Applying Neural Networks to Model Monthly Energy Consumption of Commercial Buildings in Singapore(ICCAS2004)

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Abstract: The methodology for modeling building energy consumption is well established for energy saving calculation in the temperate zone both for performance-based energy retrofitting contracts and measurement and verification (M&V) projects. Mostly, statistical regression models based on utility bills and outdoor dry-bulb temperature have been applied to baseline monthly and annual whole building energy use. This paper presents the application of neural networks (NN) to model landlord energy consumption of commercial buildings in Singapore. Firstly, a brief background information on NN and its application on the building energy research is provided. Secondly, five commercial buildings with various characteristics were selected for case studies. Monthly mean outdoor dry-bulb temperature (T_0), Relative Humidity (RH) and Global Solar Radiation (GSR) are used as network inputs and the landlord monthly energy consumption of the same period is the output. Up to three years monthly data are taken as training data. A forecast has been made for another year for all the five buildings. The performance of the NN analysis was evaluated using coefficient of variance (CV). The results show that NNs is powerful at predicting annual landlord energy consumption with high accuracy.
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Keywords: Landlord Energy Consumption, Neural Network, Weather variables, Singapore

1. INTRODUCTION

Since the energy crisis broke out in 1974, people became aware of the critical role of energy use in the national economy. Previous building energy research carried out by Building and Construction Authority in Singapore showed that the energy consumption of the existing building accounted for approximately 57% of the whole electricity consumption in Singapore. In addition, such high energy consumption is because of inefficiency use of building systems. One of the cheapest and useful ways to reduce such high consumption is energy retrofitting by applying energy conservation measures (ECMs). An important element in any energy retrofitting program is to verify savings as accurate as possible. However, after retrofitting all previous conditions are changed. As such, it is therefore important to establish a baseline model to verify pre-retrofit energy consumption and subsequently, the adjusted energy use in the post retrofit period. The baseline model can tell how much energy the building would have used if the retrofit had not been made [1]. Furthermore, the differences between baseline energy use and adjusted post-retrofit energy use are the real energy savings from ECMs. There are several world-wide methodologies to establish such kind of baseline model to model building energy use including regression analysis methods, calibrated simulation and artificial neural networks. According to the result of ASHRAE competition on the Energy Predictor Shootout II, it is approved that NN-based model ranked top one in predicting building energy use for a specific pre-retrofit period.

In additional, through literature review, artificial neural networks are finding increasing application in many different fields for forecast of building energy use for both short and long term periods. They provide an attractive way for determining the dependence of energy consumption on a variety of schedule and occupancy dependent factors as well as weather variables [2]. It is appropriate to view neural networks as a set of powerful non-linear regression tools. The early application of neural networks for the prediction of building energy consumption utilized feed-forward networks, which require the use of immediate past consumption as an input [3]. In terms of savings measurement and baseline model establishment, recurrent neural networks are more appropriate. Such a prediction is useful in the case of building that has already been retrofitted with energy conservation features, to estimate the building energy consumed if it had not undergone retrofit. While their predictions show about twice the error of feed-forward nets [4], they have been found to often be more accurate than the classical prediction methods [5]. Kreider et al. (1995) [4] concluded that recurrent nets offered an accurate method for predicting hourly energy use well into the future for thermal end uses when only weather data were known.

This paper mainly focuses on applying neural networks to establish the baseline model in the pre-retrofit period and also to predict landlord energy consumptions. The landlord energy consumption refers to the energy utilized inside part of the building, typically comprising: a) Air-conditioner central plant system which supply air-conditioning inside the building; b) Vertical transportation service i.e. escalator and lift; c) Ventilation system such as exhaust fan and ventilator; d) Artificial lighting system in the common area i.e. corridor or public common service area i.e. toilet and lift. These energy consumption show a non-linear relationship with weather data, occupancy density and operation hours. The objective of this study is to evaluate the feasibility and accuracy of neural networks methodology applied in building energy research in the tropical region. This study is only a primary exploration study of methodologies for future research. The projected baseline model is important for energy service companies to secure energy savings and also for energy performance contracting.

2. BACKGROUND ON NEURAL NETWORKS

2.1 Neural Networks

A neural network can be any model in which the output variables are computed from the input variables by compositions of basic functions or connections. However, one of the most commonly used neural network models is the multilayer perceptron. This neural network consists of several layers of neurons that are connected each other. A “neuron” is a simplified mathematical model of a biological neuron. A connection is an information transport sending from one neuron to another. Fig 1 shows the structure of a neural network. The first and last layers of neurons are called input and output layers, respectively. Between these two layers are the hidden layers.

