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Using artificial neural networks to assess HVAC related energy saving in retrofitted office buildings

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ABSTRACT

This study aims to develop prediction models for HVAC related energy saving in office buildings. The data-driven modelling makes use of data gathered from several energy audit reports. These reports entail building and energy consumption data for 56 office buildings in Singapore. The two models are developed using Multiple Linear Regression (MLR) and Artificial Neural Network (ANN). The methodology to select the most appropriate input variables forms the essence of this study. This variable selection procedure involves 819,150 iterations, taking all possible combinations of the 14 input variables to determine the most accurate model. The dependent variable is taken as the change in energy use intensity (EUI, measured in kWh/m^2.year) between pre- and post-retrofit conditions. The results show that the ANN model is more accurate with a mean absolute percentage error (MAPE) of 14.8%. The best combination of variables to achieve this comprises of gross floor area (GFA), air-conditioning energy consumption, operational hours and chiller plant efficiency. The information on these four variables, along with the prediction model can be used to predict HVAC related energy savings in office buildings to be retrofitted.

1. Introduction

The challenges posed due to climate change have accelerated research in energy efficient buildings. Many studies now present ways to reduce cooling load in buildings by active as well as passive means (Ascione, 2017). A lot of research has also been carried out on exploring the effect of external environmental changes on building energy consumption (Wong et al., 2011; Pisello, 2017; Santamouris et al., 2001). There is also a growing awareness on not just net zero- but positive-energy buildings (Kolokotsa et al., 2011). Although renewable energy technologies have a promising outlook, it is important to simultaneously advance research in energy efficient buildings and avoid wastage in energy consumption.

Energy efficiency in buildings is one of the five measures to secure long term decarbonisation as per the International Energy Agency (IEA)[1] (IEA, 2015). Energy consumed in the building sector consists of residential and commercial end users and accounts for about 20% of the total delivered energy worldwide. According to the U.S. Energy Information Administration (EIA), energy consumption in the commercial building sector is projected to be the fastest growing, at a rate of 1.6%/year (EIA, 2016). Due to this, governments around the world have embarked on various initiatives. A survey by the World Energy Council (WEC) shows that most countries have employed either voluntary or mandatory energy efficiency regulations for buildings (Council, 2004). This survey consisted of 63 countries that constitutes 83% of the global energy consumption. These regulations not only aim to achieve energy efficiency in new buildings but also in existing buildings by outlining retrofitting guidelines. This is because the number of existing buildings constitutes a large part of current and future building stock. Energy use forecasts also show that portion of energy consumed per capita by the commercial building sector is expected to increase while that of the residential building sector is expected to decrease (U.S. Department of Energy, 2011). This signifies the importance of realizing the potential of energy efficiency in the commercial building sector. Although there is a vast scope of retrofitting opportunities, the literature and current retrofit practices show that energy efficiency improvement projects have been conducted on an ad hoc basis without a systematic decision making process (Ruparathna et al., 2016; Hall, 2014).

There have been many advances in research in building energy performance. Currently, there exists a wide variety of methodologies to identify energy conservation opportunities for retrofitting buildings. These range from a detailed analysis of an individual building to a

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Nomenclature

AHU	Air handling unit
ANN	Artificial Neural Network
EIA	U.S. Energy Information Administration
ESCO	Energy service company
EUI	Energy use intensity
GFA	Ground floor area
HVAC	Heating ventilation and air-conditioning
IEA	International Energy Agency
LM	Levenberg-Marquardt
MAPE	Mean absolute percentage error
MLP	Multilayer perceptron
MLR	Multiple linear regression
SSE	Sum of squared errors
WEC	World Energy Council
%ΔEUI	Percentage change in EUI

group of buildings. For individual buildings, computer simulation tools are often utilized for analyzing retrofitting scenarios, whereas for a data set of groups of buildings, statistical methods are employed for comparison and modelling. A thorough understanding of building and climatic variables that influence energy performance of buildings is critical to identify opportunities for energy saving (Harish and Kumar, 2016). Ma et al. have provided a comprehensive review on existing building retrofits (Ma et al., 2012). This paper highlights the lack of decision making methods to identify the most cost effective retrofit measures in contrast to the wide range of retrofit technologies that are currently available. While computer simulation provides detailed analysis of a building on an individual level, statistical techniques are handy when analyzing groups of buildings.

