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107

Thermal Control Performance of a Network-based Learning Controller in a Very Hot and Humid Area

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ABSTRACT

Purpose: In order to improve the energy strategies for a building space, various control methods of supply air have been examined in aspects of its energy efficiency and users' thermal satisfaction. This simulation study examines the network-based learning model's capability to maintain the thermal comfort without compromising on its energy efficiency especially in a very hot and humid area. **Method:** A network-based learning controller is proposed to optimize the supply air conditions to meet desired values of set-point temperature and comfort levels by regulating the amount of air and its temperature elaborately. **Result:** In a comparison with two other types of controllers, the proposed model improves the thermal comfort by about 29.3% than the conventional thermostat controller, and increases the energy efficiency by about 17.2% than the fuzzy-based controller. It is concluded that the network-based learning algorithm properly works to manage its supply air condition to improve spatial thermal quality in a very hot and humid area.

KEYWORD

Energy Use
Thermal Comfort
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1. Introduction

Thermal energy systems have developed the performance of the operation to effectively improve their energy efficiency and comfort levels. In order to find optimized performance, several mechanical and statistical methods have mainly examined using series of architectural and mechanical elements in buildings. Among them, controlling the Heating, Ventilation, and Air Conditioning (HVAC) system was gradually developed to define the optimized quantitative solutions by means of modifying parameters, functions, and operational coefficients of energy conservation measures. For improving internal control rules, the Proportional Integral Derivative (PID) rule has been commonly used at the phase of planning, manufacturing, and operating of thermal system[1-3]. With the PID algorithm, the control models combined advanced methods, such as the Fuzzy Inference System (FIS) and Artificial Neural Network (ANN), to increase their performances. The major purpose of using the FIS is that linguistic approaches can help to solve several ambiguous questions requiring not numerical and parametric values like traditional mechanical methods. By using the strategy of combining the FIS and thermal control models, many variations of control rules have been tested to maximize control efficiencies on how to supply appropriate amounts of fuel, air, water, and district heating in buildings and their networks[4-6]. In other words, they have successfully improved control models in fields where elaborate controls demanded to determine various and unpredictable and subjective inputs from occupant. In the FIS model, its internal structure dealing with ambiguous outputs were able to examine a wide range of complex regression models. By using either of experimental or simulated data, its genetic algorithm adjusted model's signals in the cases of radiation, convention, ventilation, and infiltration accordingly. It proposed adequately reliable signals to find possible correlations between subjective and objective variables[5, 6]. Similarly, the ANN algorithm have helped researchers to solve more complex systems dealing with boilers, exchangers, dampers, valves, and mechanical devices. The complexity of multivariate regression models requires enormous resources generated from both of the hardware and software in computing systems. Due to the complexity, it demands effective algorithms and advanced hardwares that enable to correspond to exponentially increasing numbers in calculations as variables and nodes are increased one by one. New approaches could be sought as the ANN structures are optimized, and computer technology advances to perform better on these calculations. Especially, the positive effects of the ANN is to define efficiency of comprehensive methods utilizing multiple distinct elements such as generator, exchanger, valve, damper, resistance coil, and fan motor speed. Through the data-driven regression analyses dealing with specific thermal demands linked to either lab-scaled or true-sized models, the performance efficiency of combining two different control

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algorithms were investigated [5, 6].

The improvement of building's thermal comfort has been investigated through the different types of survey-based researches for the qualitative and qualitative approaches. In order to increase objectivity in results, the Predicted Mean Vote (PMV) and the Predicted Percentage of Dissatisfied (PPD) indices were frequently used with experimental and simulated genetic algorithms for numerical controls. Many methods utilizing advantages of the FIS dealt with human factors and indoor thermal conditions derived from both architectural and occupant characteristics, and they were tested to confirm reliable tuning rules for better performance of the PMV models [7, 8]. There were several approaches reflecting the envelope conditions to calculate precise thermal loads to develop current methods, meanwhile, several traditional approaches were improved responding to modern standards and regulations in buildings [9]. On the other hand, advanced co-simulation applications were developed to effectively combine thermal calculation applications and programming languages. These methods were used to determine the real-time performance responding to the change of outdoor temperature, relative humidity, and precipitation. Also, many different types of energy conservation measures were selected and adopted to address the effect of architectural and mechanical factors. The data-driven approaches mainly dealt with some hidden interactions between the energy conservation measures by use of multi-layered matrixes [10-12].

