Energy and Buildings 109 (2015) 65–74

Contents lists available at ScienceDirect

Energy and Buildings

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

Residential heating energy consumption modeling through a bottom-up approach for China's Hot Summer–Cold Winter climatic region

Zhe Wang [a,b], Zhen Zhao [a], Borong Lin [a,b,*], Yingxin Zhu [a,b], Qin Ouyang [a,b]

[a] Department of Building Science, Tsinghua University, Beijing 100084, China
[b] Key Laboratory of Eco Planning & Green Building, Ministry of Education, Tsinghua University, China

ARTICLE INFO

Article history:
Received 25 June 2015
Received in revised form 4 August 2015
Accepted 23 September 2015
Available online 26 September 2015

Keywords:
Residential heating energy consumption
Bottom-up building energy modeling
Occupant behavior
China's Hot Summer–Cold Winter climate region

ABSTRACT

A bottom-up subnational physics-based model has been developed in this paper to estimate the residential heating energy consumption in China's Hot Summer–Cold Winter climate region. This model is constituted of data collecting module, core calculation module (including occupant behavior modeling component, building simulation component and aggregation component), calibration module and prediction module. In order to investigate occupant heating behaviors in this area, a field measurement and questionnaire survey has been carried out. This model is validated by comparing the modeled heating energy consumption with the investigated. It is calculated that currently the residential heating energy usage is 9.8 kWh/m^2 and is predicted to rise by 31% due to the increase of residents' expectation for indoor environment. Sensitivity analysis shows that residential heating energy consumption is significantly influenced by heating triggering/set-point temperature. The households with the retired consume averagely 47% more heating energy than those without the retired.

1. Introduction

In November 2014, the Chinese government promised that Chinese CO_2 emissions would peak in 2030. Buildings account for 28% of total China carbon emissions [1], and this proportion is expected to further increase due to the rapid urbanization and economic development China is expected to experience. Thus reducing the emissions from the building sector is vital in Chinese transition toward a low carbon society and to fulfill Chinese government's commitment.

Residential heating in China's Hot Summer–Cold Winter (HSCW)[1] climate region attracts increasing research attention recently. According to Chinese heating policy, no district heating is provided in this region. With the increase of household disposable income, individual heating facilities are widely installed and utilized for residential heating, increasing dwelling heating energy consumption and carbon emission significantly in this area [1]. The Community Domestic Energy Model built by Firth et al. showed that space heating accounts for 53% of domestic carbon emission [4] in the UK. Since China's HSCW area has the similar weather condition with the UK in winter, space heating is expected to be a major domestic carbon emitter in this region.

1.1. Residential energy consumption modeling

To curtail rising residential heating energy usage, it is essential that a robust and accurate heating energy consumption model is available to estimate the heating energy consumption, to predict the future trend and to identify the major determinants of heating energy usage. There are two approaches to develop residential heating energy consumption model: the top-down approach and the bottom-up approach.

The top-down approach focuses on the relationship between the aggregated energy consumption with the related econometric, meteorological and technological variables. Typically, there are three top-down modeling methods: regression analysis, decision tree and neural network. Catalina et al. [5] and Caldera et al. [6] developed statistical models to regress heating energy consumption with the building geometric and thermophysical properties.

* Corresponding author at: Department of Building Science, Tsinghua University, Beijing 100084, China.
E-mail address: linbr@tsinghua.edu.cn (B. Lin).

[1] Hot Summer – Cold Winter (HSCW) climate region of China: refers to the region with the average temperature in the coldest month varying from 0 to 10 °C [2], and the HDD18 (Heating Degree Day 18) varying from 1000 to 1800 [3]. HSCW covers the area alongside Yangtze River. Many China's major cities, including Shanghai, Chongqing, Chengdu, Wuhan to mention a few, lie within this region.

http://dx.doi.org/10.1016/j.enbuild.2015.09.057
0378-7788/

Catalina et al. [7] developed a polynomials regression model to predict Romanian residential heating energy demand based on only three variables, the building global heat loss coefficient, the south equivalent surface and the difference between the heating set-point temperature and the ambient temperature. Yu et al. [8] utilized decision tree method to predict Japanese residential energy consumption. Tso and Yau [9] compared those three approaches – regression analysis, decision tree and neural network – in predicting domestic energy consumption in Hong Kong. No significant difference was found among these three approaches in terms of the accuracy of the prediction. Though top-down approaches are able to illustrate the impact of various factors on heating energy usage, the physics behind this relationship is unclear since the top-down approaches are "black box" models.