This article aims to study energy performance of buildings by inferring data from a group of 56 buildings. The data is extracted from several energy audit reports for both pre-retrofit and post-retrofit conditions. These energy audits are carried out by accredited Energy Service Companies (ESCO) in Singapore. The measured data recorded in these reports forms the data set for this study. In addition, the availability of post-retrofit data makes it possible to perform a systematic validation of the proposed methodology. It is supported by the development and validation of prediction models using regression analysis and artificial neural network (ANN). The results obtained here can enhance the energy audit procedure by providing information on the best variables that influence energy performance between pre- and post-retrofit conditions. The prediction models can also be used to quickly determine the potential of retrofitting a building. This study does not quantify the different retrofitting scenarios due to the unavailability of accurate post-retrofit data on retrofitting measures. However, the developed models provide a comparative platform for ESCOs to benchmark their assessment before going for the retrofitting options. The next section chronologically outlines crucial research on energy performance of buildings using large datasets of measured data.

1.1. Development in building energy modelling research

This section highlights prominent research on energy performance of buildings using large dataset. One of the first published research in this field was done by Hirst et al. in 1980 (Hirst et al., 1980). Two separate articles were published based on this research, one focusing on the energy audit data collection and recommendation analysis while the other focused on multiple regression models to predict monthly energy consumption based on few basic variables (Hirst et al., 1981). The energy audits covered 270 buildings and included 2010 individual energy conservation recommendations. A year later, Cooper discussed on the theory and practice of energy management in non-domestic buildings in the UK (Cooper, 1982). In the same year, Ross and Whalen analyzed energy audit data from 223 retrofitted office buildings (Ross and Whalen, 1983). It was reported that for the entire sample, there was an average saving of 20% and that the savings exceeded predictions for 60% of these cases. About four years later, Probert discussed the challenges in adoption of energy conservation measures due to the nature of market orientated retrofit industry (Probert, 1987).

One of the first attempts to analyze entire datasets for energy performance comparison among groups of similar buildings was done by Santamouris et al. in 1996 (Santamouris et al., 1996). Based on the energy audit reports of 158 hotels in Greece, it was calculated that it was possible to achieve an overall saving of 20%. This was followed by a research paper published on the PhD work of Martinot on challenges and barriers for promoting energy efficiency and renewable energy in Russia (Martinot, 1998). Vine et al. discussed the evolution of US energy service company (ESCO) Vine et al. (1999). Deng and Burnett studied energy performance of 16 quality hotel buildings in Hong Kong based on energy use index (EUI) which is energy use of a building normalized by its gross floor area (Deng and Burnett, 2000). Several factors that affected the energy use in hotel buildings, such as year of construction, hotel class, etc., were analyzed in detail. This was the time when studies comparing EUI of buildings with the average of the building stock gained momentum. Flourentzou and Roulet (2002 presented a systematic method based on a multi-criteria analysis and a constructivist approach, which helps an audit expert in designing retrofit scenarios. This approach included several steps and followed an iterative process.

This was followed by Li, who studied the energy performance and efficiency improvement procedures of 19 government offices in Hong Kong (Li, 2008). The study compared the energy use index (EUI) for these offices with the energy audit and benchmarking codes for Hong Kong. Several possible energy management strategies were discussed but none were validated.

The next step in the research on energy audit and benchmarking was the development of virtual datasets and the increasing role of computer simulations. Nikolaou et al. presented a methodology for a virtual building data set for office buildings in Greece (Nikolaou et al., 2009). The data set consisted of 30,000 buildings with their detailed constructional and operational data along with simulation outputs that included specific energy consumption for heating, cooling, artificial lighting, office equipment and an indoor thermal comfort indicator. The results of this virtual data set were compared to two energy audit datasets with 174 and 42 buildings respectively. Heo et al. discussed on calibration of building energy models for retrofit analysis under uncertainty (Heo et al., 2012).

The use of multiple regression analyses to study the energy consumption in office buildings had also been employed in many studies. Aranda et al. developed regression models for energy consumption in the banking sector (Aranda et al., 2012). The data set comprised of 55 bank buildings and it was found that the model used to predict the energy consumption of the whole banking sector is appropriate to study existing energy performance and for detecting inefficiencies in bank branches with poor consumption performance. Lam et al. developed regression models for office building energy consumption using 12 key design variables for five major climatic regions in China (Lam et al., 2010). The difference between regression-predicted and DOE-simulated annual building energy use were largely within 10%. Korolija et al. developed regression models for predicting energy consumption for office buildings in UK using computer simulation (Korolija et al., 2013). Lam et al. performed sensitivity analysis using computer simulation for 10 office buildings in Hong Kong (Lam et al., 2008). The analysis suggested that indoor design condition (from 22 to 25.5 °C), electric