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Full Length Article

Modeling energy-related CO_2 emissions from office buildings using general regression neural network

Hong Ye[a,b,*], Qun Ren[a,c], Xinyue Hu[a,b], Tao Lin[a,b], Longyu Shi[a,b], Guoqin Zhang[a,b], Xinhu Li[a,b]

[a] *Key Lab of Urban Environment and Health, Institute of Urban Environment, Chinese Academy of Sciences, Xiamen 361021, China*
[b] *Xiamen Key Laboratory of Urban Metabolism, Xiamen 361021, China*
[c] *Xiamen University, Xiamen 361102, China*

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ABSTRACT

Carbon dioxide (CO_2) emissions from urban office buildings energy usages (BEC) constitute a substantial component of anthropogenic greenhouse gas emission, and are set to rapidly increase with further urbanization. Establishing a concise, accurate, and realistic model that can predict future emissions is challenging but essential for strategies to develop low carbon construction and sustainable development in urban areas. In this paper, the operational energy use for 294 office buildings across China was collected and analyzed. We focus on four main variables, and analyze a further ten second-level variables, to elucidate the role that a building's occupants, its structural characteristics, and localized natural conditions play in determining energy consumption. Using general regression neural network (GRNN), the factors' direct and indirect effects on energy consumption were tested. A building's structural attributes had the most impact on energy-related CO_2 emissions, followed by the relevant socioeconomic conditions, the micro-climate, and finally the regional climate. A version of the model that was constructed with interaction between the four main variables was found to be the most precise. GRNN combined with urban development scenarios was used for the prediction of cities' future CO_2 emissions. Economic development and improving standards in the construction industry could have significant impacts on future CO_2 emissions. This study provides a detailed method that could be used to explore the dynamics of office energy use and competing options for the construction of low-carbon office buildings.

1. Introduction

Carbon dioxide (CO_2) emissions are an important cause of climate change, and how to decrease these, especially those arising from energy use, is a great challenge. The continued use of finite fossil fuels mitigates efforts to fight climate change and avert energy crises. In 2008, China became the largest CO_2-emitting country as the country's rapid development has led to significant growth in the amount of energy used. Indeed, energy use in 2008 was 9.408×10^4 GJ (China, 2009), which increased to 1.249×10^5 GJ in 2014 (China, 2015) with annually 5.128% increasing rate. The industrial, transport, and construction sectors contributed more than 70% to total energy-related emissions with construction playing an increasingly large role. Buildings contributed about one-third of total CO_2 emissions in 2012 (Hirst, 2013). The situation in China is similar with buildings responsible for 28% of the total emissions in 2011, a figure that is expected to reach 35% by 2020 owing to a drive for improved living conditions (Chen et al., 2015). The increasing carbon footprint of the construction sector places great pressure on achieving the government's greenhouse gas (GHG) emission targets.

Office buildings provide space for many socioeconomic activities, and play an important role in supporting sustainable urban development (Lin and Liu, 2015). Currently, per m^2 floor area office buildings consume 22% of the total urban electricity, approximately 10–20 times more than residential buildings of China (Construction, 2007). Previous studies (Gao et al., 2017; Thomas and Azevedo, 2013a, 2013b) have shown that rebound effects (e.g. government financial support may lead to more energy wastage) can lead to more energy consumption. Across a building's lifecycle, 85% of total energy-related CO_2 emissions arise during the operational period, far larger than the 13% and 2%, respectively, from the construction and demolition stages (Luo et al., 2016; Peng, 2016). Decreasing office buildings' operational energy consumption is therefore critical for the development of low-carbon cities in China (Wu et al., 2012).

Since the 1960s, the energy performance of buildings has been widely studied (March, 1972). At the building level, many energy models and tools have been applied to precisely investigate the relevant thermodynamics, especially from a construction point of view.

* Corresponding author at: Key Lab of Urban Environment and Health, Institute of Urban Environment, Chinese Academy of Sciences, Xiamen 361021, China.
E-mail addresses: hye@iue.ac.cn, yehongg@gmail.com (H. Ye).

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Nomenclature

Abbreviation

FA	Occupied floor area
ECM	Energy consumption membership
GRP	Gross regional production
Wage	Average wage of employed staff
EST	Expenditure on science and technology
EE	Expenditure on education
HDD	Heating degree days
CDD	Cooling degree days
BF	Building floors
DCBD	Distance to CBD (commercial business district)
BUI	Building's attributes
SEC	Socioeconomic conditions
MAC	Regional climate conditions
MIC	Micro-climate conditions

Typically, census and energy use data are combined by models to estimate a building's potential energy demand (Clarke, 2001). Statistical correlations (e.g. linear regression models) are sometimes used as an alternative method of predicting the variations in energy demand patterns (Liu and Sweeney, 2012). Moreover, most models require time-consuming geometric modeling and painstaking data compilation to produce valid assessments (Jaffal and Inard, 2017). Even so, the uncertainties associated with numerous input parameters can result in misleading outputs. The impacts on energy consumption in office buildings from construction attributes, climatic and socioeconomic conditions have been investigated individually using a range of models (Robati et al., 2017; Tian et al., 2016; Yuan et al., 2017; Zhou et al., 2015). However, few tools are available to evaluate the impact on energy consumption caused by changes and interactions between these variables (Ratti et al., 2005; Reinhart et al., 2013). This work aims to fill this gap by integrating parameters that have impacts on a building's thermal and lighting demands to attain a more robust method for predicting energy demand in office buildings.

