Jurnal Mekanikal
December 2014, Vol 37, Issue 2, 37 - 41

PREDICTION AND ANALYSIS OF BUILDING ENERGY EFFICIENCY USING ARTIFICIAL NEURAL NETWORKS AND DESIGN OF EXPERIMENTS

S. Sholahudin, Azimil Gani Alam, Chang-In Baek, and Hwataik Han*

College of Mechanical Engineering,
Kookmin University,
77 Jeongneung-ro, Seongbuk-gu, Seoul. 136-702, Korea

Suwon Science College,
288 Sejaro, Jeongnam-myun, Hwaseong-si, Gyeonggi-do. 445-742, Korea

ABSTRACT

In this paper, an artificial neural network model has been developed to predict the heating and cooling loads of a building based on simulation data for building energy performance. The input variables include the overall height, relative compactness, surface area, wall area, roof area, orientation, glazing area, and glazing area distribution of building. The output variables are the heating and cooling loads. The simulation data used for training the model are the data published in the literature for various parametric combinations of a residential building. Artificial neural networks (ANNs) have a merit in estimating output values for given input values satisfactorily, but they have a limitation in acquiring the effects of input variables individually. In order to analyze the effects of the individual variables, we used a method for the design of experiment (DOE) and conducted an analysis of variance (ANOVA). As the result, overall height, relative compactness, wall area, and glazing area have significant effect to reduce heating and cooling loads. Moreover, the surface area is influential on the heating load and the roof area in regard to the cooling load only.

Keywords: *Building, Energy, Prediction, Neural Networks, Design of Experiment*

1.0 INTRODUCTION

Building energy consumption has been steadily increasing over the past few decades worldwide [1,2]. It is necessary to provide controls to building operations and initial building design to increase the energy efficiency. Building design concerning the aspect of heating and cooling loads is very important in reducing the total energy consumption in buildings. In the practice of establishing an energy efficient building design, the architects and building designer need to analyze the parameter that has significant impact on the heating load (HL) and cooling load (CL) [3]. In recent years, several researchers have studied some factors that highly influence heating and cooling energy in buildings [4-7].
Building energy simulation programs are useful in identifying the parameters for optimum building design. However, a skill is required to operate the program and it is time-consuming to investigate the effects of various parameters. Many researchers rely on machine learning tools to study the effects of various building parameters based on some variables of interest because uses of these methods are easier and faster [8-11]. Schiavon et al. [12] studied the influence of a raised floor, structure type, window-to-wall ratio and the presence of carpet to determine the CL. The results showed that orientation and the presence of the carpet are the most important predictors.

*Corresponding author: hhan@kookmin.ac.kr

Tsanas et al. [13] obtained 768 simulation data-sets using Ecotect to study HL and CL. They then explored the statistical relationship between architectural building parameters and two output variables of HL and CL using random forest and the iteratively reweighted least-square (IRLS) methods. The results showed that relative compactness, wall area, and roof area are mostly associated with HL and CL, and that the glazing area is not correlated with HL and CL. This paper will apply the ANNs and DOE method to analyze the effect of some building parameters on HL and CL. The parameters include the overall height (OH), relative compactness (RC), surface area (SA), wall area (WA), roof area (RA), orientation (OR), glazing area (GA), and glazing area distribution (GAD) of a building.

2.0 METHODOLOGY

ANNs are complex non-linear model that can be used to find the relation between inputs and outputs through mathematical functions. They can be applied in many research fields such as classification, function approximation, forecasting, clustering, and optimization [14, 15]. In this paper, static neural networks are used to train 768 data sets from reference [13] using eight input variables, one hidden neuron, and one output. HL and CL estimation is conducted separately. The architectural neural network model can be seen in Fig. 1. X's are input variable, N is a hidden neuron, and Y is an output variable. The trained network model is then used to estimate HL and CL for data inputs of the Taguchi design of experiment (DOE).

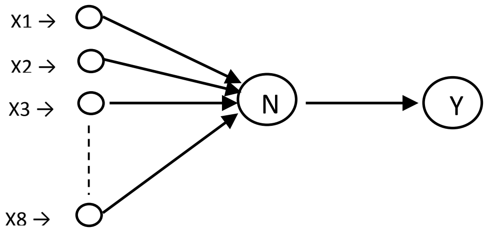

Figure 1: Architectural neural network model

DOE is a structured and organized way of conducting and analyzing controlled tests to evaluate the factors that are affecting a response variable [16]. In this study, we select two levels for OH and four levels for the variables other than OH to generate the Taguchi design. The list of level values for each variable can be seen in Table 1. Detail of each input variables can be found in reference [13]. The level values for SA, WA, RC, and RA are chosen from the highest, the lowest, and from two values in the middle.

