Applied Energy 169 (2016) 14–27

Contents lists available at ScienceDirect

Applied Energy

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

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.

ARTICLE INFO

Article history:
Received 14 July 2015
Received in revised form 16 January 2016
Accepted 21 January 2016

Keywords:
Building energy performance
Fault detection and diagnostics
Multiple-level diagnosis
Sub-metering

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.

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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http://dx.doi.org/10.1016/j.apenergy.2016.01.054
0306-2619/

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 multivariable 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 submetered 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 submetering'; since then, more and more large commercial buildings are sub-metered [34]. For example, the California Public Utilities