(2)	$Y = C_0 + C_1 \times \mathrm{WW} + C_2 \times E_{\mathrm{ACT}}$
(3)	$Y = C_0 + C_1 \times E_{\mathrm{ACT}}$

Except for the characteristic upper-lower-limit method, the second move of the algorithm is to compare the sub-metering data to the expected benchmark consumption. The residual and absolute error (AE) are used as the judgment parameter within the process.

The threshold is closely bound up with the prediction methods, therefore for different methods, the threshold of residual is set following the rules in Table 7. The algorithm flags the energy consumption as high/low when it exceeds the baseline by the predetermined threshold. However, the residual alone cannot differentiate the severity grades of the building power consumption. In other words, though residual of some small power sub-items far exceeds its threshold, it has slight impact on the building energy because it contributes little to the whole building power consumption. So we introduce a three-tier error output (I/II/III high/low) to reflect the severity by setting the lower and upper threshold of absolute error. In the weekly diagnosis for instance, the lower threshold of absolute error is defined as the 1% of the median weekly total building power consumption in a whole year. And the upper threshold of absolute error is defined as the 10% of the median weekly total building power consumption in a whole year. Likewise, the lower and upper threshold of absolute error are defined as the 1% and 10% of the median daily total building power consumption in a whole year respectively in the daily diagnosis.

Whereas for the characteristic upper-lower limit method discussed in Section 3.5, sub-metering data needs to fall between the proposed upper and lower bounds. When the bound is breached, we consider it as a III-level severe error due to the wide range of the method.

4.3. Energy efficiency diagnosis of HVAC components

The energy use of HVAC components is very complex and influenced by multitudinous factors. We are incapable of setting up relatively simple prediction models that fulfil the precision requirement only with the sub-metering power consumption. In this case, rule-based diagnostic algorithm assisted by the energy performance index of HVAC components is adopted for HVAC component level diagnosis.

4.3.1. Daily diagnosis

The daily diagnosis involves the inspection on the on/off state and operating efficiency of the key HVAC components.

We detect abnormal HVAC component operation mainly depending on the operation time of the building and the cooling/heating demand in that period of time. The diagnosis of key HVAC components follows this order: cold and heat sources, distribution systems, and HVAC terminals. When chillers are not in operation, the diagnostic of the distribution systems and HVAC terminals are meaningless.

Under the circumstance that the cold/heat source operates normally, the first diagnose is its operation efficiency. Energy performance indices (EPI) of different HVAC components are introduced, as shown in Table 8.

Table 5
Specific function of characteristic average models and their applicable situation.

Model		Specific function	Comment
Weekly	(1)	$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$	• Where x is weekly power consumption; n is the number of weeks in that year • Model is for the cases that $\bar{x}$ is not correlated to season
	(2)	$\bar{x}_s = \frac{1}{n_s}\sum_{i=1}^{n_s} x_i$	• Where subscript s represents seasons: cooling, heating and transition season; n_s is the number of weeks in that season • Model is for the cases that $\bar{x}_s$ is correlated to season
Daily	(1)	$\bar{y}_m = \frac{1}{p_m}\sum_{i=1}^{p_m} y_i$	• Where y is daily power consumption; Subscript m means month: 1–12; p_m is the number of days in that month • Model is for the cases that $\bar{y}_m$ is neither correlated to season nor day type
	(2)	$\bar{y}_{m,w} = \frac{1}{p_{m,w}}\sum_{i=1}^{p_{m,w}} y_i$	• Where subscript w is day type: workday and nonworkday; $p_{m,w}$ is the number of days of same type in a month • Model is for the cases that $\bar{y}_{m,w}$ is not correlated to season but correlated to day type
	(3)	$\bar{y}_s = \frac{1}{p_s}\sum_{i=1}^{p_s} y_i$	• Where subscript s represents seasons: cooling, heating and transition season; p_s is the number of days in that season • Model is for the cases that $\bar{y}_s$ is correlated to season but not correlated to day type
	(4)	$\bar{y}_{s,w} = \frac{1}{p_{s,w}}\sum_{i=1}^{p_{s,w}} y_i$	• Where $p_{s,w}$ is the number of days of in that season • Model is for the cases that $\bar{y}_{s,w}$ is correlated to both season and day type
Hourly	(1)	$\bar{z}_{m,w,h} = \frac{1}{q_{m,w,h}}\sum_{i=1}^{q_{m,w,h}} z_i$	• Where z is hourly power consumption; Subscript h means hour: 0–23; $q_{m,w,h}$ is the number of days of same day type at hour h in that month • Model is for hourly prediction of lighting-plug, power and special submeters

Table 6
Hourly lighting-plug and power submeters prediction models of different building types.