Several types of studies have also conducted to improve the energy efficiency of the systems by means of modifying building geometries, occupant characteristics, and system operation. However, there have been some weaknesses to obtain optimized conditions of heating and cooling supply air for a space scale associated with a specific outdoor temperature condition. This research proposes an combined model for optimizing heating and cooling supply air conditions at a very hot area dealing with air mass and temperature. In results and discussion, the performances of the three different models are compared, and their control patterns are addressed to define their strengths or weaknesses in energy consumption and thermal comfort. In conclusion, the strength and the weakness of this simulation approach are described, and a follow-up study is addressed.

2. Methodology

2.1. Initial Configuration

For optimized control patterns in the season when the heating and cooling air supply is required in a day, this simulation model utilizes a weather condition of USA_FL_Orlando.Intl.AP.722050_TMY3. From the Commercial Building Energy Consumption Survey data, Orlando is located in the zone having more than 2,000 Cooling Degree Days and less than 4,000 Cooling Degree Days. As indicated in Table 1., heating and cooling energy transfer is calculated based on given geometries and parameters, and, simultaneously, the model calculates the PMV levels. If the result is more than 0.5 or less than −0.5, the model changes the T_{set} as a setting value. If the result is still over or under the setting values, the thermal model performs the process repeatedly. However, if the PMV value is within the setting value during the process, there is no any additional change of T_{set}.

Table 1. Design Parameters

Parameter	Unit	Value
Building Type	N/A	Small Office
Floor Area	m^2	520.0
Building Height	m	4.3
Area of Walls and Roof	m^2	915.5
Thermal Resistance of Walls	hour·°C/J	1.60×10^{-6}
Area of Fenestrations	m^2	6.0
Thermal Resistance of Fenestrations	hour·°C/J	5.94×10^{-7}

This system utilizes a heater and a cooler in a single unit. A proposed ANN model is compared to a thermostat model and a fuzzy-based model to determine their performance of the energy use and the thermal comfort. In the ANN structure, one additional switch works to adjust indoor set-point temperature reflecting the PMV results.

2.2. Energy transfer model

A function of thermal energy transfer in a space is given by a reference[13]:

$$Q_{loss} + Q_{gain} = \frac{du}{dt} \quad \text{(Eq. 1)}$$

where, Ql_{oss} is the heat transfer from an indoor space to an outdoor space (J). Q_{gains} is the heat transfer from a heater to a room (J). U is the internal energy (J). t is the time.

From the conduction through building envelopes, energy loss of a room, is given by:

$$Q_{loss} = (T_{room} - T_{out}) \Big/ \left\{ \frac{1}{(h_{out}A)} + \frac{D}{(kA)} + \frac{1}{(h_{in}A)} \right\} \quad \text{(Eq. 2)}$$

where, h_{out} and h_{in} are the heat transfer coefficients (W/m·K), k is the transmission coefficient (W/m·K), A is the area (m^2), D is the depth of envelope (m).

Assuming that there is no work in the system, energy gain of a room, and the rate of internal energy is given by:

$$\frac{du}{dt}=m_{room}C_v\frac{dT_{room}}{dt} \quad \text{(Eq. 3)}$$

Then, the time derivative of T_{room} is obtained:

$$\frac{dT_{room}}{dt}=\frac{1}{m_{room}C_v} * \left(\left(\frac{T_{room}-T_{out}}{\frac{1}{h_{out}A}+\frac{D}{kA}+\frac{1}{h_{in}A}}\right)+\left(\dot{m}_{ht}C_p\left(T_{heater}-T_{room}\right)\right)\right) \quad \text{(Eq. 4)}$$

