International Journal of Technology (2015) 6: 946-953
ISSN 2086-9614

HEATING LOAD PREDICTIONS USING THE STATIC NEURAL NETWORKS METHOD

S.Sholahudin[1], Hwataik Han[2*]

[1] *Graduate School of Mechanical Engineering, College of Engineering, Kookmin University, Seongbuk-Gu, Seoul 02707, Korea*
[2] *Department of Mechanical Engineering, College of Engineering, Kookmin University, Seoul, Seongbuk-Gu, Seoul 02707, Korea*

(Received: June 2015 / Revised: September 2015 / Accepted: September 2015)

ABSTRACT

Heating load calculations are essential to optimize energy use in buildings during the winter season. Instantaneous heating loads are determined by the outdoor weather conditions. It is intended to develop a method to predict instantaneous building heating loads, depending on various combinations of current input parameters so as to apply HVAC equipment operations. Heating loads have been calculated in a representative apartment building for one month in Seoul using Energy Plus. The datasets obtained are used to train artificial neural networks. Dry bulb temperature, dew point temperature, global horizontal radiation, direct normal radiation and wind speed are selected as the input parameters for training, while heating loads are the output. The design of experiments is used to investigate the effect of individual input parameters on the heating loads. The results of this study show the feasibility of using a machine learning technique to predict instantaneous heating loads for optimal building operations.

Keywords: Building; Energy; Heating loads; Neural networks, Orthogonal array

1. INTRODUCTION

The International Energy Agency (IEA) predictions show that the energy consumption in buildings has steadily increased, reaching 32% of total final energy consumption (Aqlan, 2014). The increase of building energy consumption is caused by several factors such as building operation, high indoor air quality standards and building services (Perez, 2008). Energy used in buildings can be minimized through the proper design, optimization of system, operation, and maintenance. In Korea, energy in buildings is mostly consumed by HVAC systems, especially for heating in the winter season. Hence, the proper calculation of heating loads is necessary to reduce energy consumption in buildings. Heating load estimation can be conducted manually or using simulation software. However, it needs skills to operate the software and it takes a long time to calculate the heating load, using energy simulation software. Machine learning can be used as alternative tool to estimate heating load. Instantaneous heating load estimation can help building energy management to formulate a control strategy in the heating system to reduce energy consumption efficiently.

Several studies related to energy efficiency in buildings have been carried out. The feasibility of artificial neural networks (ANNs) has been studied to conduct energy building estimation

* Corresponding author's email: hhan@kookmin.ac.kr, Tel. +82-2910-4687, Fax. +82-2910-4839
Permalink/DOI: http://dx.doi.org/10.14716/ijtech.v6i6.1902

(Kreider, 1991; Chonan, 1996; Yang, 2005; Gonzalez, 2004). In reference (Aqlan, 2014) to the integration of ANNs, cluster analysis has been developed to assess energy efficiency of buildings. Moreover, ANNs were also used to predict electricity, natural gas, water and steam consumption based on weather, building occupancy and activity (Ansett, 1993). In this paper, static neural networks (SNNs) will be used to estimate heating loads, using weather parameters as the input. Heating load is highly affected by the outdoor weather conditions. However, we should select some significant weather parameters for estimation. Therefore, the objective of this research is to find the important weather parameters for heating load estimation.

2. METHODOLOGY

2.1. Building Description

The building used in this study is a 9-story apartment building with multi-units which refer to reference (Park, 2004). A single unit located in the middle of the building is chosen for simulation. The heat loss of the unit is assumed to occur only through exterior walls facing south and north, since the unit is located next to the other units side-by-side. The heat losses through ceiling and floor are neglected. The floor area of the unit is 84.7 m^2 and the height is 2.3 m. Details of the building configuration can be seen in Figure 1. Structure of building and properties of material are provided in Tables 1 and 2, respectively. Indoor design temperature is set at 20^oC for heating load simulation. Leakage area of infiltration is assumed to be 63.5 cm^2 which is equivalent to medium tightness, according to ASHRAE standard (ASHRAE, 2001). The standard weather data of Seoul is used in this simulation. The weather data is obtained by measuring weather parameters for ten years, and then the average of each parameter is applied for simulation. Moreover, the occupants, light and electric equipment are neglected, so the heating load calculation is purely based on the outdoor conditions only. Heating load is calculated by using Energy Plus software for one month in January.

