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# Improving sustainable office building operation by using historical data and linear models to predict energy usage

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ABSTRACT

Offices and retail outlets represent the most intensive energy consumers in the non-residential building sector and have been estimated to account for more than 50% of a building's energy usage. Accurate predictions of office building energy usage can provide potential energy savings and significantly enhance the efficient energy management of office buildings. This paper proposes a method that applies multiple linear regression (MLR) and artificial neural network (ANN) models to predict energy consumption based on weather conditions and occupancy; thus, enabling a comparison of the use of these two types of modelling methods. In this study, four models of office sites at research institutions in different New Zealand regions were developed to investigate the ability of simple models to reduce margins of error in energy auditing projects. The models were developed based on the monthly average outside temperature and the number of full-time employees (FTEs). A comparison of the actual and predicted energy usage revealed that the models can predict energy usage within an acceptable error range. The results also demonstrated that each building should be investigated as an individual unit.



## 1. Introduction

In light of today's sustainable development (SD) goals, buildings need to be constructed and operated so they have a minimal environmental impact, a controlled consumption of natural resources, and limited use of the primary energy life cycle (Gustavsson and Joelsson, 2010). Significant increases in energy consumption and costs due to rising populations, the expanding economy, and improved qualities of life in recent years, have raised concerns about the environment and the possible exhaustion of energy resources (Azhar, Brown, & Sattineni, 2010; Pérez-Lombard, Ortiz, & Pout, 2008; Harish and Kumar, 2016a; Yu, Haghighat, Fung, & Yoshino, 2010). For example, in the US, buildings represent about 74% of electricity usage and 41.1% of primary energy consumption (Li and Wen, 2014). Optimal building energy consumption, along with its design and operation, has been discussed in a number of recent research papers (Li, Liu, & Fang, 2010; Lund, Marszal, & Heiselberg, 2011; Santamouris, 2013; Thyholt and Hestnes, 2008; Thomsen, Schultz, & Poel, 2005; Xu and Niu, 2006; Xue and Chen, 2014; Yilmaz and Basak Kundakci, 2008; Zhang, Lin, Yang, Di, & Jiang, 2006).

Offices and retail outlets represent the most intensive energy users in the non-residential buildings, and account for more than 50% of energy usage (Pérez-Lombard et al., 2008). In New Zealand, typical office buildings consume electricity more than other energy resources. A study by the Building Research Association of New Zealand (BRANZ) showed that only 3.5% of non-residential buildings used diesel and fuel oil and 11% of non-residential buildings used natural gas and that was mostly for heating (Isaacs et al., 2010). The majority of electrical usage in the buildings investigated was for plug loads, water heating, lighting, and air-conditioning (HVAC) (Harish and Kumar, 2016a; Isaacs et al., 2010; Pérez-Lombard et al., 2008; Yu, Haghighat, & Fung, 2016). HVAC systems have a significant influence on energy consumption and the occupant's comfort in commercial building. Lighting systems probably account for the second highest electricity use in commercial buildings, which mostly depends on occupancy pattern, day light available and the control system used (Harish and Kumar, 2016a)

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The optimal operation of office buildings is a critical component in the reduction of overall energy usage in buildings. Such optimization requires robust systems to monitor and audit energy use (Juan, Gao, & Wang, 2010). Modelling is the most significant part when designing building energy controls and optimisation strategies (Harish and Kumar, 2016b).

Several studies have shown that improving the energy efficiency of an existing building has a considerable, and positive, influence on the value of the building as well as on its environmental impact (Daly, Cooper, & Ma, 2014; Harish and Kumar, 2016a; Li and Wen, 2014). Yu et al. (Yu, Fung, & Haghighat, 2013) categorised the energy modelling studies based on analysing building-related data into typical indicator method, statistical analysis method, and building simulation method (Yu, Fung et al., 2013).

The primary objective of this study was, therefore, to develop and compare two forecasting models for predicting office building energy usage to enable the measurement of energy savings during energy auditing projects. In this research, the ability of simple models to decrease margins of error in energy management and sustainability projects was investigated by comparing two energy prediction models in four research company offices in different regions of New Zealand.

Determining and managing a practical energy savings plan for existing buildings is a complex optimization problem that has a number of technical limitations (Daly et al., 2014; Diakaki, Grigoroudis, & Kolokotsa, 2008). Building a performance simulation is a useful tool widely employed in the building design industry for monitoring and predicting the process of optimizing energy savings (Daly et al., 2014; Ma, Cooper, Daly, & Ledo, 2012). However, significant 'performance gaps' between operational energy consumption and the predictions produced by building performance simulations have been observed (Daly et al., 2014; Menezes, Cripps, Bouchlaghem, & Buswell, 2012). A number of factors, such as inaccurate data input variables or inappropriate simulation methods, could have resulted in these gaps (Menezes et al., 2012). Establishing an appropriate simulation method and accurate input variables is, therefore, crucial for the development of a practical prediction model.