An artificial neural network (ANN) is a mathematic model that deals with information processing in a manner that simulates the behavior of neurons in the brain (Antanasijević et al., 2015; Benedetti et al., 2016; Jing et al., 2017; Khayatian et al., 2016). Work has shown that some ANN models (for example, back propagation (BP) calculations) are used to solve complicated problems and have many advantages over linear regression models (Abu Qdais et al., 2010; Pombeiro et al., 2017). However, BP neural network has the disadvantages of slow convergence and easily converging to a local minimum (Yu, 1992). The accuracy of predictions made using BP neural networks is difficult to quantify owing to the long training process that is required. Proposed in 1991 by Specht, general regression neural networks (GRNNs) involve a one-pass learning algorithm, are able to solve non-linear problems, and have been widely used in signal processing, energy prediction and decision making. GRNNs offer the advantages of needing fewer training samples, having a flexible network structure, and a high fault-tolerance. Moreover, the GRNN has few parameters that need to be artificially set in advance, so it can learn the potential relationship between variables (Li et al., 2017). Therefore, in this study, we focused on constructing a GRNN model to predict a building's energy-related CO_2 emissions. Strict selection of the input variables is used to make the model realistic. To avoid magnifying errors during the computation process, the input variable was concisely selected also. Furthermore, when integrated with an analysis of a future scenarios, such a model can be used to simulate various projections of regional CO_2 emissions.

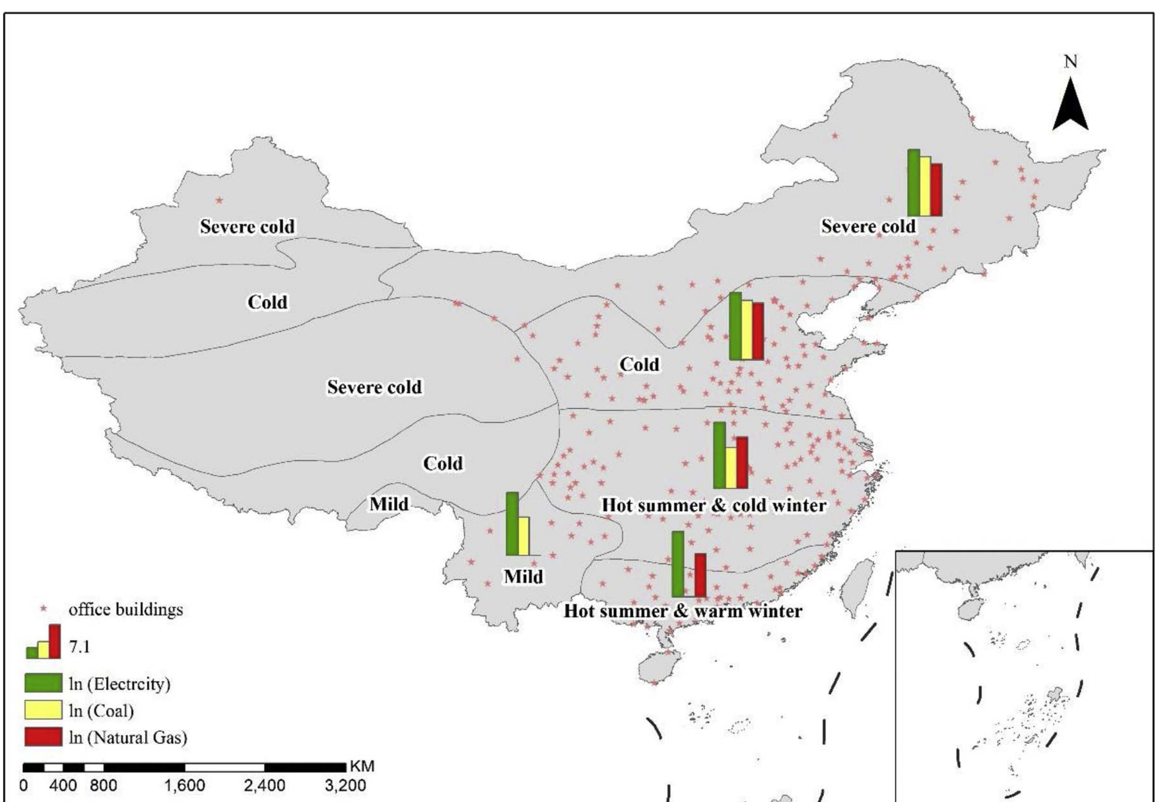

Fig. 1. Samples' distribution and attribute.