2.2. Static Neural Networks

ANNs are machine learning tools that can be used to correlate between inputs and outputs through neurons. The inputs are multiplied by weights, and then computed by a mathematical function, which determines the neurons' activation. Feed-forward, back-propagation neural networks methods are developed to estimate heating load using dry bulb temperature, dew point temperature, global horizontal radiation, direct normal radiation and wind speed as the input variables. The architecture of static neural networks can be seen in Figure 2. It consists of five input variables, one hidden neuron, and one output. Bayesian Regulation (BR) algorithm and the tangent sigmoid transfer function are used for training and estimation. The accuracy of estimation is analyzed using RMSE (Root Mean Square Error) (Yang, 2005).

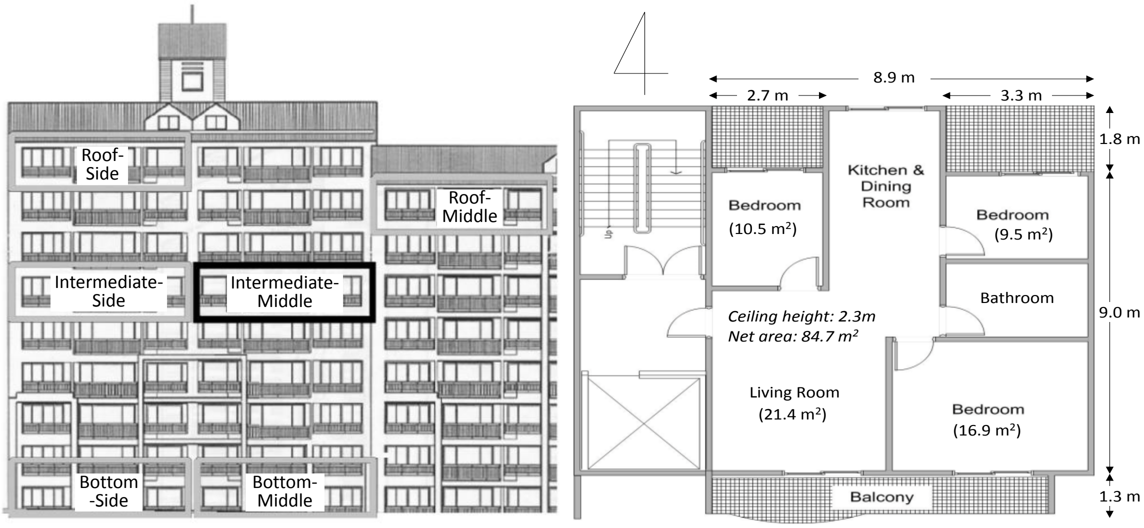

Figure 1 Representative house at apartment building in Seoul

Table 1 Structure of building construction

Layer	Front/Rear Wall		Side Wall		Floor		Window	
	Material	Thick (mm)	Material	Thick (mm)	Material	Thick (mm)	Material	Thick (mm)
Layer 1	Concrete	180	Concrete	180	Gypsum	9.5	Glass	3
Layer 2	Polystyrene	65	Polystyrene	90	Concrete	150	Air	5
Layer 3	Gypsum	9.5	Gypsum	9.5	Polystyrene	30	Glass	3
Layer 4					Light Concrete	50		
Layer 5					Mortar	40		
Total		239.5		279.5		279.5		11
U-Value	0.451 W/m^2.K						2.8 W/m^2.K	

Table 2 Properties of construction material

Material	Thermal Conductivity (W/m.K)	Specific Heat (kJ/kg.K)	Density (kg/m^3)
Gypsum Board	0.210	1.13	910
Polystyrene	0.034	1.25	28
Concrete	1.620	0.79	2400
Mortar	1.510	0.79	2000
Level Mortar	0.370	0.79	2000
Light Concrete	0.170	1.09	600

