# Possibility on Increasing Timesteps of Radiant Systems with Intelligent Load Predictions for Reducing Calculation Time

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**ABSTRACT**

As the occupants in the building require better quality of the thermal environment for the higher productivity, smart buildings started to apply the predictive control for maintaining the thermal comfort. In order to reflect actual building conditions, the data-driven method is used with intelligent method, which can explain the correlation between the significant parameters and building load from the historical data. Recent researches propose smaller timestep for load prediction in order to precisely maintain the thermal comfort. However, intelligent method with smaller timesteps may consume a lot of calculation time that will cause the difficulty on applying the predictive control when calculation time is longer than the timesteps. Therefore, possibility to increase the timesteps of load predictions for reducing the calculation time should be inspected without significant changes in thermal comfort.

In order to inspect the possibility to increase the timesteps without changing the thermal comfort, the characteristics of the thermal comfort should be analyzed. One of the most popular index to indicate the thermal comfort is Predicted Mean Vote (PMV). And in predicted mean vote, the radiant temperature is one of the most important factors. Since radiant temperature may be changed with different terminal systems, thermal comfort and mechanisms of radiant system and air system was analyzed to determine the appropriate timesteps for each system.

Typical office building was simulated with EnergyPlus and one of the common data-driven method, artificial neural network, was selected. Variety of timesteps were used for the simulation and PMV was analyzed to select the appropriate timesteps. As a result, since radiant system may provide the better thermal comfort, the timesteps of load prediction may be longer than the timesteps of load prediction for the air system. Possibility of longer timesteps of the load prediction may open the possibility to reduce the calculation time maintaining the thermal comfort.

**KEYWORDS**

Timesteps, Calculation Time, Neural Network, Predicted Mean Vote

## INTRODUCTION

Recently, the intelligent office buildings started to use the predictive control for energy conservation by increasing the efficiency of the heating and cooling systems with maintaining the thermal environment. Typical timesteps of the predictive control is one hour, because most of the critical factors that affects the building conditions are measured and predicted hourly. Since thermal environment of the office space is directly related to the productivity of the workers, recent researchers started to apply the smaller timesteps in the predictive control. Problem may arises when calculation time exceeds the timesteps in complex and large-scale buildings, which will require more time to calculate. Thus, the possible reduction in calculation time was observed through inspecting different types of the terminal system.

Office buildings started to use radiant systems instead of air systems to maintain the building condition, because radiant systems may conserve the energy, reduce the plenum height, and decrease the operation noise. Among many advantages, the radiant systems may reduce the mean radiant temperature for cooling and increase the mean radiant temperature for heating. According to the most famous index of thermal comfort, Predicted Mean Vote (PMV), the thermal comfort is closely related to the mean radiant temperature, which means the radiant systems may have better thermal comfort than the air systems with the same setpoint temperature. In this study, the possibility of longer timesteps of the radiant system with intelligent load predictions for decreasing the calculation time was observed through comparison of thermal comfort with different timesteps.

## METHODS

Typically, the room temperature is controlled with feedbacks from the room to maintain the comfortable conditions. However, the feedback control can only react to the changes in the room, and the operation of heating and cooling systems cannot be planned ahead for increasing the energy efficiency. The energy efficiency may be increased especially on storage systems and operating number control with multiple plants or pumps. In order to operate the heating and cooling system with better efficiency, the load prediction was performed first and determine the operation strategy. Figure 1 demonstrates the process of the efficient operations for the heating and cooling system.

