Determination of the Optimum Set-point to Balance the Thermal Comfort and Operation Energy Consumption

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ABSTRACT

The objective of this research is to suggest a method that can be used to obtain the optimal control set-point that considers weights of thermal comfort and heating, ventilation, and air conditioning (HVAC) energy consumption; this is done using a multi objective genetic algorithm (MOGA). An artificial neural network (ANN) is adopted in order to determine a prediction model for the thermal load, HVAC energy consumption and thermal comfort based on the properties of individual buildings. In this research, 64 building cases were simulated with Energy Plus and Open Studio to produce synthetic data. To make a thermal load model, 14 parameters that are representative of building thermal load were selected. In order to obtain the HVAC energy consumption model, 5 parameters that have a strong influence on the HVAC energy consumption were selected. After the prediction models were built, the MOGA tool in MATLAB was used for optimization. The simulation results of optimization showed that the control variables set by MOGA, which improved the thermal comfort, led to only a small increase in the HVAC energy consumption compared to the base case when weight factors were biased against thermal comfort.

KEYWORDS

Optimal set-point, Prediction model, Genetic algorithm, Artificial neural network, HVAC energy

INTRODUCTION

In many countries, HVAC systems are operated by on/off, proportional integral (PI), or proportional integral derivation (PID) controls; however, these control methods produce unnecessary cooling and heating energy consumption. This has caused HVAC energy consumption to represent 50% of the total building energy consumption (Dong 2010). To prevent the overconsumption of HVAC energy caused by conventional control methods, much research has been conducted in attempts to optimize the tradeoff between energy consumption and thermal comfort.

Before optimization, determining objective functions that represent energy consumption and thermal comfort is required. Lam et al. (2010) built multiple

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regression models for HVAC energy prediction in Harbin, Beijing, Shanghai, and Kunming of China and in Hong Kong. These models relied on 12 input parameters. These prediction models showed accurate prediction with R^2 values from 0.89 to 0.97. Also, ANN has been used to build prediction models. Kalogirou et al. (2000) selected parameters for synthetic data training; these included the existence/nonexistence of wall insulation, season, wall thickness, and transient or steady state in the heat transfer calculation. This suggested ANN model obtained an R^2 value of 0.9991, which provides acceptable accuracy for thermal load prediction.

Additionally, Dong (2010) compared the effects of input/output linearization control, simulink optimizer control, and nonlinear programming control on reducing the fan and pump energy consumption. Furthermore, Atthajariyakul and Leephakpreeda (2004) suggested an optimization process based on a gradient descent algorithm to obtain the optimal point among the predicted mean vote (PMV), carbon dioxide concentration, and cooling load. This process also had an effect on the cooling energy savings. Kim and Park (2014) found the optimal set-point for the chilled water supply temperature and cooling tower supply temperature through a genetic algorithm (GA) and verified the effectiveness of energy savings in one case study.

However, optimization processes between energy and PMV are insufficient for random buildings. Therefore, this study suggests an optimum set-point decision process between the HVAC energy consumption and thermal comfort.

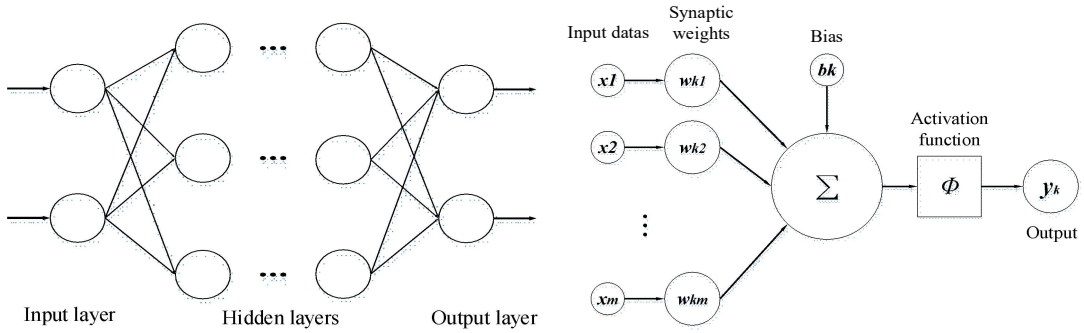
METHOD

In this study, ANN was used to build models for the thermal load, chiller energy consumption, boiler energy consumption, and PMV. Then, MOGA was used to find the optimal point between the chiller energy consumption, boiler energy consumption, and PMV of the core zone.