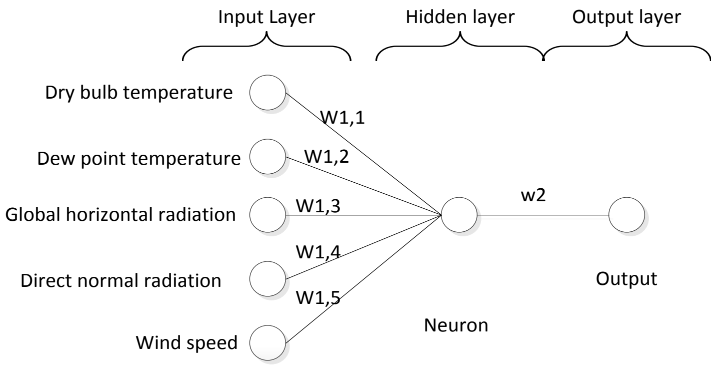

Figure 2 Architecture of the static neural network model

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}\left[y_{pred}(t)-\bar{y}_{data}(t)\right]^2}{n}} \tag{1}$$

where n represents the number of data, $y_{pred}(t)$ is the predicted heating load at time t by ANNs, $y_{pred}(t)$ is the calculated heating load at time t, and $\bar{y}_{\text{data}}$ is the average of calculated data.

2.3. Orthogonal Array

The design of experiments (DOE) is a series of tests in which purposeful changes are made to the input variables and the effects on response variables to evaluate the influence of inputs on the response of variables (Telford, 2007). In this paper, Taguchi method for orthogonal array design is used to investigate the effect of some weather parameters on the heating load. The power of the orthogonal array is that it can cover all combinations, using only a few combinations. So it can reduce time effectively for calculation purposes. Twenty-seven orthogonal array combinations are generated using five factors and three levels. The input values for data combinations are selected based on minimum (1), average (2), and maximum (3) values of each parameter and provided in Table 3. Meanwhile, the orthogonal array of data combinations can be seen in Table 4.

Table 3 Input values for design of experiments

Level	A Dry Bulb Temperature (^{o}C)	B Dew Point (^{o}C)	C Global Horizontal Radiation (Wh/m^2)	D Direct Normal Radiation (Wh/m^2)	E Wind Speed (m/s)
1	-14.90	-17.40	0.00	0.00	0.00
2	-3.27	-9.34	82.96	105.81	2.50
3	9.10	1.30	595.00	968.00	14.20

Table 4 Orthogonal array

A	B	C	D	E	Heating Load
1	1	1	1	1	2096.9
1	1	1	1	2	2143.5
1	1	1	1	3	2272.6
1	2	2	2	1	2101.2
1	2	2	2	2	2147.1
1	2	2	2	3	2274.0
1	3	3	3	1	2159.8
1	3	3	3	2	2195.5
1	3	3	3	3	2292.5
2	1	2	3	1	1515.2
2	1	2	3	2	1615.4
2	1	2	3	3	2014.7
2	2	3	1	1	1523.6
2	2	3	1	2	1623.7
2	2	3	1	3	2020.1
2	3	1	2	1	1412.0
2	3	1	2	2	1510.3
2	3	1	2	3	1941.5
3	1	3	2	1	958.9
3	1	3	2	2	993.0
3	1	3	2	3	1279.9
3	2	1	3	1	942.8
3	2	1	3	2	972.7
3	2	1	3	3	1233.1
3	3	2	1	1	925.7
3	3	2	1	2	951.0
3	3	2	1	3	1179.5

Combination of ANNs and DOE methods are developed in this research. Several datasets generated by Energy Plus software are used for training using neural networks. Furthermore, orthogonal arrays of weather data are considered as input for predicting heating loads, which are provided in Table 4. Then, analysis of variance (ANOVA) is used to analyze the effect of individual input parameters.

3. RESULTS AND DISCUSSION

Comprehensive analyses have been conducted in this research. Figure 3 shows the heating load estimation results by ANNs compared to original Energy Plus results for a month. The training results using a static model with five input parameters show a precise estimation with RMSE of 60.82 W. Estimated heating load values are ranging from 974 W to 2187 W approximately. The validation of training is conducted using training data. The neural networks obtained from this training are used to estimate twenty-seven Taguchi orthogonal array data combinations to investigate the effect of the parameters. Then, the estimated heating load results of the orthogonal array are shown in Table 4.