Table 1: Level values for each variable

Level	OH (m) Overall height	RC Relative compact	SA (m^2) Surface area	WA (m^2) Wall area	RA (m^2) Roof area	OR Orientation	GA Glazing area	GAD Glazing area distribution
1	3.5	0.62	514.5	245.00	110.25	2	0.00	2
2	7	0.74	612.5	302.17	147.00	3	0.13	3
3	-	0.86	710.5	359.33	183.75	4	0.27	4
4	-	0.98	808.5	416.50	220.50	5	0.40	5

3.0 RESULTS AND DISCUSSION

Figure 2 shows the ANNs training results for the HL and Fig. 3 the results for the CL as output variables. Comparison between the predicted and original data values elicits a good agreement, especially for HL. ANNs training result yields a root means squared error (RMSE) equal to 2.8 for HL and 3.1 for CL in comparison to the original data. The individual variables have been assumed to be independent and the cross-interactions between variables have been neglected. The predicted HL has values ranging from 9 to 39, and the predicted CL from 13 to 39, approximately. The ANOVA result of 32 data combinations can be seen in Table 2. The fact that the p-value is less than 0.1 indicates that the corresponding variable has a strong effect on the output at a significance level over 90%. The results show that OH, RC, WA, and GA are mostly associated with HL and CL. Correspondingly, the OR and GAD do not have significant effects on either HL or CL. Variation of the building configuration and GAD that refers to [13] is not influential on HL and CL owing to the fact that the building surface is not flat from the top to the bottom for some variations of building configuration, so that the effect of sun is not significant. This means that the change of OR and GAD will not affect HL and CL too much for these building configurations. Furthermore, the SA has a significant effect on HL only, and the RA has a significant effect on CL only. This is because the solar radiation through the roof top of the building has a significant effect on CL. However, it will not influence HL during the winter season.