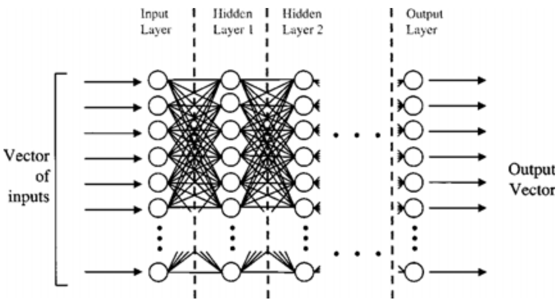

Fig 1. Structure of a neural network [6]

2.2 Back-Propagation

The neural network toolbox applied in this study can provide simple command for creating, training, and simulating a fully-connection, feed-forward network. Fully-connected means that each node is connected to all the nodes in the adjacent layers. Fee-forward indicates that information is passed in a single direction from the input to the output nodes. The learning algorithm employed here is the back-propagation, generalized delta method. In this algorithm, the value of the output of the NN is compared to a target value to determine an error. The weights associated with the connection between nodes are then adjusted in a backward direction from the output layer to the input layer in order to minimize this error. The detailed functions of training algorithm can be outlined as follows [7]:

1) Forward Activation flow

During the first stage, the network is presented with a set of inputs and the desired output. The Summed input, I, is determined by multiplying each input signal by the weight of its interconnection:

$$I = f(\sum w_i * x_i) \tag{1}$$

Where, w and x are the weights and input signals respectively; and f(x) is the activation function of the processing element (PE)

For a Back-propagation network, this function should be sigmoidal

$$f(x) = 1/(1+\exp(-x)) \tag{2}$$

The output value of this function has a value of 1.0 when the input is a large negative number and a value of 0.0 for large and positive input.

2) Backward Error Flow

In the second stage, the actual output of the network is compared with the desired output. The difference between them, or the error, is used to adjust the weights to complete this iteration of the network. To compute the weight changes, the Generalised Delata rule is applied:

$$\Delta W_{t+1} = \alpha EX / |X|^2 + \beta \Delta W_t \tag{3}$$

Where, ΔW_{t+1} is the current change in the weight vector

E is the vector value

X is the input pattern vector

$|X|$ is the length or magnitude of the input pattern vector;

α is the learning constant;

β is the momentum term; and

ΔW_t is the previous change in the weight vector.

During this stage, the errors are also back-propagated for each output-layer PE to the hidden layer using the same interconnections and weights as the hidden layer used to transmit outputs to the output layer. The complete cycle of forward activation propagation and backward error propagation constitutes one iteration of the nerwork. The network is usually trained with many input patterns. Generally speaking, this iterative procedure will stop once the error distance has converged to zero or a minimum specified value.

Some variations of back-propagation learning procedure have been successfully used. In particular, Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. This algorithm appears to be the fastest method for training moderate-sized feedforward neural networks. It is applied in this study.

3. METHODOLOGY

The methodology in this paper is as follows. Firstly, five commercial builings were selected randomly from the central business area. Upon to four years' building energy consumption data as utility bills were collected from Singapore Power Services Company. The first three years' data was used for training and establishing the baseline model. Another one year utility bill was used for prediction. At the same time, the weather data was collected from National Environment Agency of Singapore. The weather data period is the same as energy consumption data period. All the weather data are monthly mean values. Secondly, when all the data are ready, the NN was applied to set up the baseline model. This NN was implemented using a standard mathematical package that had a built networks toolbox as discussed in section 2. The weather data included the outdoor dry-bulb temperature, relative humidity and global solar radiation. The network had one hidden layers of different neurons. Hence, the total input parameters are three. The output is the whole building landlord energy consumption. The network was trained for each building using the monthly baseline data for the selected building. The total training period is three years. Thirdly, after training, the baseline model was used to predict the energy consumption during the projected period. In this study, the projected year was selected forward to year 2001. It is the same when someone wants to predict backward. The same input information was collected from year 2001. Finally, the predicted annual whole building landlord energy consumption was compared with measured one.

In addition, we need to remove the effects of year-to-year changes in conditioned areas and population, although in this study they are both insignificant. Fels and Keating (1993) [8] assumed a proportional relationship between annual daily energy use and changes in conditioned area. Hence, normalize area-changed energy use is merely the annual mean monthly energy use divided by the conditioned area for that particular year. However, until now there is no clear methodology for normalize population-changed energy use. Here, we assumed that normalizing energy use by conditioned area would also implicitly normalize energy use for population changes. Here, for the landlord energy consumption, we should normalize energy use by landlord area because any changes in the landlord area will affect the whole landlord energy consumption.

Finally, the criterion used to select the most appropriate model is to maximize the goodness-of-fit using the simplest model or combination of models [9]. (Draper and Smith, 1981). Previous research shows that CV-RMSE is a major measure to evaluate the goodness of fit of the model. It is defined below:

$$\text{CV-RMSE}=\frac{RMSE}{\bar{Y}}\times 100 \tag{4}$$

Where

$$\text{RMSE}=\left[MSE\right]^{1/2}=\left[\frac{\sum_{i=1}^{n}\left(Y_i-\hat{Y}\right)^2}{n-p}\right]^{1/2} \tag{5}$$

$\hat{Y}$ is the value of Y predicted by the model, n is the number of observations; p is the number of model parameters.