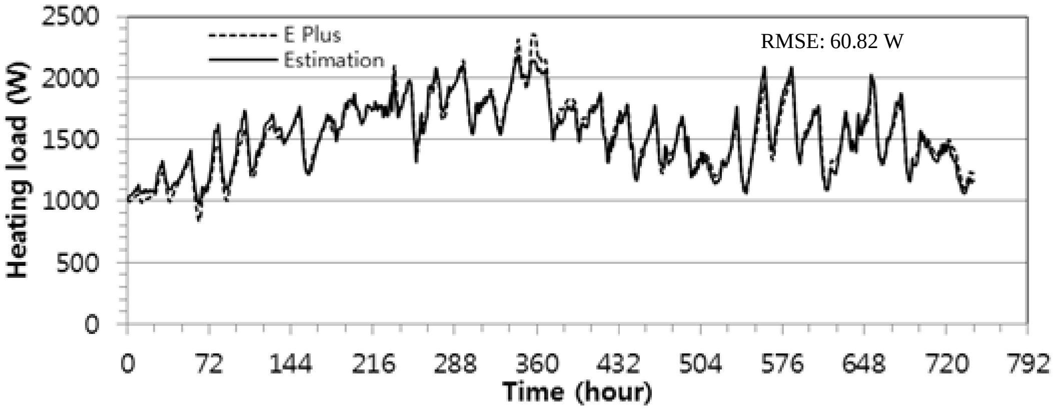

Figure 3 Original and estimated heating load

Table 5 shows the ANOVA results. F and P values for each parameter are important indicators to determine the parameters that have a significant influence on heating load. Dry bulb temperature and wind speed have P values less than 0.05. It indicates that these parameters have a significant effect statistically on the heating load at a 95% confidence level. Moreover, the F values of dew point, global horizontal radiation, and direct normal radiation are less than $F_{0.05}(2,26) = 3.37$. It indicates that these parameters do not have a significant effect on the heating load. The dry bulb temperature has the highest F-value that indicates the parameter has the most significant effect on heating load. Since dry bulb temperature and wind speed have a significant effect on heating load, these parameters are selected as input parameters for heating load prediction.

Table 5 ANOVA results

Variable	DF	Seq SS	Adj MS	F value	P value
A	2	5860985	2930493	427.79	0
B	2	6659	3329	0.49	0.62
C	2	15392	7696	1.12	0.35
D	2	5962	2981	0.44	0.66
E	2	520834	260417	38.02	0
Residual Error	16	109604	6850		

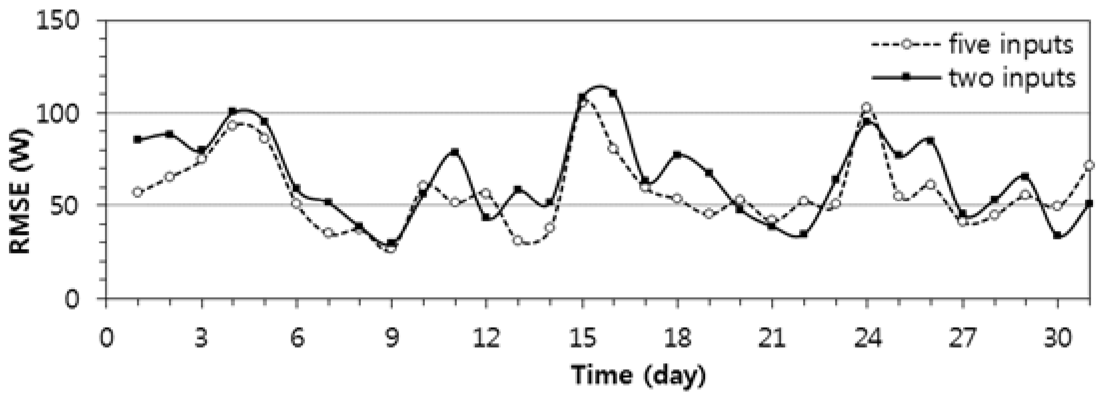

Figure 4 Comparison of training results using different number of input parameters

The heating load estimation using input of dry bulb temperature and wind speed have been tested. Figure 4 shows the accuracy of training using two and five input parameters. The training using two selected inputs has a similar result with using five inputs. The error difference is not quite great. This validation proves that DOE and ANOVA test have been successful in reducing the number of input parameters for training. Moreover, the static ANNs model, using reduced number of inputs has been validated. This network was trained using input data from January for a month. Figure 5 shows the estimated heating load on February for three days. The results show the precise estimation with the RMSE of 37.7 W, 45.2 W, and 58 W for Days 1, 2, 3, respectively.

