COUPLING SIMULATION AND NEURAL NETWORK FOR PREDICTING BUILDING ELECTRICITY CONSUMPTION AT THE URBAN SCALE

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ABSTRACT
The electricity consumption of a building is affected by a number of variables. In order to enhance the electricity forecast model during the design process, only simulation or statistics is not enough. This research seeks to use a hybrid method (simulation and neural networks) to predict the electricity consumption of public residential (HDB) buildings in Singapore. It is found that the adoption of a baseline model improves the accuracy and efficiency of the neural network significantly. The patterns derived from the neural network will also benefit energy performance assessment within the architectural and urban design process.

INTRODUCTION
Based on the annual report from the National Climate Change Secretariat (NCCS, 2014), buildings (including residential and non-residential) consume about half of the total electricity use in Singapore (Fig 1). Therefore, it is essential to focus on energy reduction in the building sector via design or engineering technologies that can significantly improve the energy efficiency of buildings, while ensuring livability and sustainability. From the design point of view, the evaluation of the performance of a building is trending upwards to play an important role during the urban/building design process, hence the energy prediction model becomes more important to designers and researchers.

The process of energy use prediction of buildings involves dealing with uncertainties. Uncertainty is related with the building energy loads. Understanding building loads is a complex topic because there are so many interrelated terms to navigate. These loads which include electricity and fuel consumption can be the result of the micro-climate, the effectiveness of passive design, and occupant behavior, among others. This research focuses on the electricity consumption from cooling loads, plug loads and lighting loads, considering the research scope of public residential (HDB) buildings in Singapore.

This research explores the use of a hybrid method (simulation and neural networks) to predict the electricity consumption of HDB buildings, considering the variables: Green Plot Ratio, Floor Area Ratio, Sky View Factor, Building Compacity, Number of Stories, Gross Floor Area and Energy Usage Intensity. The objective is to use this method for energy performance assessment in both the architectural and urban design process.

![Figure 1 Electricity consumption of buildings in Singapore (NCCS, 2014).](image)

Research objectives
In this research context, we address two research questions:
1. Can any patterns be discerned between the variables: Green Plot Ratio, Floor Area Ratio, Sky View Factor, Building Compacity, Number of Stories, Gross Floor Area and Energy Usage Intensity?
   The design process involves decision-making actions at different stages. While the priority of these variables will impact the design process, a sense of understanding of these variables will also play an important role during the design stages.

2. Is the Energy Usage Intensity (w/m²) of a baseline model helpful to increase the accuracy and efficiency of the energy prediction model?
   In order to improve the accuracy and efficiency of the data analysis process during the design stages, the computer needs to understand some fundamentals to ignore tediously repeated calculations. For example, if the results fluctuate within a certain range, we can apply the basis value to avoid repeated calculations which are out of the reasonable range. Hence, if we...
can suggest some baseline for the analysis process, the process will be reasonably strengthened.

Roadmap
The remainder of the paper is organized as follows: first, related work is reviewed; next, the proposed method is presented; subsequently, the case study and analysis results are discussed; finally, the conclusion is presented.

RELATED WORK

Urban and building texture variables
The influence of urban texture variables on the building energy performance is obvious from previous research (Adolphe, 2001; Wong et al., 2002; Chua and Chou, 2010; Wong et al., 2011; Zhang et al., 2012; Marcel et al., 2015). Urban texture involves a complex interaction between a variety of miscellaneous parameters, whether geographical, economic, geometrical, topological, astronomical, religious, or doctrinal (Adolphe, 2001). The rules of this interaction seem different for every urban fabric. Adolphe (2001) made a simplified model of the urban morphology in order to evaluate the environmental performance of cities; this model contains the following aspects: rugosity, porosity, sinuosity, occlusivity, compactness, contiguity, solar admissibility, and mineralization. From his research, building compacity has a major impact not only on heat transmission through the building envelope (taking part in the creation of the urban heat island effect), but also on available natural lighting.

Wong et al. (2002) evaluated the impact of the surrounding urban morphology on building energy from different parameters, such as: air temperature, green plot ratio (GnPR), sky view factor (SVF), surrounding building density, the wall surface area, pavement area, albedo, etc. They identified a varying degree of impact for each variable. The highest impact is attributed to GnPR due to the shading effect of trees, followed by height and density. Chua and Chou (2010) focused more on the envelope thermal transfer value (ETTV) to evaluate the energy performance of building. Their parameters include materials, window-to-wall ratio (WWR), shading coefficient (SC), coefficient of performance of the chiller (COP), etc. Zhang et al. (2012) developed a case study to reveal the relationship between density, urban block typography and sky exposure. The results indicate that the existing environmental performances as indicated by facade and ground level sky exposures vary across the representative built form typologies under study.