Building type	Specific function
Office building	$E = \alpha + \sum_{n=1}^{6}[\delta_n \sin(2\pi\omega_n h) + \delta_n \cos(2\pi\omega_n h)] + \varepsilon$
Commercial building	$E = \alpha + \sum_{n=1}^{11}[\delta_n \sin(2\pi\omega_n h) + \delta_n \cos(2\pi\omega_n h)] + \varepsilon$

Table 4
Data analysis of daily lighting-plug submeter consumption of different building types.

Building type	Day type	2013.1		2014.1		2015.1		CV (%)
		Mean	CV (%)	Mean	CV (%)	Mean	CV (%)	
Office	WD	3022.7	4.28	2806.2	4.91	2908.4	11.14	8.12
	NWD	1346.4	9.06	1361.9	9.27	1263.9	9.72	9.55
Mixed-use	WD	9436.3	3.72	9545.4	5.85	9291.4	2.82	4.34
	NWD	4979.6	7.74	5160.1	7.15	5029.6	5.7	6.76
Commercial	–	15,448	1.28	16,022	2.67	14,264	1.81	5.22

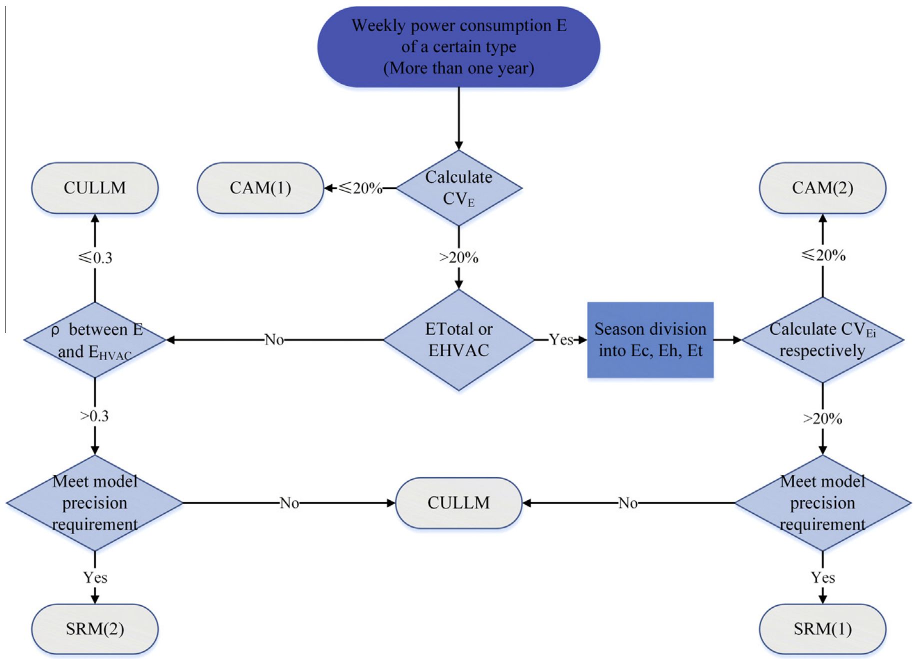

Fig. 4. Flow chart of automatically selecting prediction methods in the weekly diagnosis.

