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Algorithm for optimal application of the setback moment in the heating season using an artificial neural network model

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ABSTRACT

The objective of this study was to develop an artificial neural network (ANN) model to predict the optimal start moment of the setback temperature during the normal occupied period of a building and to suggest an algorithm employing the developed ANN model to enhance indoor thermal comfort and building energy efficiency. To achieve this objective, three major steps were undertaken: the development of the initial ANN model, optimization of the initial model, and development of control algorithms and performance tests. The development and performance testing of the model and algorithm were conducted by employing numerical simulation methods using transient systems simulation (TRNSYS) and matrix laboratory (MATLAB) software. The results of the development and tests revealed that the indoor temperature, outdoor temperature, and temperature difference from the setback temperature were the three major variables predicting the optimal start moment of the setback temperature. Thus, these variables were used as input neurons in the ANN model. In addition, the optimal values for the number of hidden layers, number of hidden neurons, learning rate, and moment were found to be 4, 9, 0.6, and 0.9, respectively, and these values were applied to the optimized ANN model. Comparative performance testing of a conventional algorithm and two ANN-based predictive algorithms demonstrated that the ANN-based algorithms were superior in advancing indoor thermal comfort or building energy efficiency.

1. Introduction

Buildings consume a significant amount of energy, accounting for 22.3% of the overall national energy consumption in South Korea. Energy consumption by residential buildings is a major component of this, amounting to 51.0% of the total building energy use. In particular, 58.1% of consumed residential energy is used for space heating and cooling [1,2]. Thus, 6.61% ($100 \times 0.223 \times 0.51 \times 0.581$) of the total energy consumed in Korea is used for thermal conditioning of residential buildings. Therefore, control strategies to reduce energy consumption during thermal conditioning are required in residential buildings.

The application of a setback temperature in residential buildings during the unoccupied periods of both the day and night is a potential method of reducing heating and cooling energy consumption. Previous studies concerning the application of the setback temperature including experiments, computer simulations, and field tests demonstrated that significant energy savings of up to 23% for cooling and 53% for heating could be achieved by this method [1,3–9]. In particular, 28.2% of the heating energy and 9.5% of the cooling energy in a cold climate, and 53.0% of the heating energy and 16.9% of the cooling energy in a hot and humid climate could be saved when daytime and nighttime setbacks are utilized [1]. Therefore, an energy-conscious thermal conditioning strategy such as the application of a setback has been seriously considered in residential buildings.

The thermal comfort of occupants is another principal factor related to the overall quality of life in residential buildings. Optimal setback strategies, such as setting the proper setback starting and finishing moments, are required if a comfortable indoor thermal environment is to be created. A previous study proved that the optimal finishing of the setback temperature and re-heat of the heating system could be more comfortable and energy efficient [10]. Combined with the optimal finishing moment, a setback application with an optimal start time will also create comfortable thermal conditions within the designated comfort range during the setback period without compromising thermal comfort before the setback period. Thus, if the optimal starting moment of the setback temperature can be determined and applied, the setback applica-

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Nomenclature

$\Delta TIME_{SBT}$	Predicted time duration required to reduce the current indoor temperature to the setback temperature, minutes
$TEMP_{IN}$	Indoor air temperature, °C
$\Delta TEMP_{IN}$	Change from the indoor air temperature of the preceding control cycle, °C
$TEMP_{OUT}$	Outdoor air temperature, °C
$\Delta TEMP_{OUT}$	Change of the outdoor air temperature from one hour prior, °C
$\Delta TEMP_{DIF}$	Temperature difference from the setback temperature, °C
$TIME_{CUR}$	Current time of day
NHL	Number of hidden layers
NHN	Number of hidden neurons
LR	Learning rate
MO	Moment
N_i	Number of input neurons
N_o	Number of output neurons
N_d	Number of training data sets

tion can both support comfortable thermal conditions and improve building energy efficiency.

As such, the objective of this study was to develop a prediction model to determine the optimal start moment of the setback temperature during the normal occupied period of a building and to develop an algorithm employing the prediction model to create a comfortable indoor space with an improved building energy efficiency. If the proper start time of the setback temperature can be determined, unnecessary energy consumption during the normal period can be prevented and the indoor temperature can be brought closer to the designated temperature range during the setback period.