With respect to the development of energy consumption models for the construction industry, finding and accessing detailed data about the construction and energy performance of specific buildings is always a major challenge. This step is, therefore, critical for predicting the energy consumption of buildings. In many energy auditing projects, energy savings are predicted, based on a comparison of the current energy consumption with data from previous years (Abrahamse, Steg, Vlek, & Rothengatter, 2005; Brandon and Lewis, 1999). Because of environmental conditions, changing occupancy and other causes, energy consumption could be significantly different from year to year. Modelling energy consumption based on previous energy usage has the potential to deliver precise estimates of the energy savings. It should be noted that some energy information and variables are of more consequence than others, implying that the selection of variables is an important consideration during the modelling process (Ramesh, Prakash, & Shukla, 2010).

A number of studies have analysed energy consumption in a variety of buildings. However, because of the lack of the advanced metering technologies available today, monthly electricity bills were used for analysing energy usage (Kavousian, Rajagopal, & Fischer, 2013) in most early energy modelling studies. If the data mining as the primary tool to analyse building-related data develop in future, huge amount of useful data will be available for similar studies (Yu, Haghighat et al., 2016; Yu, Fung et al., 2013). Also, many of the energy forecasting models look complicated mathematical equations especially for common users without advanced mathematical knowledge. Which make it more difficult to understand and use for energy conservation (Yu, Fung et al., 2013).

The first important step in analysing energy usage in buildings is to obtain a clear understanding of most significant parameters with respect to energy usage in different types of buildings. Kavousian et al. (Kavousian et al., 2013) categorised four main effective parameters in residential buildings: appliances and electronic stock, weather and location, physical properties of the building, and occupancy. Nevertheless, in the survey of commercial buildings, Issacs et al. (Isaacs et al., 2010) classified buildings based on staff numbers, client numbers, business sector and activities, and operating periods.

For sustainability plans and energy auditing projects, predicting energy consumption is a significant challenge. Forecasting energy usage is challenging because of the complexity of office buildings, which differ substantially with respect to design, construction, occupancy and activity. Such wide discrepancies make it is too challenging to classify the small numbers of buildings that could serve as representative samples in the majority of office buildings (Ahmad et al., 2014; Korolija, Marjanovic-Halburd, Zhang, & Hanby, 2013). An examination of numerous studies revealed that environmental parameters have been the primary factors used in most research directed at estimating energy consumption in buildings, with humidity, temperature and lux level constituting the most important environmental factors that can directly impact energy usage (Considine, 2000; Gugliermetti, Passerini, & Bisegna, 2004; Harish and Kumar, 2016a; Isaacs et al., 2010; Johnsen, 2001; Li and Wen, 2014; Moral-Carcedo and Vicéns-Otero, 2005; Pardo, Meneu, & Valor, 2002; Yu et al., 2010). Additional factors, such as electrical devices, geographical location and the timing of building use, can also indirectly influence energy usage predictions (Ahmad et al., 2014; Erkoreka, Garcia, Martin, Teres-Zubiaga, & Del Portillo, 2016).

While few optimization methods have been developed for estimating energy consumption; however, a variety of modelling techniques have been applied over recent years. Energy forecasting models are made up of input variables, output variables and the structure of the model (Ahmad et al., 2014; Harish and Kumar, 2016a; Mathews, Botha, Arndt, & Malan, 2001; Moral-Carcedo and Vicéns-Otero, 2005; Mukherjee et al., 2010; Ma, Qin, Salsbury, & Xu, 2012; Magnier and Haghighat, 2010; Pandharipande and Caicedo, 2011; Roche and Milne, 2005; Rubinstein, Neils, & Colak, 2001; Safa and Allen, 2014; Üçtuğ and Yükseltan, 2012; Vakiloroaya, Su, & Ha, 2011; Wang, Zmeureanu, & Rivard, 2005). Lack of validation data, the small size of input variables, complications in their use, and focusing only on construction elements and environmental factors, would be the main limitations of many of the energy usage prediction models developed.

In many studies, such as Erkoreka, A. *et al*'s. (Erkoreka et al., 2016), the energy prediction models in buildings have been developed mostly based on details of the building structure, such as HVAC systems, insulation, design, material and orientation. The models look practical but the model development process would be very complex and time consuming, and with several factors needing to be considered.

If the appropriate historical data are available, developing models to estimate energy usage in buildings is much easier and it is possible to develop models with a small number of input variables. However, the model of each building would be completely different and all changes during the investigation process should be considered carefully (Safa and Allen, 2014).

Linear regression (Catalina, Virgone, & Blanco, 2008; Cheung and Braun, 2016; Ghiaus, 2006) and artificial neural networks (ANNs) (Magnier and Haghighat, 2010; Zhang and Haghighat, 2010; Deb, Eang, Yang, & Santamouris, 2016; Mba, Meukam, & Kemajou, 2016; Sholahudin and Han, 2016) have been used more frequently than other modelling methods for forecasting energy usage in build-