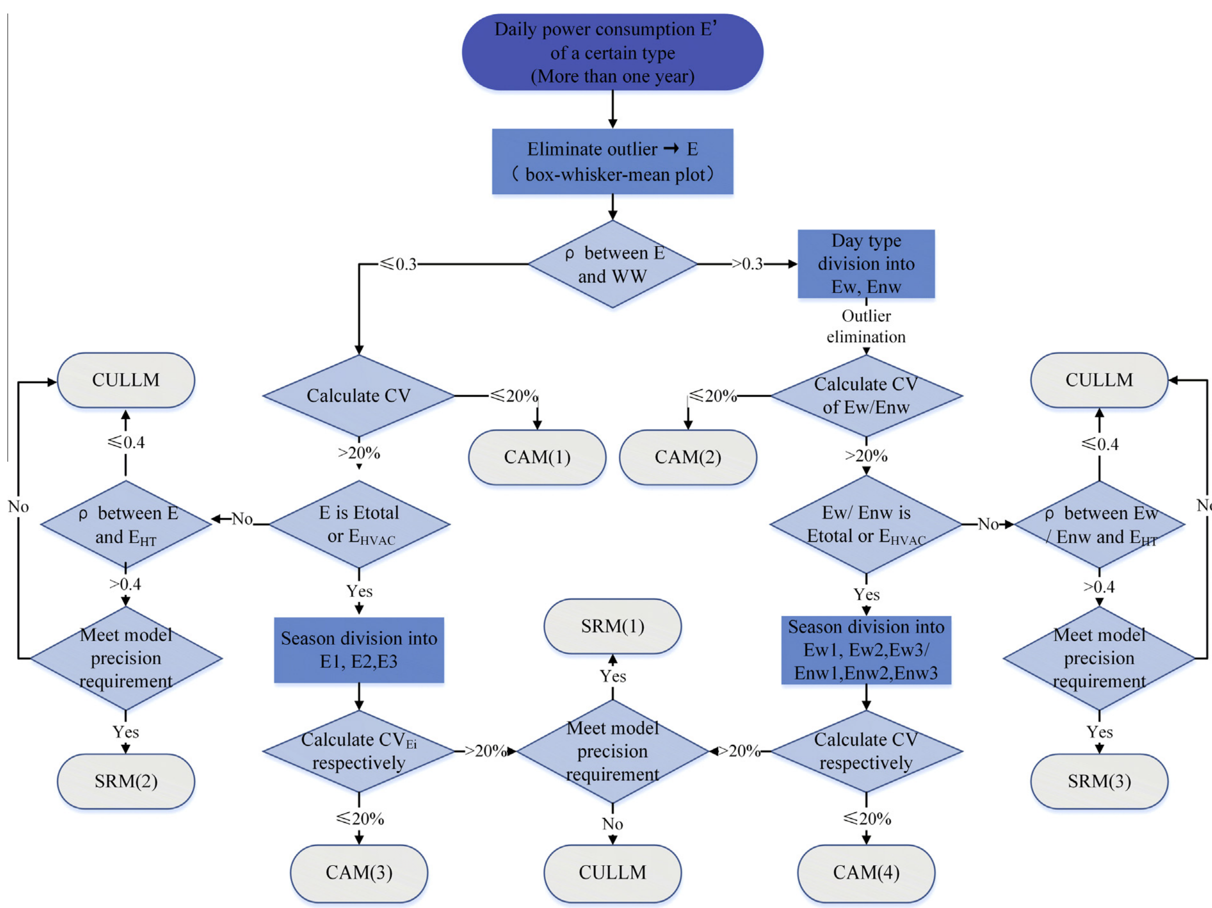

Fig. 5. Flow chart of automatically selecting prediction methods in the daily diagnosis.

The above thresholds follow the standard and average performance of large commercial buildings in Shanghai. Where in other part of the world, these numbers may be changeable.

Where coefficient of performance (COP), water transportation factor (WTF) and energy efficiency ratio (EER) are the energy performance indices (EPIs) for cold/heat source, pumps and HVAC

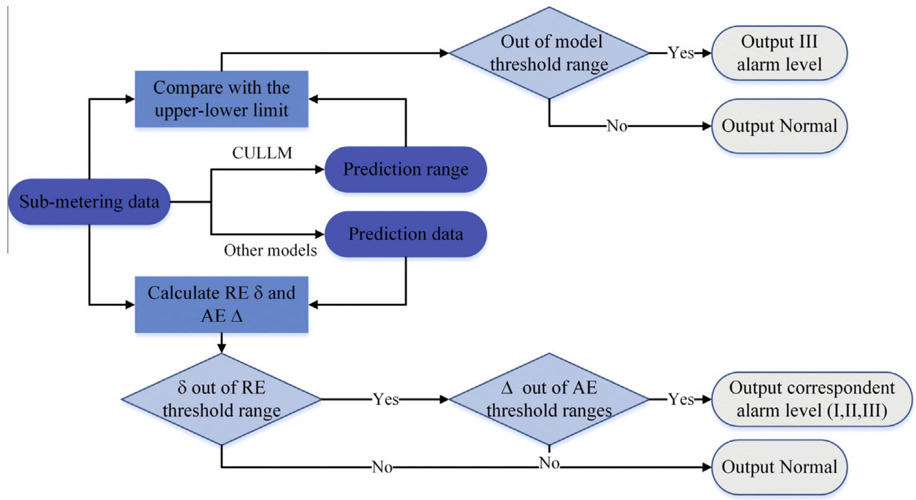

Fig. 6. Flow chart of the general rules for the weekly, daily and hourly diagnosis.

Table 7
Threshold setting of residual for different prediction methods.

Specific regression method		Characteristic average method	
Condition	Threshold	Condition	Threshold
$R^2 \geqslant 0.6$, CV(RMSE) < 5%	±20%	$CV_\sigma \leqslant 10\%$	±20%
$R^2 \geqslant 0.6$, 5% ⩽ CV(RMSE) < 15%	±25%	$10\% \leqslant CV_\sigma < 20\%$	±25%
$R^2 \geqslant 0.6$, 15% ⩽ CV(RMSE) < 25%	±30%	$CV_\sigma \geqslant 20\%$	±30%

Table 8
Energy performance indices (EPI) of different HVAC components.