In order to develop a more flexible and efficient electricity consumption model, this research will use some typical variables that describe urban and building features. Climate parameters such as global solar radiation (SR), relative humidity (RH), and outdoor dry-bulb temperature (TDB) will be replaced by a single parameter, the Energy Usage Intensity (EUI), which can be generated by a simulation tool (EnergyPlus). Therefore this research will adopt the following reference variables:

1. Green Plot Ratio (GnPR): Total Leaf Area / Site Area (Ong, 2003)
2. Floor Area Ratio (FAR): Gross Floor Area / Site Area (URA, 2015)
4. Building Compacity Factor (BCF): Exterior Wall Area / Part of Total Volume (V0.5) (Adolphe, 2001)
5. Number of Stories (ST): total number of stories of the building
6. Gross Floor Area (GFA): total area of the covered floor space (BCA, 2010)
7. Energy Usage Intensity (EUI): normalizes energy use by floor area (kwh/m2) (Autodesk, 2015)

Simulation methods
Simulation methods use physical principles to calculate thermal loads and energy performance on the whole building level or for sub-level components (Zhao and Magoulès, 2012). Many simulation tools have been developed for evaluating energy efficiency, renewable energy, and sustainability in buildings, such as DOE-2, EnergyPlus, BLAST, ESP-r. Many researches have been carried out to predict building performance by using different simulation tools (Yik et al., 2001; Zhai et al., 2002; Pan et al., 2007; Wang and Wong, 2008). Zhao and Magoulès (2012) and Fouquier et al. (2013) also made a review on predicting building energy consumption by different methods. Fouquier et al. (2013) point out that an important drawback of simulation is the fact that it requires a detailed description of the physical behaviour. Therefore, the simulation methods need extensive knowledge on the physical system, especially on the mechanisms occurring inside and outside the building geometry. This makes the simulation not efficient enough to predict the energy consumption for number of buildings during the design process. Hence, this research will not only involve simulation, but also machine learning/data mining (artificial neural network). This coupling is expected to develop a more efficient model. While extensive knowledge is still required to perform the simulation, the baseline simulation here adopted is applicable to all HDB design briefs and, therefore, does not have to be repeated for each design process.

Machine learning/data mining (artificial neural network)
The artificial neural network (ANN) is a nonlinear statistical technique principally used for prediction; the method was inspired by the central nervous
system with their neurons, dendrites, axons and synapses (McCulloch and Pitts, 1943). Many researchers have applied ANNs to analyze various types of building energy consumption in a variety of conditions, such as heating/cooling load, electricity consumption and optimization, and estimation of usage parameters (Kalogirou et al., 1997; Olofsson et al., 1998; Olofsson and Andersson, 2001; Ekti and Aksoy, 2009). However, Foucquier et al. (2013) also document that the ANN is hugely limited by its lack of interpretability and the fact that it requires a large amount of learning data and mainly a relevant and complete database (that is, no missing data in the database and the same amount of information for each variable). In order to avoid this limitation, this research will use simulation to feed the ANN method.

**METHODOLOGY**

This research proposes using the EnergyPlus simulation tool and an artificial neural network together to predict the building consumption at an urban scale. There are two steps in this research (Fig. 2). Firstly, a baseline model within the Singapore context is created according to data obtained from literature. The assumption of different components is introduced in the following sections. Secondly, the optimized variables and annual electricity bills of HDB buildings from the Singapore Energy Market Authority (EMA, 2014) are used to build the ANN model. The dataset is collected from the official government website (OneMap, 2015), which is an integrated map system for government agencies to deliver location-based services and information in Singapore. The dataset includes the existing HDB locations by postcode. The annual electricity consumption bill is collected from the Singapore Energy Market Authority (EMA, 2014). The basic HDB data is imported from OneMap into GIS software (ArcGIS) by postcode. The variables green plot ratio, sky view factor and building compacity are calculated based on their equations. Floor area ratio, number of stories and gross floor area are all obtained from the website of the Singapore Urban Redevelopment Authority (URA, 2015).

**Step 1: Baseline modeling in EnergyPlus**

The Treehotel@Punggol is Singapore’s first experimental eco-friendly public housing project and was awarded the Green Mark Platinum Certificate in 2010 (Fig. 3). Hence, this research will use the HDB buildings in Treehotel@Punggol as the baseline model.