Fig. 1 conceptually compares the indoor temperature conditions created by the conventional algorithm and the two ANN-based algorithms developed in this study. Since the conventional algorithm maintains the normal set-point temperature during the entire occupied period, the indoor temperature is maintained well within the normal operating range. Then, after the unoccupied period begins, the heating system targets the setback temperature. Thus, the temperature is unnecessarily high for a certain period after the setback temperature is applied. Therefore, this algorithm should be the most energy-inefficient strategy.

On the other hand, the two ANN-based algorithms used the $\Delta TIME_{SBT}$ value calculated by the ANN model at every control cycle. $\Delta TIME_{SBT}$ was affected by relevant components which were always changing such as the outdoor and indoor thermal conditions. These changing components were used as input variables in the ANN model. Thus, the ANN model was expected to successfully predict the target output ($\Delta TIME_{SBT}$) by properly responding to the relevant surrounding thermal conditions.

The first ANN-based algorithm employs the setback operating range when the summation of the current time of day and the $\Delta TIME_{SBT}$ value relative to the lower limit of the normal operating range (e.g., 20 °C) reaches the starting moment of the setback period. Since the heating system is operated in a predictive manner, the indoor temperature drops to the edge of the normal operating range at the moment the setback is applied. This algorithm should not hamper the thermal comfort during the occupied period. On the other hand, the temperature will be maintained higher than the setback operating range for a certain period after the setback temperature has been applied.

The second ANN-based algorithm employs the setback operating range if the summation of the current time of the day and the $\Delta TIME_{SBT}$ value relative to the upper limit of the setback operating range reaches the starting moment of the setback period. Since the setback temperature is applied earlier by this algorithm than by the first ANN-based algorithm, the indoor temperature decreases to the setback operating range at the moment the setback is applied. Thus, this should be the most energy-efficient strategy among the three algorithms, but an uncomfortable period will occur during the occupied period.

To achieve the research objectives, three major steps were undertaken, as shown in Fig. 2. The first step was the development of an initial prediction model with an artificial neural network (ANN). In this step, the initial structure of the ANN model was established, learning methods were designed, and statistical analysis of the input and output variables was performed. The final input variables of the ANN model were determined based on this analysis.

The next step was the optimization of the initially determined structure and learning method. ANN models with different numbers of hidden layers and neurons, learning rates, and moments were parametrically tested for their prediction accuracy. Based on these tests, the final optimized model was suggested and its prediction performance was evaluated.

The final step was the development of a control algorithm considering the conventional algorithm and two ANN-based predictive algorithms. The performance of these three algorithms was tested in terms of thermal comfort and the amount of heat supplied by

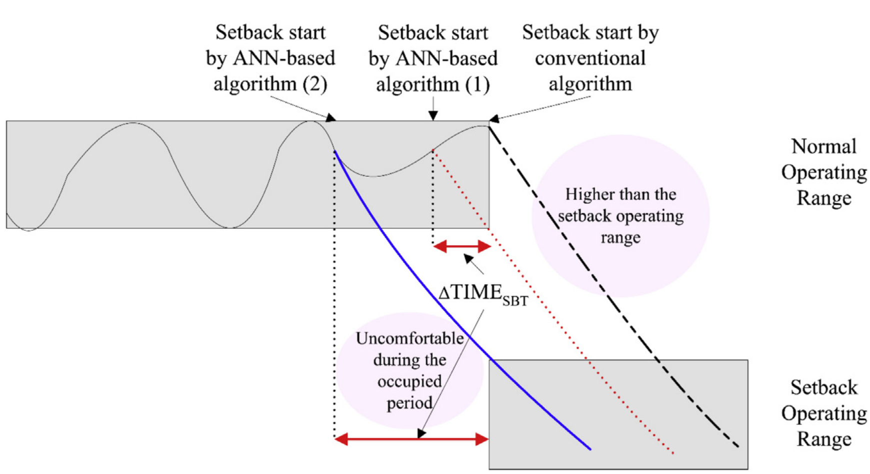

Fig. 1. Conceptual temperature profiles y the three algorithms.