ANN is a predicting output method that is based on learning input data; it operates like a human brain. The structure of ANN is composed of neurons and hidden layers, which exchange information with each other. The knowledge is saved as weights that connect each neuron (Kalogirou et al. 2000).

As shown Figure 1(a), a typical multilayer feedforward neural network, which is one of the structures of ANN, has an input layer, hidden layers (the data training part), and an output layer. During this training process, the weights are modified continuously until the training is completed. Figure 1(b) illustrates the process used to calculate the parameters in each neuron. The parameters are multiplied with weights, and these are put into an activation function. Next, the outcome of the activation function is multiplied with the subsequent weights. This process finally provides an output value.

GA, which includes selection, crossover, inversion, and mutation as operators, is a global optimization method based on natural selection. Non-dominated-and-crowding sorting genetic algorithm II (NSGA-II) which is one of the MOGA is an efficient algorithm that is used to converge multi-objective functions to optimum points called the Pareto frontier. This is desirable because the Pareto frontier can surmount the weaknesses of weight-sum approaches (Magnier and Haghighat 2010).



(a) Feedforward neural network *(b) Calculation process of each neuron*

***Figure 1**. Artificial neural network structure*

SIMULATION

In this simulation, 64 building cases were simulated to produce the synthetic data that were used for training in ANN. The Levenberg-Marquardt method was selected as the training algorithm. Using design of experiments, the cases were built with 12 parameters that affected the building thermal load, HVAC energy consumption, and PMV. The minimum and maximum values of the parameters are shown in Table 1 and Table 2 describes each of the model parameters for prediction and optimization. All of the synthetic data were generated by Energy Plus and Open Studio with weather data of Incheon, South Korea.

***Table 1.** Minimum and maximum ranges of parameters*

Parameter	*Minimum value*	*Maximum value*
Wall U-value [W/m²K]	0.04	3.01
Window U-value[W/m²K]	0.75	8.6
Window to wall ratio [-]	0.1	0.9
Aspect ratio [-]	1	10
Height [m]	2.4	5
Area [m²]	1000	10000
Number of stories [-]	1	10
Orientation [degrees]	0	90
Heating thermostat [˚C]	20	24
Cooling thermostat [˚C]	24	27
Hot water supply temperature [˚C]	65	82
Chilled water supply temperature [˚C]	4.5	9

In this research, we made building thermal load prediction models for the core zone via ANN with the neural network tool of MATLAB. These models can predict the thermal load of random buildings within these parameter ranges. It is necessary to predict the chiller and boiler energy consumption of random buildings because the thermal load is one of the most important factors that affects the chiller and boiler energy consumption. Therefore, the predicted thermal loads of random buildings are used as a portion of the input data to predict the chiller and boiler energy consumption. The inputs of the chiller or boiler energy consumption models consist of the cooling load or heating load, cooling thermostat or heating thermostat, chilled water supply temperature or hot water

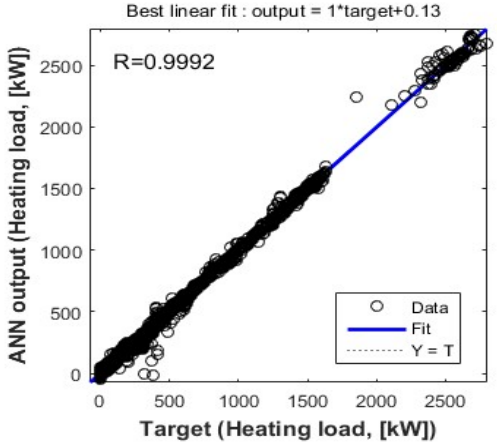
supply temperature, chilled water return temperature or hot water return temperature, and supply air temperature. The cooling load and chiller energy consumption data were used from June to September and the heating load and boiler energy consumption data were used from December to February. Finally, it was assumed that PMV was set by the heating or cooling thermostat and that occupants wear clothes with a value of 1.0 clo throughout the year and that air velocity was 0.137 m/s.