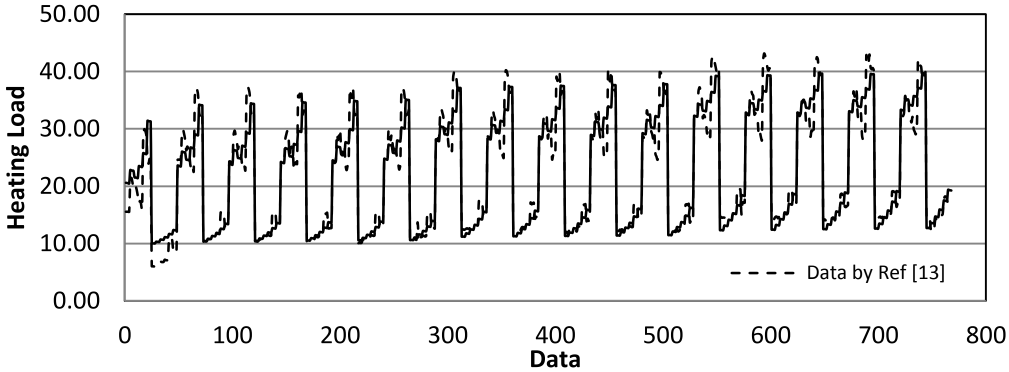

Figure 2: Original and estimated heating load data

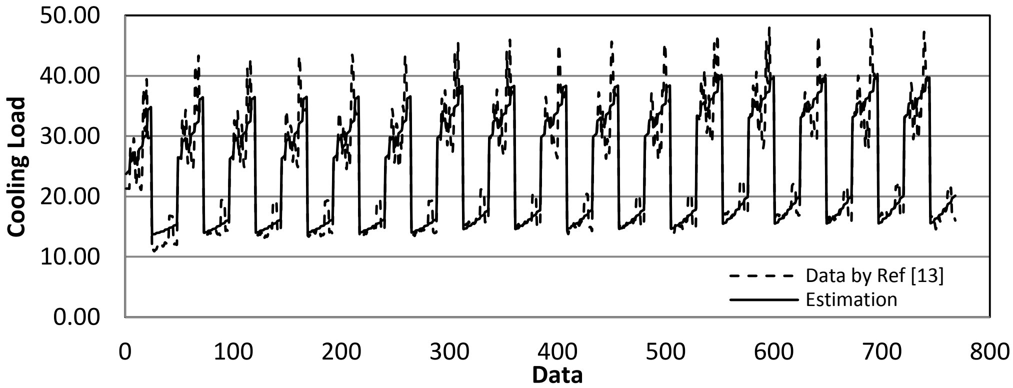

Figure 3: Original and estimated cooling load data

Table 2: P-values from ANOVA tests

p-value	OH	RC	SA	WA	RA	OR	GA	GAD
Heating load	0	0.069	0.028	0.001	0.481	0.741	0.001	0.21
Cooling load	0	0.001	0.213	0.077	0.043	0.506	0.004	0.388

4.0 CONCLUSIONS

In this paper, building energy performance has been investigated using ANNs model to predict heating and cooling loads, and using analysis of variance to determine the effect of the input variables based on the data in the literature. A simple static neural network model elicits a very good prediction in comparison to the original data-sets. ANOVA results show

that the overall height, relative compactness, surface area, wall area and glazing area have significant effects on the HL for the present problem. For CL, overall height, relative compactness, roof area, wall area and glazing area are all very important.
The orientation and glazing area distribution do not have any effect on either the HL or the CL. The results of this research can only be applied to buildings that have specification as those listed in [13].

ACKNOWLEDGEMENTS

This research was supported by the Brain 21 Plus Program funded by the Ministry of Education (S14SN01D0502), and by the Human Resources Development Program of KETEP funded by the Ministry of Trade, Industry, and Energy, Republic of Korea (No. 20134040200580).

REFERENCES

1. Lombard, L.P., Ortiz, J., and Pout, C., 2008. A review on buildings energy consumption information, *Energy and Buildings 40 (3)*, 394-398.
2. Cai, W.G., Wu, Y., Zhong, Y., and Ren, H., 2009. China building energy consumption: situation, challenges and corresponding measures, *Energy Policy 37 (6)*, 2054-2059.
3. Yu, Z., Haghighat, F., Fung, B.C.M., and Yoshino, H., 2010. A decision tree method for building energy demand modelling, *Energy and Building 42*, 1637-1646.
4. Wan, K.K.W., Li, D.H.W., Liu, D., and Lam, J.C., 2011. Future trends of building heating and cooling loads and energy consumption in different climates, *Building and Environment 46*, 223-234.
5. Enshen, L., 2005. Influence of inner heat sources on annual heating and cooling energy consumption and its relative variation rates (RVRs), *Building and Environment 40*, 579-586.
6. Yildiz, Y. and Arsan, Z.D., 2011, Identification of the building parameters that influence heating and cooling energy loads for apartment buildings in hot-humid climates, *Energy 36*, 4287-4296.
7. Grygierek, J.F., 2014. Indoor environment quality in the museum building and its effect on heating and cooling demand, *Energy and Buildings 85*, 32-44.
8. Magnier, L. and Haghighat, F., 2010. Multiobjective optimization of building design using genetic algorithm and artificial neural network, *Building and Environment 45*, 739-746.
9. Dong, B., Cao, C., and Lee, S.E., 2005. Applying support vector machines to predict building energy consumption in tropical region, *Energy and Buildings 37*, 545-553.
10. Catalina, T., Virgone, J., and Blanco, E., 2008. Development and validation of regression models to predict monthly heating demand for residential buildings, *Energy and Buildings 40*, 1825-1832.
11. Gonzalez, P.A. and Zamarreno J.M., 2005. Prediction of hourly energy consumption in buildings based on a feedback artificial neural network, *Energy and Buildings 37*, 595–601
12. Schiavon, S., Lee, K.H., Bauman, F., and Webster, T., 2010. Influence of raised floor on zone design cooling load in commercial buildings, *Energy and Buildings 42*, 1182-1191.

13. Tsanas, A. and Xifara, A., 2012. Accurate quantitative estimation of energy performance of residential buildings using statistical machine learning tools, *Energy and Buildings 49*, 560-567.
14. Krose, B. and Smagt, P., 1996. *An introduction to neural network 8th edition*, The University of Amsterdam.
15. Ripley, B.D., 1996. *Pattern Recognition and Neural Networks*, University Press, Cambridge.
16. Telford, J.K., 2007. *A Brief Introduction to Design of Experiments*, Vol. 27 No. 3, Johns Hopkins APL Technical Digest.