2.3. Thermal comfort model

A thermal comfort model utilizes the PMV index which reflects on thermal loads and occupant metabolic rate [14, 15].

$$PMV=3.155\left(0.303e^{-0.114M}+0.028\right)L \quad \text{(Eq. 5)}$$

$$\begin{aligned} L = {} & q_{met,heat}-f_{cl}h_c\left(T_{cl}-T_a\right) \\ & -f_{cl}h_r\left(T_{cl}-T_r\right)-156\left(W_{sk,req}-W_a\right) \\ & -0.42\left(q_{met,heat}-18.43\right) \\ & -0.00077M\left(93.2-T_a\right) \\ & -2.78M\left(0.0365-W_a\right) \end{aligned} \quad \text{(Eq. 6)}$$

where, M is the metabolic rate (W/m^2), L is the thermal load, T_{cl} is the average surface temperature of clothed body (°C), fcl is the ratio of clothed surface area to DuBois surface area (A_{cl}/AD), R_{cl} is the effective thermal resistance of clothing (m·K/W), T_a is the air temperature (°C), h_c is the convection heat transfer coefficient (W/m^2·K), T_r is the mean radiant temperature (°C), h_r is the radiative heat transfer coefficient (W/m^2·K), W_a is the air humidity ratio, W_{sk} is the saturated humidity ratio at the skin temperature.

2.4. Control models

A thermostat model works within the dead-band, ±1°C. If the difference between T_{set} and T_{room} is greater than ±1°C, it sends an either on-signal or an off-signal to the heating and cooling supply model.

The FIS model uses two different input values for the optimized values of amounts of air supplied and its temperature. It reads the difference between T_{set} and T_{room}, wherein the temperature differences between the set-point and room temperature (E) are used for the calculation of a derivative of the temperature difference (ΔE) [16]:

$$E=T_{set}-T_{room} \quad \text{(Eq. 7)}$$

$$\Delta E=\frac{\left(E_n-E_{n-1}\right)}{\Delta t} \quad \text{(Eq. 8)}$$

$$\text{if } x \text{ is } A \text{ and } y \text{ is } C \text{ then } f_1=p_1x+q_1y+r_1 \quad \text{(Eq. 9)}$$

For the output, the FIS uses two membership functions for each input variables with universal of discourse 0 (0%) to 1 (100%) for the amount of air and -10°C to 10°C for its temperature. The FIS, utilizes triangle membership functions as a maximum value is 1 and a minimum value is 0 [16].

$$\mu(x)=\triangle\left(x;a_i,\ b_i,\ c_i\right)=\begin{cases} x\le a_i \rightarrow 0 \\ a_i\le x\le b_i \rightarrow \dfrac{\left(x-a_i\right)}{\left(b_i-a_i\right)} \\ b_i\le x\le c_i \rightarrow \dfrac{\left(c_i-x\right)}{\left(c_i-b_i\right)} \\ c_i\le x \rightarrow 0 \end{cases} \quad \text{(Eq. 10)}$$

The ANN algorithm includes a large class of several structures, and the appropriate selections of a nonlinear mapping function x with a network are required [17, 18]. The network algorithm consists of two input layers, ten hidden layers, and one output layer. The inputs $x_1,\cdots x_k$ to the neuron are multiplied by weights w^k_i and summed up with the constant bias term θ_i., and the resulting ni is the input to the activation function g [17, 18]. The ANN model used in this study consists of the two inputs of E and ΔE from the thermostat and fuzzy-based controllers. It is trained to investigate control patterns which are able to maintain the range of the PMV setting value effectively. For the ANN training, a scale conjugate gradient algorithm, 1,000 times iterations, and 7 epochs were utilized, and the results of the statistical validation, R^2 values, were calculated as much as 0.99557 for air mass and 0.99038 for air temperature.