Table 2. *Parameters of the building thermal load, HVAC energy consumption, and PMV*

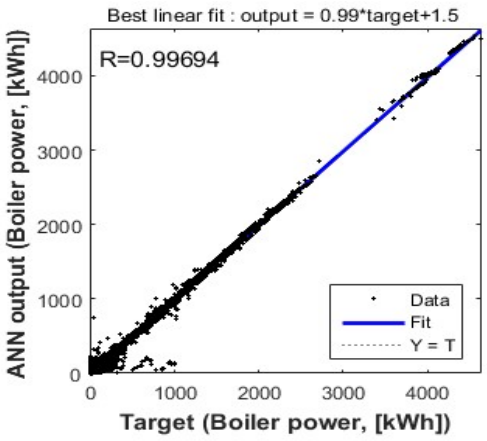
Model		*Controllable variable*	*Uncontrollable variable*
Building thermal load	Cooling load [kW]	Cooling thermostat, supply air temperature	Outdoor air temperature, outdoor air humidity ratio, U-values (wall and window), window to wall ratio, aspect ratio, height, area, number of stories, orientation, zone temperature, occupant density
	Heating load [kW]	Heating thermostat, supply air temperature	
HVAC system	Chiller energy [kWh]	Cooling thermostat, supply air temperature, chilled water supply temperature	Cooling load, chilled water return temperature
	Boiler energy [kWh]	Heating thermostat, supply air temperature, hot water supply temperature	Heating load, hot water return temperature
Thermal comfort	PMV	Cooling and heating thermostats	-

Figure 2 shows the neural network training regressions of the heating load, cooling load, boiler energy, chiller energy, and PMV between the ANN models and targets. Based on their R-values, which are greater than 0.9, these models can predict the output accurately.

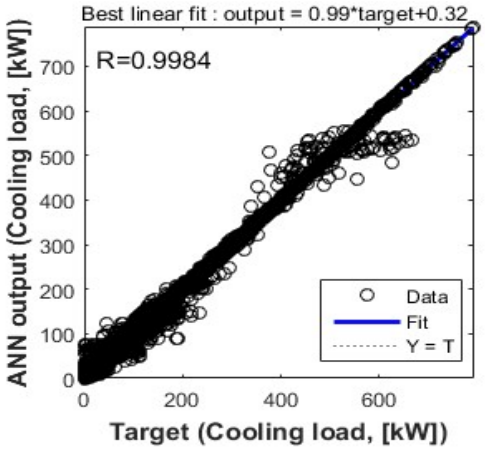
NSGA-II, which is an optimization tool of MATLAB, was adopted to optimize the tradeoff between HVAC energy consumption (boiler or chiller) and PMV after the prediction models were built.



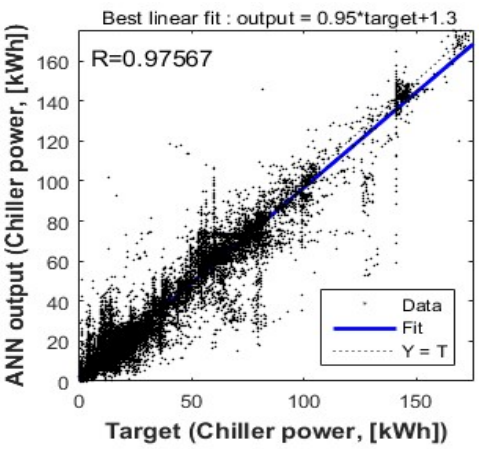
(a) Heating load regression



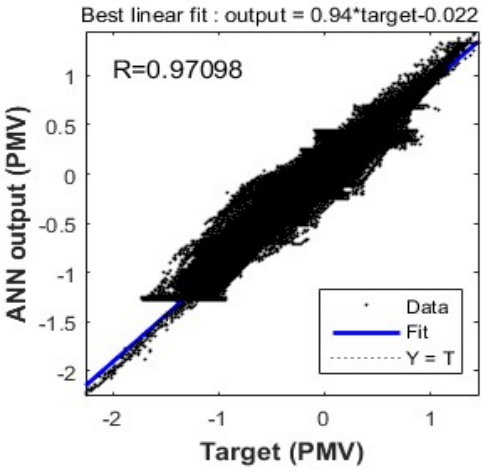
(b) Boiler energy consumption regression