HVAC components	EPI	Component type	EPI threshold
Cold and heat source	$COP = \frac{CL}{E_{source}}$	Air source heat pump	Cooling/ heating 2.8/ 2.4
		Chiller	4.8
Distribution systems	$WTF = \frac{CL}{E_{pump}}$	Chilled water pump	30
		Cooling water pump	25
		Hot water pump	30
		Chilled and hot water pumps	30
HVAC terminal	$EER = \frac{CL}{E_{terminal}}$	All-air system	6
		Fan coil unit with independent fresh air system	9
		Fan coil unit	24

terminal respectively. E_{source}, E_{pump}, $E_{terminal}$ are the power consumption of the components, which can be obtained directly from the sub-metering data. Cooling load (CL) is calculated in Eq. (7). using the first thermodynamic law. $Q_{Electricity\text{-}indept}$ equals to the heat gain from the building envelope, fresh air and occupants. $E_{internal}$ represents the heat gains released from internal equipment and lighting while $E_{delivery}$ represents heat gains produced by cooling delivery system (i.e chilled water pumps air handing unit fans), which is assumed to be the same as the power consumption measured by the sub-metering system.

$$CL = Q_{Electricity\text{-}indept} + E_{internal} + E_{delivery} \tag{7}$$

4.3.2. Hourly diagnosis

The scope of the hourly diagnosis is almost the same as the daily diagnosis. Similarly, we are about to diagnose the on/off state and operating efficiency of the HVAC components. The difference lies in that we need to think more carefully, considering the condition that the chiller may be switched off in advance and HVAC pumps and terminal may shut down after the chiller. The overall rule-based HVAC components diagnosis results are listed in Table 9.

Table 9
Overall rule-based HVAC components diagnosis results.

Diagnostic results and categories		Diagnostic objects and time					
		Air source heat pump/ chiller		Electric boiler		Pumps/HVAC terminal	
		Daily	Hourly	Daily	Hourly	Daily	Hourly
On-off status	Standby or off	✓	✓	✓	✓	✓	✓
	Should not start but actually do	✓	✓	✓	✓	✓	✓
	Should start but actually not	✓	✓	✓	✓	✓	✓
	Normal			✓	✓		
	Auto-follow the chiller					✓	✓
Operation efficiency	Low efficiency	✓	✓			✓	✓
	Slightly low efficiency	✓	✓			✓	✓
	Normal	✓	✓			✓	✓
	Cooling/heating supply is not sufficient	✓	✓				
On-off time	Switch on in advance		✓		✓		
	Switch off in advance		✓		✓		
	Switch off later than the chiller						✓

Table 10
Weekly prediction method of different energy type and its threshold.

Data classification (CV_σ)		Model selection	Model precision		Threshold
Submeters (CV_σ)	Season (CV_σ)		R^2	CV(RMSE)	
Total (32.2%)	Cooling (27.0%)	$Y = 18481.3 + 2033.6 \times \text{Days} + 15.2 \times \text{ACDH20}$	0.8640	10.2%	±25%
	Transition (15.5%)	Weekly characteristic average models (2)			±25%
	Heating (25.8%)	$Y = -6667.5 + 7466.2 \times \text{Days} + 22.7 \times \text{AHDH12}$	0.8281	11.1%	±25%
HVAC (50.1%)	Cooling (39.6%)	$Y = 4916.3 + 1312.2 \times \text{Days} + 12.1 \times \text{ACDH20}$	0.8128	17.5%	±30%
	Transition (34.7%)	$Y = 4893 + 1063 \times \text{Days} - 10 \times \text{ACDH20} + 27\text{AHDH12}$	0.7032	20.4%	±30%
	Heating (36.6%)	$Y = -17767.8 + 6206.7 \times \text{Days} + 20.9 \times \text{AHDH12}$	0.8271	15.8%	±30%
Lighting and plug (19.9%)		Weekly characteristic average models (1)			±25%
Power (4.4%)		Weekly characteristic average models (1)			±20%
Special (24.2%) ($\rho_{AC} = 0.698$)		$Y = 59.32 + 5.45 \times \text{Days} + 0.0019 \times E_{AC}$	0.6597	13.9%	±25%

Table 11
Weekly energy performance diagnosis result of the building.

Season	Starting Saturday	Total	HVAC	Lighting	Power	Special
Heating	2014/1/18	Normal	I level high	Normal	Normal	Normal
Transition	2014/3/29	Normal	Normal	Normal	Normal	Normal
Cooling	2014/8/23	Normal	I level high	I level low	Normal	Normal

5. Case analysis

The methodology described above has been made into a prototype toolkit for comprehensive building energy performance diagnoses. The toolkit has been validated in 50 large commercial buildings of different types in Shanghai. The total area of these buildings is more than one million square meters.