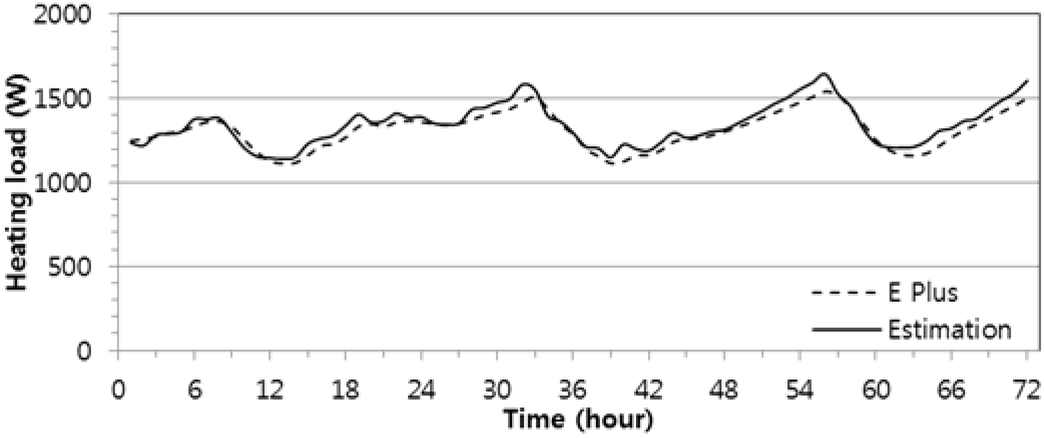

Figure 5 Heating load estimation on February (Day-1,2,3)

4. CONCLUSION

In this study, ANNs and a statistical approach have been conducted to estimate heating loads and analyze the effect of input parameters. ANNs estimation results show a good estimation with high accuracy. Five weather input variables have been selected and analyzed. The results obtained from the DOE and ANOVA test show that dry bulb temperature and wind speed have a significant effect on the heating load. Meanwhile, dew point, global horizontal radiation, and direct normal radiation are not as influential. Accordingly, dry bulb temperature and wind speed should be selected for heating load estimation, and for other variables these can be neglected. Heating load estimation using two significant inputs have been tested and the results show there is no significant difference in accuracy. Moreover, the static ANNs using dry bulb temperature and wind speed have been validated and the result is quite good. In conclusion, the design of experiments and analysis of variance test can be applied to reduce the number of inputs for neural network training.

5. ACKNOWLEDGEMENT

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).

6. REFERENCES

American Society of Heating, Refrigerating and Air Conditioning Engineers (ASHRAE), 2001. *Ventilation and Infiltration.* Atlanta, G.A.

Ansett, M., Kreider, J., 1993. Application of Neural Networking Models to Predict Energy Use. *ASHRAE Transactions*, Volume 99, pp. 505−505

Aqlan, F., Ahmed, A., Srihari, K., Khasawneh, M.T., 2014. Integrating Artificial Neural Networks and Cluster Analysis to Assess Energy Efficiency of Buildings. *Proceedings of the 2014 Industrial and System Engineering Research Conference*, pp. 3936−3943

Chonan, Y., Nishida, K., Matsumoto, T., 1996. Great Energy Predictor Shootout II-A Bayesian

Nonlinear Regression with Multiple Hyperparameters. *ASHRAE Transactions*, Volume 102(2), pp. 405−411

Gonzalez, P.A., Zamarreno, J.M., 2004. Prediction of Hourly Energy Consumption in Buildings based on a Feedback Artificial Neural Network. *Energy and Buildings*, Volume 37, pp. 595−601

Kreider, J., 1991. Artificial Neural Networks Demonstration for Automated Generation Energy Use Predictors for Commercial Buildings. *ASHRAE Transactions*, Volume 97(1), pp. 775−779

Park, Y.W., Hong, H., Lee, S.H., Yoo, H., 2004. Natural Ventilation Model for Estimating Heating Energy of Korean-Style Apartment Houses. *Proceedings of SAREK*, pp. 1202−1207

Perez-Lombard, L., Ortiz, J., Pout, C., 2008. A Review on Building Energy Consumption Information. *Energy and Buildings*, Volume 40(3), pp. 394−398

Telford, J.K., 2007. A Brief Introduction to Design of Experiments. *Johns Hopkins APL Technical Digest*, Volume 27(3), pp. 224−232

Yang, J., Rivard, H., Zmeureanu, R., 2005. Building Energy Prediction with Adaptive. *Ninth International IBPSA Conference*, 15−18 August, Montreal, Canada