(c) Cooling load regression



(d) Chiller energy consumption regression



(e) PMV regression

***Figure 2**. Regressions between outputs of the ANN models and targets*

CASE STUDY OF OPTIMIZATION

This case study compared the base case and the optimized case during a peak heating day. Table 3 illustrates the base case parameters for the building used in the case study. Here, PMV was changed to the predicted percentage of dissatisfied (PPD) via equation 1. Also, the weight factors were considered because one optimal set-point must be obtained for optimal HVAC control. In this optimization case study, we planned two cases; the first case used a weight factor of 0.2 for the boiler energy consumption model and a weight factor of 0.8 for the PPD model, while the second case used a weight factor of 0.8 for the boiler energy consumption model and a weight factor of 0.2 for the PPD model.

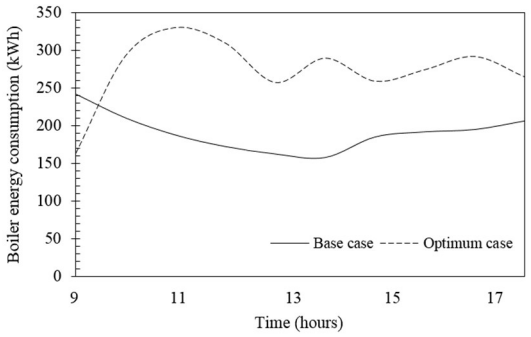
$$\text{PPD}\ \ (\%) = 100 - 95\exp^{-\left(0.03353\text{PMV}^4 + 0.2179\text{PMV}^2\right)} \quad (1)$$

Table 3. *Base parameters for the building used in the case study*

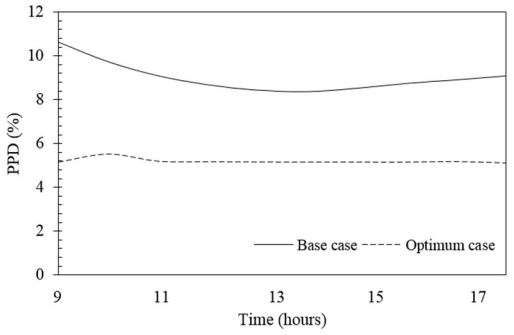
Parameter	*Base case*
Wall U-value [W/m²K]	2
Window U-value [W/m²K]	2
Window to wall ratio [-]	0.6
Aspect ratio [-]	4
Height [m]	3
Area [m²]	6325
Number of stories [-]	4
Orientation [degrees]	45
Heating thermostat [˚C]	21
Hot water supply temperature [˚C]	77

RESULTS OF THE CASE STUDY

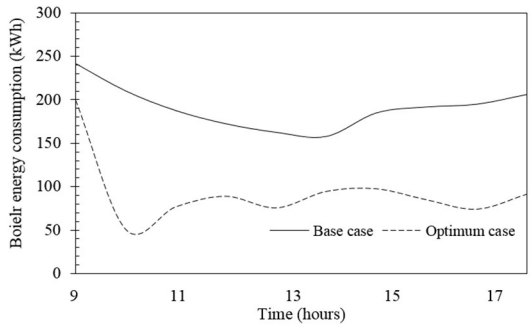
Figure 3 shows the boiler energy consumption and PPD during office hours (from 9 am to 6 pm) during a peak heating day in the heating season. The first optimization case study is shown in Figure 3(a, b). Here, the average boiler energy consumption increased by about 30%; however, PPD was kept to 5%, indicating the optimum thermal comfort. The second optimization case study is shown Figure 3(c, d). Here, the average boiler energy consumption was decreased by about 50% for the optimal control; however, average PPD was maintained at about 11.2%. This indicates that the thermal comfort range, which is below 10% of PPD, was exceeded.