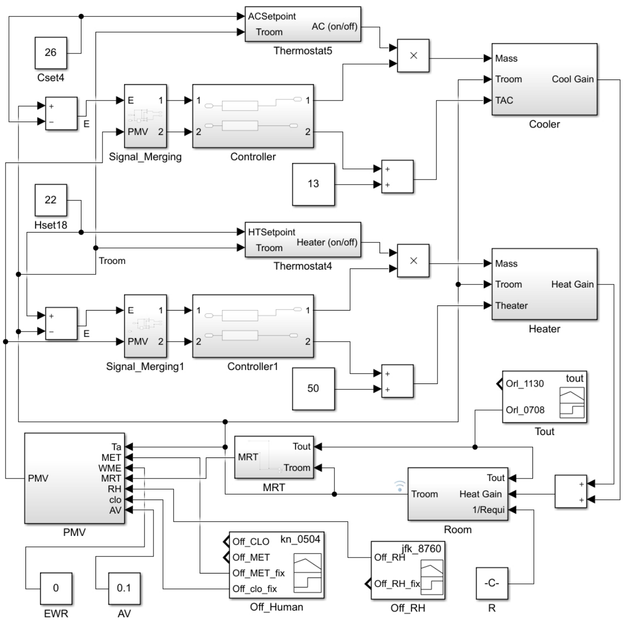

Fig. 1. Simulation Model

Fig. 1. describes a simulation model, which consists of overall five different modules such as Control, Thermostat, Room, PMV, and Signal Generator. The thermal system produces exact amount of cooling or heating supply air. During this process, the PMV value is calculated at every one minute. At every phase, the adaptive model changes the amount of supply air to mitigate possible thermal dissatisfaction.

3. Results

3.1. Room temperature

Fig. 2. displays T_{out} at the City of Orlando on July 8th, which was extracted from the weather data of the US Department of Energy. Fig. 3., 4., and 5. describe the controlled patterns of T_{room} regulated by three different controllers. The change of T_{room}, for the thermostat performed regular patterns between 25° C and 27° C is derived from the dead-band setting of ±1° C. This result implies the fact that the control by the thermostat can be effective in reducing its energy consumption as it turns on and off as T_{room} reaches the preset value in overall performance, yet it may show a weakness to maintain the indoor thermal comfort within the comfort range.

Fig. 4. displays the improved performance of the FIS model which produces fair consistent T_{room} patterns. It effectively reduced the fluctuations of T_{room} except in time ranges of 07:00 to 09:00 and 19:00 to 20:00. As T_{out} reaches to the T_{set}, the control errors was observed at the beginning and the end of the FIS algorithm working. Fig. 5. displays the advantages of the ANN algorithm which gently maintains T_{room} to target T_{set} near 26° C. The ANN's network-based learned algorithm made the pattern of T_{room} steady and less fluctuated at the preset value. However, it is required to confirm whether an unexpected extra energy consumption happens and how much more energy consumption demands to keep the patterns improved.

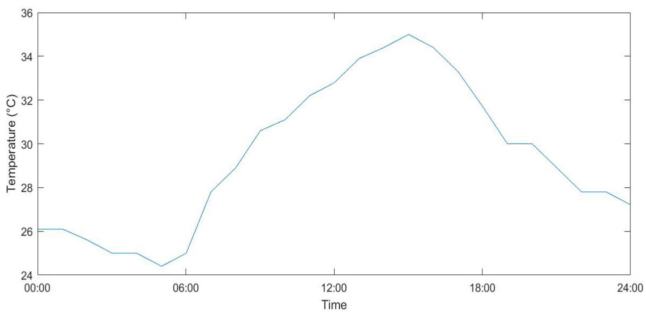

Fig. 2. Outside Temperature of July 8^th in Orlando, USA

3.2. Cooling energy

Fig. 6., 7., and 8. compares the cooling gain required to maintain T_{room} within T_{set} by the thermostat, FIS, and ANN models. The result of the thermostat shows that from 07:00 to 23:00, T_{room} was properly controlled within T_{set}. However, even though it was repeatedly turned on and off, the maximum cooling gain reached near 50 MJ from 07:00 to 23:00, which implies the fact that the capacity design for the thermal supply system needs to be reconsidered with its wide range of cooling gain from 0 to 50 MJ.