Following Reddy *et al.* (1997a) [10], the equation for percentage between actual energy use and predicted energy use is below:

$$\Delta y(\%)=\frac{\bar{y}_{measured}-\bar{y}_{baseline-projected}}{\bar{y}_{baseline-projected}}\times 100 \tag{6}$$

Here, $\bar{y}_{measured}$ is the annual mean monthly energy use found by simply averaging 12 monthly utility bills for the projected year. $\bar{y}_{baseline-projected}$ is the annual energy use predicted by the baseline model for the projected year. This percentage change is normally taken as prediction accuracy.

4. APPLICATION TO FIVE COMMERCIAL BUILDINGS

4.1 data collection

Five buildings were selected randomly among all the buildings around the Central Business District. They are all office buildings for commercial use. The utility bills of these five buildings were collected through surveys which were carried by the previous research on building efficiency [11]. In order to retain the individual building anonymity, these five buildings are referred to as building A,B,C,D and E. The surveys processed in two periods. One is from October 1996 to October 1998,another is from 2000 to 2001. Hence, the period of all utility bills is four years. Table 1 shows the building size and the annual energy use of these six buildings. For building A, B, C and E, Oct.1996 to Oct.1998 and year 2000 are their baseline year. They are also periods of training data. Building D takes Oct.1996 to Oct.1998 as its baseline year period.

The correspondent weather data is taken from National Environment Agency, Singapore. There are four weather stations in Singapore. They are Tengah, ChangGi, Seletar and Senbawang. The station in Seletar is selected which is nearest to five buildings among four stations because the onsite weather data are not available. Actually, there is little difference among these four weather points in terms of monthly mean temperature. The monthly data is found by averaging the hourly data of the whole month.

Table 1: Size and Energy Use in Five Buildings

Building	Total BLDG. Area(m^2)	Landlord Area(m^2)	Total Landlord Energy Consumption (MWh/yr)
A	36,629	14,938	5,291
B	46,400	22,627	6,024
C	60,895	16910	7,681
D	123,933	63,591	12,865
E	108,000	41,364	1,283

4.2 Using Neural Networks to Model Monthly Energy Consumption

After all the data collection, the NN toolbox was used to train the baseline data and then to predict the monthly energy consumption of the projected year. This NN only has one hidden layer with different neurons in different cases. Table 2 shows the results of NN training and Prediction.

Table 2 shows that for every case study, the optimum point is different in terms of neuron numbers in the hidden layer. For example, building A has the optimum point when neuron number is 12, while the prediction value will both increase when n=10 or 14. For building B, the optimum point lies at n=14, while building C is at n=23, D and E are both at n=10. The prediction results of other neuron number points are larger than the optimum point which indicates the characteristics of neural network.

Table 2 also shows the results of training CV and prediction CV. Training CV are all better than prediction CV, except for building B. Three out of five building have training CV lower than 10%, which means the neural network models of these three are excellent models. However, only one prediction CV is less than 10%. It shows that in terms of monthly energy consumption, the NN model did not work very well. However, the prediction accuracies, which show the annual energy consumption prediction error, are all below 10%. The NN model has a good performance in forecasting the annual energy consumption.

Table 2. Results of NN Training and Prediction

Building Name	Actual Consumption (kWh/month/m^2)	Neuron Numbers in The Hidden Layer/Predicted Consumption							
		8	10	12	14	16	21	23	25
A	10.55		11.5	10.57	11.35				
B	11.05			12.27	11.62	12.39			
C	9.54						10.34	9.89	11
D	8.65	9.1	8.13	9.35					
E	12.59	13	12.1	13.06					

(Continued)

Building Name	Training CV (%)	Prediction CV (%)	Prediction Accuracy (%)
A	9.33	15.5	1.9
B	12.19	9.69	8.5
C	20.46	26.42	3.68
D	6.5	26.06	6.01
E	9.4	23.41	3.38

5. DISCUSSION AND CONCLUSION

Overall, the NN can well predict the annual energy consumption but not the monthly one. The reason could be below:

1) Small number of training data. Due to the limitation of data source, only four year monthly energy consumption data have been collected. Generally, the neural network needs a large pool of data for training. This is also the reason for high training CV.
2) Limited input variables. Although previous research showed that climate variables are the main contribution to the changes of building energy consumption, there should be some human factors that was not considered as inputs in this study.

In conclusion, this study used an NN for prediction monthly and annual landlord energy consumption in Singapore. The results suggest that NN is necessary and important when modeling the energy use of commercial buildings due to some non-linear performances in them. The research presented in this paper is just an exploration study. It is believed that with a large data pool, NN could work better. The future research will focus on the short term energy consumption forecast.

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