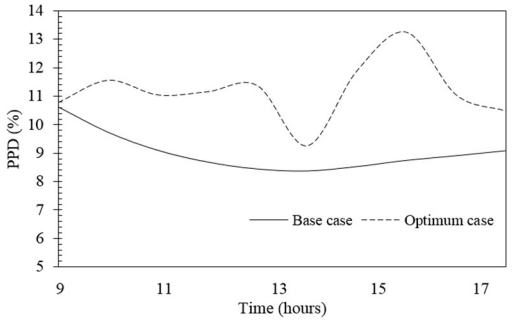
(a) Boiler energy consumption
(Weight factors: Energy = 0.2, PPD = 0.8)



(b) PPD
(Weight factors: Energy = 0.2, PPD = 0.8)



(c) Boiler energy consumption
(Weight factors: Energy = 0.8, PPD = 0.2)



(d) PPD
(Weight factors: Energy = 0.8, PPD = 0.2)

Figure 3*. Comparison between the base case and the optimum case*

The values of the controllable parameters in the boiler energy consumption model are the supply air temperature, hot water supply temperature, and heating thermostat. Additionally, the controllable value of PPD is the heating thermostat. Table 4 shows the values of the controllable parameters of the base case and the optimum case. For the first case, the heating thermostat increased by an average of 1 ˚C (from 21 ˚C to 22 ˚C) when the optimal control was operated and the average supply air temperature was about 39.7 ˚C in optimum case. Also, the hot water supply temperature decreased by an average of 8.7 ˚C, as compared to the base case. For the second case, the heating thermostat decreased by 2.9 ˚C (from 21 ˚C to 18.1 ˚C). The average supply air temperature was about 33.8 ˚C in optimum case and the hot water supply temperature decreased by an average of 8.3 ˚C, as compared to the base case.

Table 4. *Optimum and base values of the controllable parameters*

Time [h]	*Base case*			*Optimum case*		
	Heating thermostat [˚C]	*Hot water supply temperature [˚C]*	*Supply air temperature [˚C]*	*Heating thermostat [˚C]*	*Hot water supply temperature [˚C]*	*Supply air temperature [˚C]*
Weight factors: Boiler energy consumption model = 0.2, PPD model = 0.8						
9	21	77	26.2	22.0	67.1	40.4
10	21	77	24.2	22.1	68.7	42.3
11	21	77	22.7	21.8	68.6	40.7
12	21	77	21.6	22.0	67.6	37.4
13	21	77	21.0	22.0	68.2	39.9
14	21	77	21.0	22.0	68.2	38.5
15	21	77	24.8	22.0	68.5	39.7
16	21	77	25.0	22.0	69.0	40.7
17	21	77	25.3	21.9	67.9	39.0
18	21	77	27.5	22.0	69.3	38.7
Weight factors: Boiler energy consumption model = 0.8, PPD model = 0.2						
9	21	77	26.2	18.1	68.1	27.0
10	21	77	24.2	18.0	69.8	34.2
11	21	77	22.7	18.1	69.2	34.8
12	21	77	21.6	18.1	68.7	34.2
13	21	77	21.0	18.0	67.9	34.9
14	21	77	21.0	18.5	69.0	34.4
15	21	77	24.8	17.9	68.0	35.0
16	21	77	25.0	17.7	68.0	33.8
17	21	77	25.3	18.1	69.3	34.7
18	21	77	27.5	18.2	68.9	34.6

CONCLUSION

This paper showed a multi-objective function optimization process based on ANN models and NSGA-II to determine the optimal set-points in random buildings. ANN models can predict the building thermal load, boiler energy consumption, chiller energy consumption, and thermal comfort with high accuracy indicated by their high R-values. Using these properties, ANN models can be adopted as objective functions of NSGA-II and then optimized. The optimization results were analyzed with a case study in order to verify the optimization process. Results showed that the optimal set-point was

changed by altering the designer's or occupant's preference (i.e., changing the weight factors). Therefore, the weight factors must be appropriately decided and controlled based on the specific requirements of a building.

In the future, we plan on increasing the accuracy of the ANN models to allow for more elaborate optimization. We will also perform a case study during the cooling season.

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