One case study of an office building is described here to show how the proposed methodology is applied to a comprehensive building energy performance diagnosis. The Shanghai Municipal Archives was built in 1991. As with many old buildings, some documentation and drawings of this building are missing. To acquire the description of the building, site visits and interviews with the facility managers were required. The building is served by three identical centrifugal chillers, each of which is associated with a constant-speed chilled water pump and a constant-speed condenser water pump. The lighting system mainly consists of incandescent lights and a small proportion of T8 fluorescent lamps. Four traction-elevators serve the office and the warehouse. The detailed

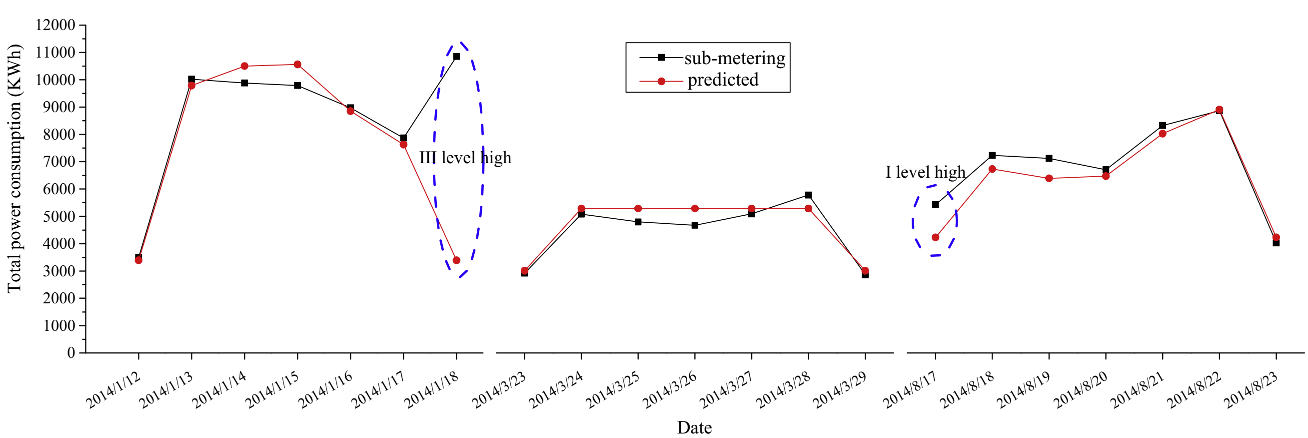

Fig. 7. Broken line graph of metered and predicted daily total power consumption.

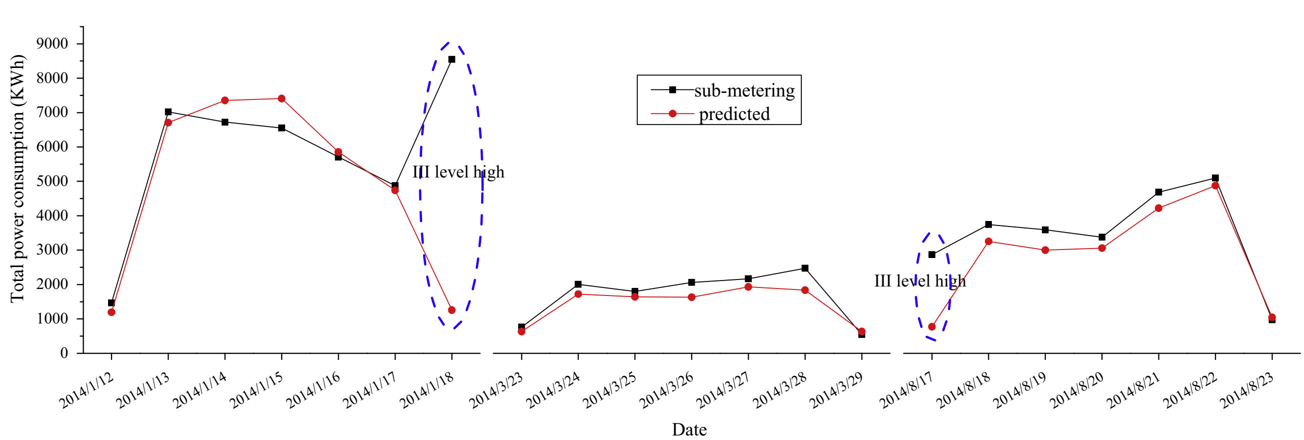

Fig. 8. Broken line graph of metered and predicted daily HVAC power consumption.