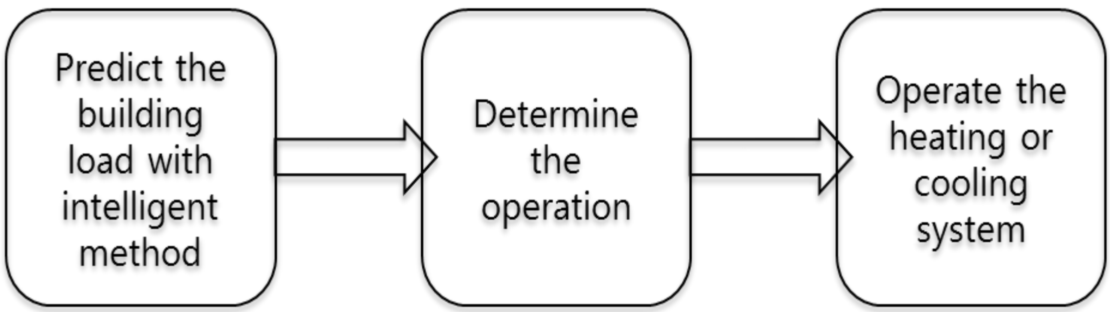


***Figure 1.*** *Operation of heating and cooling system*

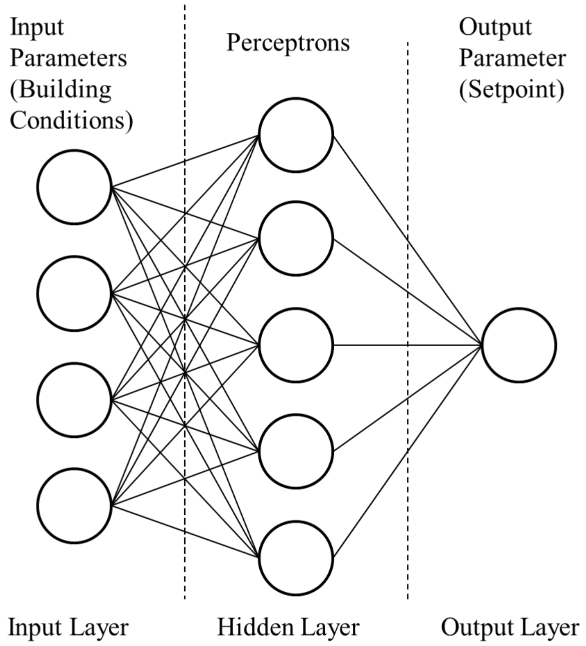


***Figure 2.*** *Structure of artificial neural network*

In order to predict the building heating and cooling load, the artificial neural network was selected to explain the correlation between building load and input parameters. The function model family with sigmoid function was used to express the complex correlations of inputs and output. The function model family is presented as follows.

$$f(x) = \sigma(w^T \times x + b) \quad (2)$$

$$\sigma(z) = 1/(1 + e^{\wedge}(-z)) \quad (3)$$

where x is input parameters, $w^T$ is a weight, and b is a bias term. Typical learning rate 0.1 was used and epoch was set to 500 times to prevent the overfitting problems. The weights were trained with back propagation.

In neural network, the critical factors that affects the building load were selected as input parameters, which are outdoor air temperature, solar radiation, occupancy schedules, and previous building load.

***Table 1.*** *Simulation Cases*

| Simulation Cases | Terminal System | Control Timesteps | Load Prediction Timesteps |
|---|---|---|---|
| Case 1 | Air Handling Unit | 1 hour | 1 hour |
| Case 2 | Air Handling Unit | 15 minutes | 1 hour |
| Case 3 | Air Handling Unit | 15 minutes | 15 minutes |
| Case 4 | Radiant Ceiling System | 1 hour | 1 hour |
| Case 5 | Radiant Ceiling System | 15 minutes | 1 hour |
| Case 6 | Radiant Ceiling System | 15 minutes | 15 minutes |

***Table 2.*** *Simulation Conditions*

| Conditions | Contents |
|---|---|
| Building Orientation | South |
| District | Chicago, United States |
| Area | 511 ㎡ (27.69m x 18.46m) |
| Window | Facing South |
| Building Use | Office |
| Setpoint Temperature | 26℃ (Cooling), 20℃ (Heating) |

***Table 3.*** *PMV of Air System*

| Cases | Timesteps of Air System | Minimum PMV | Maximum PMV |
|---|---|---|---|
| Case 1 | 1 hour | -2.8 | 2.4 |
| Case 2 | 15 minutes | -3.8 | 2.9 |
| Case 3 | 15 minutes | -2.9 | 2.4 |

***Table 4.*** *PMV of Radiant System*

| Cases | Timesteps of Radiant System | Minimum PMV | Maximum PMV |
|---|---|---|---|
| Case 4 | 1 hour | -1.7 | 1.2 |
| Case 5 | 15 minutes | -1.8 | 1.9 |
| Case 6 | 15 minutes | -1.7 | 1.3 |

## RESULTS AND DISCUSSIONS

For evaluations of air and radiant systems, the load prediction was performed with the timesteps of one hour and controlled the room with different control timesteps as shown in Table 1. For comparing the air and radiant system, typical air system in office building, air handling unit, was used, and typical radiant system, radiant ceiling system, was used for heating and cooling system.

The building conditions of small office building was referred from the reference building of the U.S. Department of Energy. Other simulation conditions are presented in Table 2. The reference building was simulated with EnergyPlus 8.5 and the building load was predicted with neural network in MATLAB 2015b.

In Table 3, results of PMV of air system with different control timesteps and load prediction timesteps are presented. Since the setpoint for heating was 20ºC and cooling was 26ºC, the PMV indicates that there are hot and cold conditions in the space. In case 2, the load prediction was performed with the timesteps of 1 hour but the room was controlled with smaller timesteps. Minimum PMV and Maximum PMV were more extreme because there were sections where the values of load predictions and the actual load were different. The difference of load prediction and actual load occurred because the patterns exists in small timesteps but only a single value of load prediction exist for hourly load prediction.

Values of PMV with radiant systems indicated that the room was in a better conditions than the air systems. Although the load prediction timesteps was one hour and control timesteps was 15 minutes, the minimum PMV was higher and maximum PMV was lower than the air system.

## CONCLUSIONS

The possibility of increasing the timesteps was observed through the simulation of different control timesteps and load prediction timesteps.

PMV of air system indicated that if load prediction timesteps is longer than control timestpes, thermal comfort will be decreased because the different pattern of building load exist in a small timesteps but only average value is presented in a longer timesteps.

The minimum PMV of radiant system with longer load prediction timesteps was much higher than the minimum PMV of air system with same load prediction timesteps. And maximum PMV of radiant system with longer prediction timesteps was much lower than the maximum PMV of air system with same load prediction timesteps. Hence, the longer load prediction timesteps may be used in a radiant system because radiant system has much better thermal comfort than the air system.

For future studies, the smaller timesteps may be applied for a detail analysis of the effect of timesteps in thermal comfort to decide the appropriate timesteps for different systems. .

## ACKNOWLEDGEMENT

This research was supported by Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education(NRF-2015R1D1A1A09061467)

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