In the bottom-up models, heating energy consumption data are processed at individual levels and then aggregated according to some estimate for their individual impact on total energy consumption. A variety of bottom-up residential energy models have been built worldwide, including the Canadian Residential Energy End-use Model (Farahbakhsh et al., 1998) in Canada [10], the North Karelia Model (Snakin, 2000) in Finland [11], the Huang and Brodick Model (2000) in the United States [12], the Hens et al. Model (2001) in Belgium [13], the BRE's Housing Model for Energy Studies (Shorrock and Dunster, 1997) [14], the Johnston et al. Model (2005) [15], the DECarb Model (Natarajan and Levermore, 2007) [16] and the Community Domestic Energy Model (Firth et al., 2010) [4] in the UK. Though there are a number of limitations associated with these models, including the lack of transparency, lack of quantification of inherent uncertainties, lack of knowledge about occupant behaviors, lack of multidisciplinary, etc. [17], the bottom-up residential energy model provides a useful tool to estimate the impact of various energy efficiency measures on residential energy consumption, to predict the future residential energy consumption trend, to determine medium to long-term energy supply strategy, to develop sustainable building regulations, to evaluate the effectiveness of policies, etc.

1.2. Occupant behavior

The first step of bottom-up approach is to simulate the energy consumption at the individual level. During the last decades, building energy simulation has been continuously and significantly improved [18]. Neto and Fiorelli found that given the occupant behavior is described precisely, the energy consumption data simulated by EnergyPlus are within an error range of ±13% for 80% of the tested database [19]. Therefore, the robustness and accuracy of building energy simulation is determined by the precise description and prediction of occupant behaviors [20].

Occupants are active, intelligent agents interacting with the indoor environment rather than passive heat generators. Occupants react to the environment and their actions influence heating energy consumption significantly [21]. Hoes et al. [22] defined occupant behaviors as the presences of people and the actions displayed by occupants to influence the indoor environment. Yu et al. [23] defined occupant behaviors as the attitudes toward building energy consumption. Martinez-Gil et al. [24] defined occupant behaviors as activities occupants take in response to its environment. From these definitions, occupant behavior refers to the occupant's response to environment which influences the indoor environment and the building energy consumption.

Various research confirmed that the occupant behavior has a significant influence on residential heating energy consumption. Yalcintas [25] pointed out that the gap between the simulated and actual energy consumption mainly results from the gap between occupant behaviors inputted into the building simulation tools and the measured observations. Neto and Fiorelli [19] analyzed the influence of occupant behavior on heating energy consumption. It is noted that a variation range of ±20% was imposed by occupant behaviors, constituting the major source of uncertainties in the detailed model predictions. Research of Gill et al. [26] showed that occupant behavior accounts for 51% of variance in residential heating consumption. Nguyen and Aiello [27] reviewed 12 articles studying the influence of occupant behaviors on HVAC energy consumption and found that the HVAC energy saving potential of occupant behaviors can reach 42%. Kashif et al. [28] demonstrated that occupant behavior is more unpredictable and complex in home settings than in office buildings, resulting in a more significant influence on heating energy usage. Meester et al.'s research [29] found that the more the building is insulated, the more the occupant behavior proportionally influences the heating energy demand. With the increasing insulation level of residential buildings, more research attention should be paid to the occupant behavior. Therefore, occupant behavior should be considered carefully when modeling residential heating energy usage.

In this research, a novel bottom-up subnational physics-based model will be proposed to estimate the aggregated space heating energy consumption in the urban area of China's Hot Summer–Cold Winter climate region. In this model occupant heating behaviors is described as a probability function according to the result of field measurement and survey. The modeling method will be presented in Section 2. To investigate the occupant behaviors of residents in HSCW area, a field measurement and survey is carried out. The survey result as well as other key inputs of this model will be presented in Section 3 to guarantee the model we propose is as transparent as possible. In Section 4, the results will be illustrated and discussed. Conclusions will be drawn in Section 5 of this paper.

2. Methodology

The determinants of residential heating energy consumption has been identified in Fig. 1. Occupant behaviors are determined by the socio-demographic factors, psychological factors, contextual factors [30] and the building physics characteristics. Occupant behaviors and building physics characteristics determine residential heating energy usage. The Residential Heating Energy Model (RHEM) we propose focuses on the relationship between heating energy usage with occupant behaviors and building physics. Therefore how the occupant behaviors are determined by the individual and contextual determinants are outside the boundary of RHEM, and the inputs of RHEM are occupant behaviors and building physics.

2.1. Occupant behavior modeling

Occupant behavior modeling is a key component of RHEM. Hoes et al. [22] defined three resolution levels of the occupant behavior modeling: the Simple level (only considering standard user profiles), the Advanced I level (taking into account the interaction between the user and its environment) and the Advanced II level (taking both the interaction between the user and environment and the complex mobility prediction into consideration). Different resolution levels are required for different purposes. Like for instance, maximum heating and cooling load may be determined applying the Simple level user behavior while total energy use may require a more detailed modeling of user behavior, i.e. the Advanced I or even Advanced II level. In RHEM, occupant behaviors are modeled by Advanced I level resolution, rendering it suitable for the subnational level prediction.

An example of the choice of the resolution levels of occupant behavior modeling is as follows. To model the occupant presence patterns, Andersen et al. proposed inhomogeneous Markov