Table 12
Daily diagnosis for HVAC components on abnormal days.

Date	HVAC consumption	Chiller	Boiler	Chilled/hot water pump	HVAC terminal
2014/1/18	III level high	Standby or off	Should not start but do	Follow the chiller/boiler	Follow the chiller/boiler
2014/8/17	III level high	Should not start but do	Standby or off	Follow the chiller/boiler	Follow the chiller/boiler

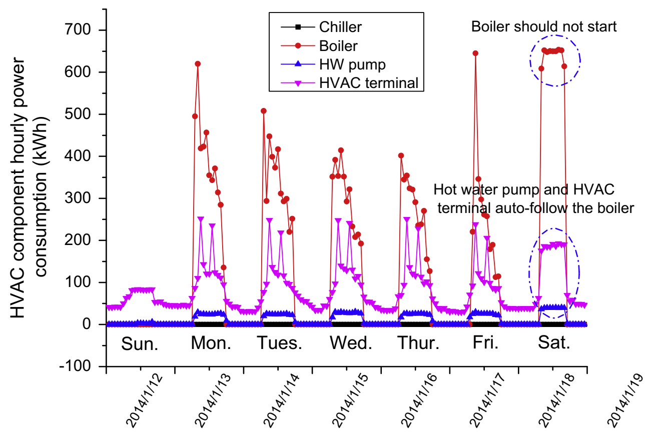

Fig. 9. Diagram of hourly HVAC component consumption.

information in terms of the HVAC, lighting, power systems is summarized in Appendix Table A1. Historical sub-metering data in 2013 was selected as the training data. The top-down time approach was used to diagnose the whole building energy performance in 2014, including the total power consumption, four sub-meters on the system level and several sub-items on the component level. A representative week was selected from each season division and then diagnosed. The energy performance of 21 days in the three weeks were subsequently evaluated. An hourly diagnosis is presented and accounts for the days when an anomaly occurred.

5.1. Weekly and daily diagnosis (Whole building and system level)

According to the method in Section 3, different types of energy consumption are aligned with respective prediction methods based on the energy use feature through an automatic model selection algorithm. A weekly prediction model and its diagnostic threshold are shown in Table 10.

The weekly diagnosis, tabulated in Table 11, is the result of the diagnosis discussed in Section 4. In the same way, the daily prediction models and diagnostic results are also tabulated in Appendix Tables A2 and A3. Figs. 7 and 8 further describe the deviation between the predicted and sub-metering data of the daily total and HVAC power consumption in these three weeks.

As the weekly and daily diagnostic outcome shows, the HVAC power consumption in the heating week appears I-level high. The HVAC power consumption on Jan. 18th was III-level high and consistent with the weekly diagnosis. Meanwhile in the cooling week, the HVAC power consumption on Aug. 17th was III-level high, leading to the I-level high in the weekly diagnosis. Lighting and plug power consumption on Aug. 18th and 20th were III-level low, resulting in the I-level low in the weekly diagnosis. The total consumption remained normal because the HVAC and lighting consumption mutually offset. A special sub-meter contributed a small share of the total consumption, but did not affect the diagnostic outcome of the total power consumption.

5.2. Daily and hourly diagnosis (component level)

To go a step further, daily and hourly diagnosis on the component level of four sub-meters were conducted to figure out the anomalies in these exceptional days. The HVAC component level daily diagnosis is illustrated in Table 12. Component diagnosis of other sub-meters is shown in Appendix Tables A4–A6.

It was found that the root causes for the extremely high HVAC consumption on Jan. 18th and Aug. 17th lay in the boiler or chiller. They should not be operated on non-workdays. The hot water pumps/chilled water pumps and terminals automatically follow the starting of boilers/chillers. To identify the exact time when the anomalies happened, we conducted an hourly diagnosis and found that the boiler operated from 7 a.m to 13 a.m on that day and the HVAC terminal ran the entire day, as shown in Fig. 9.