**Figure 3** Treehotel@Punggol public housing project in Singapore.

The general specifications of HDB buildings for external and internal wall constructions are used to define the construction properties in the energy model. The material database within EnergyPlus is used to obtain specific material thermal properties according to the specified constructions. An infiltration rate of 0.5 ACH (Air Changes per Hour) is used for the baseline model. Also, based on the Singapore National Climate Change Committee (NCCC, 2011), a list of typical household electrical equipment (including lighting) and their energy consumption is provided into the simulation model. Occupancy schedules are taken from Chua and Chou (2010). Figure 4 shows the transformation process from the design model to the simulation model.

**Figure 4** From architecture plan to EnergyPlus model.

The baseline model is simulated for a year in EnergyPlus, and the simulations output hourly electricity consumption (due to lighting and electrical equipment) and cooling loads. The cooling loads are translated into cooling energy using the nominal 4.7 coefficient of performance (COP) (BCA, 2014), and then added to the plug loads to yield energy...
consumption for the apartment. Hence, according to the Autodesk Sustainability Workshop (Autodesk, 2015), the electricity consumption from EnergyPlus is calculated as follows: 

$$E = \text{Cooling Load / COP} + \text{Plug Loads} + \text{Lighting Loads} \quad \text{(Fig. 5)}.$$

![Building Energy Loads from the Autodesk Sustainability Workshop (Autodesk, 2015).](image)

The final EUI from the simulation results is 44.11 kwh/m2*yr. We use this number as input basis value for the training process in the following step.

**Step 2: Artificial neural network**

An artificial neural network is composed of interconnected neurons as processing elements, having similar characteristics as inputs, synaptic strength, activation output and bias. The interconnections between neurons carry the weights of the network (Singh et al., 2007). The structure of a multi-layered backpropagation network as used in this research is illustrated in Fig. 6. The neurons in the network can be divided into three layers and named as input, hidden and output. In order to avoid "under-fitting" and "over-fitting" problems, the number of hidden neurons should be between the size of the input layer and the size of the output layer.

![A three-layered backpropagation artificial neural network.](image)

The neural network itself is composed of neurons of the same kind, placed within different layers. They exhibit the same characteristics. Generally, the model of a neuron can be summarized in the following block diagram (Fig. 7).

![The model of a single neuron based on (Haykin, 2008).](image)

To put it a little more explicitly, the output of a sigmoid neuron for electricity consumption with input variables $x_1, x_2, \ldots$, weights $w_1, w_2, \ldots$, and bias $b$ is:

$$\text{Electricity Consumption } f(x) = \frac{1}{1 + e^{-\sum w_i x_i + b}}$$

(1)

In order to test this neural network, the dataset is separated into three groups, a training set, a validation set and a testing set. The neural network process utilizes the library "neuralnet" in the R language platform for training and testing.

**RESULT AND DISCUSSION**

According to the dataset and results, Fig. 8 shows the existing HDB areas in Singapore. All of the HDB buildings are included in this research.

![Existing HDB areas in Singapore.](image)

Figure 9-15 relate the baseline, actual and predicted EUI (considered as the electricity consumption divided the total floor area) with respect to the postcode and other variables. With respect to the research questions stated at the beginning, these are the findings:

1. With respect to the first research question, Fig. 9 shows the EUI of the baseline model compared to the predicted and actual value of buildings by postcode. The total number of available postcodes is 8488, however, Fig. 9 only displays part of the results for clarity. The remaining parts
behave similarly. Overall, the predicted and actual value fluctuates near the baseline model. Fig. 10 shows the relationship between EUI and GFA, the chart shows the EUI is reduced with the growth of GFA. Fig. 11 does not show any strong correlation between EUI and GnPR. From Fig. 12, the EUI by SVF fluctuates at high and low proximity. From Fig. 13, the buildings are grouped into five different values of FAR, EUI displays as many continuous points in each group, hence, the FAR does not impact the EUI very much. Fig. 14 shows that the EUI will be impacted by BCF. To view the situation as a whole, a higher BCF will cause a lower EUI. Fig. 15 shows a stronger correlation between the number of building stories and the EUI. Hence, the EUI will be reduced with the increase of building stories. At the same time, this may also reveal that the potential for natural ventilation increases with the building height in Singapore.

2. Considering the second research question, we choose different variables to train the dataset. If the input variables include the baseline EUI, the training process error is 0.005146, and the iteration count is 4578 times. On the other hand, if we exclude the EUI, the error is lower 0.002196, but the iteration count is much higher, 25482 times. Although the error increases from 0.002196 to 0.005146, the error is still within an acceptable range for the forecast model. Hence, applying the baseline EUI within the learning process greatly improves the efficiency of the neural network learning process.
and design process. This hybrid method will also be developed as a design support tool in the next research stage. Considering the limitation of HDB information, and the fact that human behaviour may also play an important role, we intend to explore other types of residential buildings in Singapore as well as office buildings and industrial buildings.

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