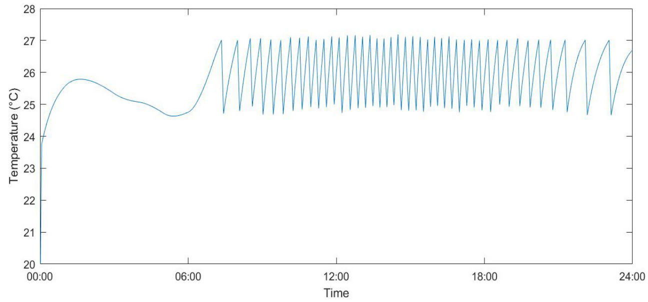

Fig. 3. Room Temperature by the Thermostat

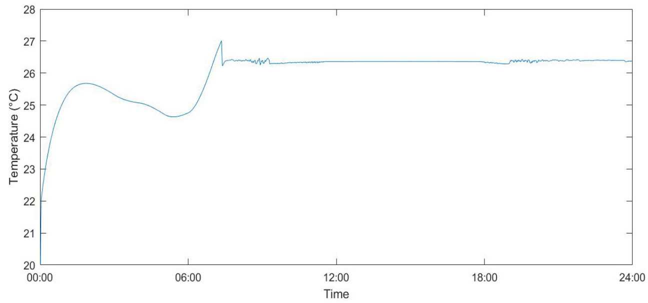

Fig. 4. Room Temperature by the FIS

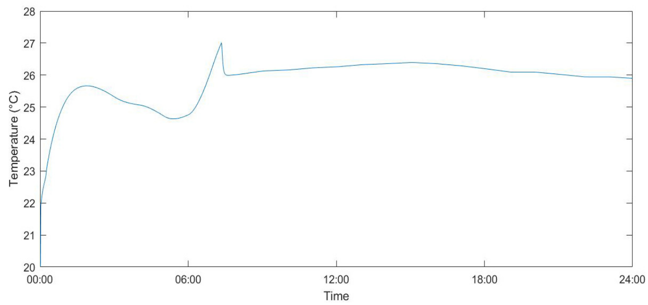

Fig. 5. Room Temperature by the ANN

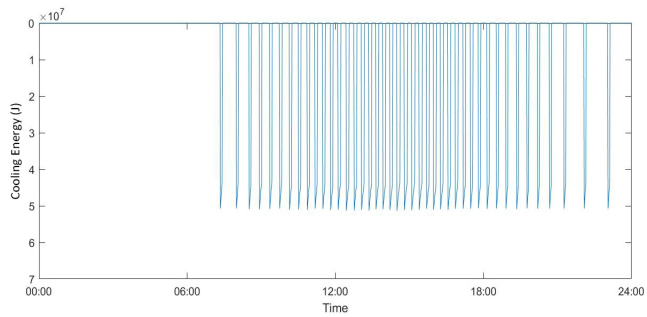

Fig. 6. Cooling Energy by the Thermostat

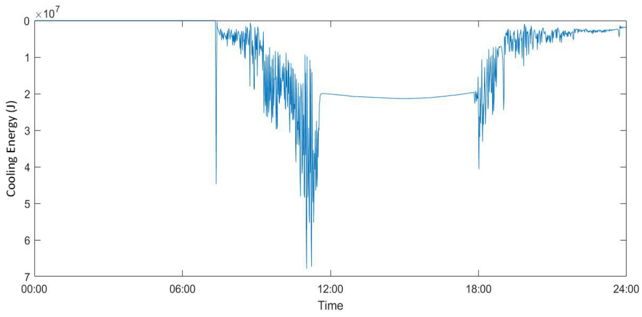

Fig. 7. Cooling Energy by the FIS

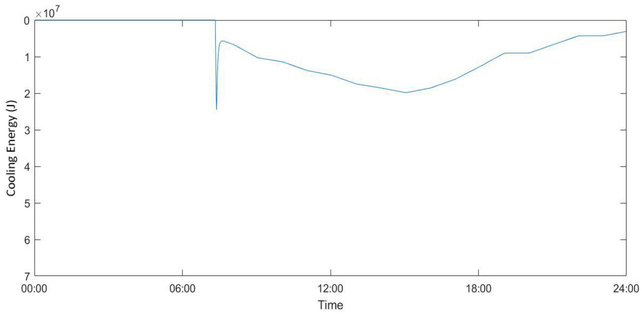

Fig. 8. Cooling Energy by the ANN

The result of the FIS demonstrates fairly complex patterns at specific time ranges of 07:00 to 11:00 and 18:00 to 20:00. As previously described, if T_{out} met T_{set}, the control deviation was relatively large at the beginning and the end of the FIS algorithm working. This implies the fact that irregular inefficient performance can occur until the signals are stabilized to find optimized signals. As indicated in Fig 8., the ANN model shows a distinctly improved the pattern of T_{room}. The cooling gain was successfully managed to stay between 0 to 25 MJ, and also the maximum requirement was properly mitigated under 30 MJ. In designing a thermal system, the result can be utilized to precisely predict daily energy consumption patterns and determine system's maximum capacity to properly respond to unexpected circumstance that may arise depending on energy demand.

4. Discussion

Table 2. displays the average values of the absolute numbers of the PMV results. As shown in the figures, the FIS model effectively controlled T_{room} as compared to the thermostat result, and it even performed slightly better than the result of the ANN. In fact, arguably all of three resulting values yielded a reasonable comfort level, for the recommended PMV values are typically positioned between −0.5 and 0.5. Thus, the results represented only relative advantages and disadvantages, yet in actual, all three models showed high performance in maintaining indoor thermal comfort in a hot climate condition.

Table 2. Comparison of the Thermal Comfort

Controller	PMV (Avg. of Abs.)	Efficiency (%)
Thermostat	0.27	-
FIS	0.18	-35.3
ANN	0.19	-29.3

Table 3. Comparison of the Cooling Energy Transfer

Controller	Daily Cooling Energy Transfer (MJ)	Efficiency (%)
Thermostat	7.83	-
FIS	9.11	16.3
ANN	7.54	-3.9