The HVAC component level diagnosis also enabled us to find that the chilled water pump operated at a low efficiency for 38.6% of the running time, as illustrated in Fig. 10. Through a site survey and preliminary analysis, we found that a small water transportation factor was caused by over sizing the pump. Furthermore, Fig. 10 demonstrates that the HVAC terminals operate at a low efficiency even for 80% of the operating time. The underlying reason is that the heat transfer effect had severely degraded

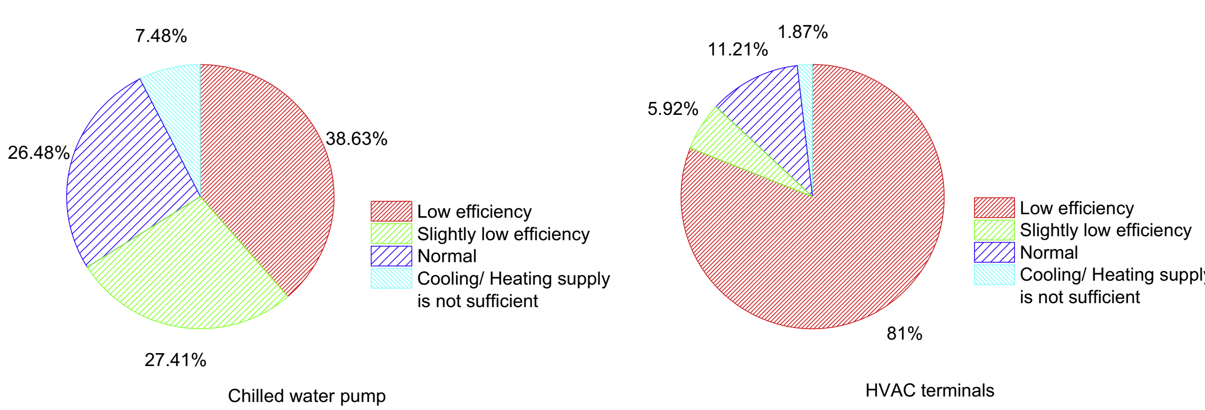

Fig. 10. Operation status of chilled water pump and HVAC terminals.

because the building was built in 1991, and the return air inlet of the air handling unit had not been cleaned for a long time. The fan has to operate at a high volume to satisfy the cooling load.

This real case study is only one of the 50 tests this study covered. These tests validated the feasibility of the methodology to isolate low efficiency parts and help to expose the causes in an existing office building. Weekly diagnosis offers us a general view of the building energy performance. If abnormally high energy consumption occurs in this week, great attention should be taken. But different sub-meters are likely to cancel each other out in the weekly diagnosis, so we need to dig deeper into the daily diagnosis even if the weekly diagnosis shows good results. As far as the hourly diagnosis is concerned, the result maintains consistency for the daily diagnosis in the methodology. As a result, hourly diagnosis can only detect energy waste in one of the sub systems and generate warnings, but mechanical failure diagnosis still relies on operations personnel.

6. Concluding remarks

This paper puts forward a comprehensive building energy performance diagnosis methodology using sub-meters in large commercial buildings. This method covers the scope of the whole building consumption, lighting-plug, HVAC, power and special sub-meters and components on the content level as well as the weekly, daily and hourly diagnosis on the temporal level.

Different prediction methods were adopted to provide a benchmark for the diagnostic procedure according to the energy use characteristics. Specific regression models are suitable in the diagnosis of the consumption in relation to the temperature. Characteristic average methods can be applied to predict daily lighting-plug and power consumption that have small fluctuations. Fourier series methods were shown to have a high precision to predict the hourly periodic power consumption, such as from lighting-plug sub-meters. The characteristic upper-lower limit method gives a rational range of power consumption. In the diagnostic algorithm, thresholds are determined according to the model precision and abnormal severity of the power consumption. The alarms are reflected by a three-tier output. Especially for HVAC components, the calculated performance indices are compared with the generic benchmarks of performance indices. The methodology has been developed into a building energy performance toolkit and was tested in 50 buildings (office, commercial and mixed-use) to validate the feasibility of the methods. Compared with traditional diagnostics, this method is more applicable and relies less on building control data. The accuracy of the prediction methods, the optimization of the diagnostic procedure and the application to more types of the buildings are key issues for future studies.

Acknowledgement

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Appendix A

See Tables A1–A6.

Table A1
Description of the validation building.

Basic information	
Building type	Office building
Gross area (m^2)	19,991
Height (m)/floor	34/8
Operating time	9:00–17:00
HVAC	
Centrifugal chiller	3 ∗ Cooling Capacity: 556 kW; Motor Input Power: 115 kW
Electric boiler	1 ∗ Heating Capacity: 730 kW; Motor Input Power: 730 kW
Chilled water pumps	3 ∗ Flow Rate: 69 m^3/h; Head: 47 m; Power: 15 kW
Condenser water pumps	3 ∗ Flow Rate: 18 m^3/h; Head: 21 m; Power: 22 kW
Cooling tower	3 ∗ Flow Rate: 150 m^3/h; Power: 6 kW
Terminal end-use	AHU + FCU
Lighting	
Incandescent lamp	129 kW
T8 fluorescent lamp	2.8 kW
TS lamp	27 kW
Lifts	
Type 1	2 ∗ 10 kW for Office
Type 2	2 ∗ 20 kW for Warehouse
Transducer	
2 ∗ 800 kVA	

Table A2
Daily prediction method of different energy type and its threshold.

Data classification			Model selection	Model precision		Threshold
Submeter (ρ_{WW})	Day type (CV_σ)	Season (CV_σ)		R^2	CV(RMSE)	
Total (0.677)	Workdays (33.2%)	Cooling (27.9%)	$Y = 33139.5 - 3994.7 \times T + 173.9 \times T^2 - 2.2 \times T^3$	0.7793	13.2%	±25%
		Transition (18.2%)	Daily characteristic average models (4)			±25%
		Heating (23.1%)	$Y = 10548.6 + 977.1 \times T - 315.4 \times T^2 + 17.7 \times T^3$	0.6981	12.7%	±25%
	Non-workdays (14.5%)		Daily characteristic average models (2)			±25%
HVAC (0.630)	Workdays (49.4%)	Cooling (39.4%)	$Y = 25978.7 - 3363.5 \times T + 146.8 \times T^2 - 1.9 \times T^3$	0.7203	21.0%	±30%
		Transition (38.7%)	$Y = -6411.7 + 3039.0 \times T - 265.1 \times T^2 + 6.7 \times T^3$	0.7086	19.2%	±30%
		Heating (32.0%)	$Y = 7409.6 + 895.1 \times T - 283.7 \times T^2 + 15.9 \times T^3$	0.7020	17.5%	±30%
	Non-workdays (31.7%)	Cooling (30.5%)	$Y = 1915.1 - 176.2 \times T + 7.1 \times T^2 - 0.07 \times T^3$	0.7728	12.6%	±25%
		Transition (15.4%)	Daily characteristic average models (4)			±25%
		Heating (23.5%)	Daily characteristic upper-lower limit model			
Lighting and plug (0.817)	Workdays (18.4%)		Daily characteristic average models (2)			±25%
	Non-workdays (17.8%)		Daily characteristic average models (2)			±25%
Power (0.113)	(4.6%)		Daily characteristic average models (1)			±20%
Special (0.760)	Workdays (24.6%)		Weekly characteristic average models (2)			±30%
	Non-workdays (18.9%)		Weekly characteristic average models (2)			±25%

Table A3
Daily energy performance diagnosis result of the building.

Date	WD	Total	HVAC	Lighting -plug	Power	Special
2014/1/12	0	Normal	Normal	Normal	Normal	Normal
2014/1/13	1	Normal	Normal	Normal	Normal	Normal
2014/1/14	1	Normal	Normal	Normal	Normal	Normal
2014/1/15	1	Normal	Normal	Normal	Normal	Normal
2014/1/16	1	Normal	Normal	Normal	Normal	Normal
2014/1/17	1	Normal	Normal	Normal	Normal	Normal
2014/1/18	0	III level high	III level high	Normal	Normal	Normal
2014/3/23	0	Normal	Normal	Normal	Normal	Normal
2014/3/24	1	Normal	Normal	Normal	Normal	Normal
2014/3/25	1	Normal	Normal	Normal	Normal	Normal
2014/3/26	1	Normal	Normal	Normal	Normal	I level low
2014/3/27	1	Normal	Normal	Normal	Normal	Normal
2014/3/28	1	Normal	Normal	Normal	Normal	Normal
2014/3/29	0	Normal	Normal	Normal	Normal	Normal
2014/8/17	0	I level high	III level high	Normal	Normal	Normal
2014/8/18	1	Normal	Normal	III level low	Normal	Normal
2014/8/19	1	Normal	Normal	Normal	Normal	Normal
2014/8/20	1	Normal	Normal	III level low	Normal	Normal
2014/8/21	1	Normal	Normal	Normal	Normal	Normal
2014/8/22	1	Normal	Normal	Normal	Normal	Normal
2014/8/23	0	Normal	Normal	Normal	Normal	I level low

Table A4
Diagnostic result of lighting-plug submeter and its component.

Date	Day	WD	Indoor illuminance	Outdoor lighting	Other circuit
2014/8/18	Mon.	1	III level low	Normal	III level low
2014/8/20	Wed.	1	III level low	Normal	III level low

Table A5
Diagnostic result of power submeter and its component.

Date	Day	WD	Elevator	Fan	Other circuit
2014/3/26	Wed.	1	Normal	Normal	Normal
2014/8/23	Sat.	0	Normal	Normal	Normal

Table A6
Diagnostic result of special submeter and its component.

Date	Day	WD	Information Center	Kitchen and canteen	Other circuit
2014/3/26	Wed.	1	I level low	I level low	Normal
2014/8/23	Sat.	0	I level low	Normal	I level low

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