Table 3. confirms the advantage of the ANN algorithm. In the case of FIS, energy consumption has increased as the indoor thermal comfort improved, but the result of the ANN shows almost identical performance in the thermal comfort to the FIS, while it has shown significant improvement in energy consumption. Thus, despite the additional working of an adaptive process for adjusting Troom for thermal comfort is suggested, it can be confirmed that network-based learning algorithms respond the most effectively to mitigate the increase in energy consumption.

Regarding the result, the network-based learning model improves the thermal comfort by 29.3% than the conventional thermostat controller and increases the energy efficiency by 17.2% than the fuzzy-based controller. It is confirmed that the network-based learning algorithm properly respond to various scenarios in thermal conditions to enrich spatial thermal quality effectively.

5. Conclusion

In this research, a network-based learning controller was proposed to determine the performance of controlling heating and cooling supply air. By comparison with the conventional thermostat and the fuzzy-based controller, the simulation result addressed each own efficiency of maintaining thermal comfort and mitigating escalation of the energy use. As indicated in the figures and tables, the proposed controller successfully improved the thermal comfort by 29.3% than the conventional thermostat controller, and increased the energy efficiency by 17.2% than the fuzzy-based controller, respectively.

As a result, it was confirmed that the proposed network-based learning controller properly responded to various changes in thermal conditions to improve spatial thermal quality. However, in the circumstance of controlling the amount of air and its temperature simultaneously, the analysis of which factor was more effective when applied first, and how to apply the output of analysis to algorithms were neglected in the processing of internal algorithms. Thus, a follow-up study will be necessary to build an advanced framework which investigates its algorithmic interactions derived from the changes in variables of building geometries, mechanical calculations and human factors.

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