論 文 の 内 容 の 要 旨

論文題目　Model predictive control of building energy system using artificial intelligence
（人工知能を用いた空調熱源システムのモデル予測制御）

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The present thesis aims to propose a model predictive control (MPC) strategy using artificial intelligence (AI) and to examine the practicality of its operational optimization of a building energy system.

Globally, the building sector accounts for approximately 20–40% of total primary energy consumption. Especially in existing buildings, heating, ventilation, and air-conditioning (HVAC) systems account for a major part of their total energy consumption during the operational phase. For this reason, effective management of building energy systems that condition the building space is crucial for reducing energy use and greenhouse gas emissions. In this respect, MPC has received significant attention as an optimal control strategy for efficient building operations.

The MPC scheme is a promising optimal control method for HVAC systems because it determines the optimal control input based on the predicted future behavior of the HVAC system Since the MPC strategy predicts the system behavior and optimizes the control input consecutively, it has been attracting huge attention. However, the performance of the MPC controller hugely depends on the accuracy of the model that predicts the behavior of the system and the efficiency of the optimization algorithm that searches for the optimum solution of the control input.

In general, the HVAC system has a non-linear behavior composed of numerous and various equipment, therefore, constructing its predictive model is complicated. Also, when applying the MPC strategy, the optimization problem must be solved in a real-time manner and thus a low computational load is required. On the other hand, in recent years, with the improvement of the technical level of AI, it is expected that high-precision and high-speed prediction models and optimization algorithms can be constructed. Using the AI in designing the MPC controller, the practicality of MPC can be further enhanced.

Therefore, in this study, an MPC strategy utilizing AI was developed and verified for a building energy system with thermal energy storage (TES) both based on the simulation and experimental analysis. The future behavior of the target system was modeled using an artificial neural network (ANN), focusing on the fact that it has high prediction accuracy and can be expected to reduce the computational load. Also, a metaheuristic method was adopted as an optimization solver since it is known to have a faster convergence speed than the conventional mathematical programming method in solving a nonlinear problem and can efficiently handle multiple constraints.

First of all, in Chapter 3, the practicality of the ANN prediction models in building energy systems was investigated. The ANN prediction models of the stratified chilled water TES system and the borehole heat exchangers (BHE) for a ground source heat pump (GSHP) system were constructed based on a case study to determine the optimal input parameters for the training dataset. During the ANN modeling process, the simulation results from a high-fidelity physical model were used as the training dataset for the TES system. On the other hand, for the BHE system, the ANN model was developed using the results of a numerical simulation. It was observed that a highly accurate ANN that results in marked reductions in the computational cost can be constructed by combining the appropriate input data parameters.

Also, the feasibility analysis of AI-based MPC strategy with the choice of a virtual office building and target energy systems including TES was conducted based on the simulation in Chapter 4. The ANN was utilized to predict the future behavior of the systems and the epsilon constrained differential evolution with random jumping (εDE-RJ) was implemented as an optimization problem solver to minimize operating costs. In addition, a significant occupancy disturbance was intentionally considered to test the ability of the MPC strategy to manage future disturbances. The simulation results for this were compared with those of the conventional rule-based control (RBC) strategy. The MPC reduced the operating costs of the building energy system by 3.4% compared to the RBC during the four-day simulation period, although a sudden increase in occupancy load was conducted intentionally.

However, the verification of MPC strategy based on the experimental analysis is necessary considering the following points. First of all, the training data obtained from the simulation analysis is quantitatively and qualitatively better than actual operational data because a large cost is consumed to collect a sufficient amount of data for training, and also the collected data generally has greater noise. Furthermore, in the simulation-based analysis, the system physics occurred in the actual system such as mechanical characteristics of equipment when the operation starts and stops the driving, the heat loss that occurs when the heat is transferred from the primary side to the secondary side, and the control time delay or the fluctuation that occurs when the heat is supplied from the primary side to the secondary side for the temperature regulation cannot be carefully considered. Finally, even if the MPC controller was constructed by software, the measurement, and control system of the actual system should be configured and tested by linking the main MPC calculator.

Therefore, the downscaled mock-up system was devised in order to validate the developed AI-based MPC strategy via experimental analysis. The experimental system for the cooling operation includes a chiller, TES, heat exchangers, and variable-speed pumps. The air-conditioning space was replaced with a water tank, and the cooling load was assigned by an electric immersion heater (Chapter 5).

In Chapter 6, the developed AI-based MPC strategy was implemented to this experimental system and compared with the RBC strategies that prioritize the TES operation with proportional integral differential (PID) controller under three different patterns of cooling load schedules where the load continues as high, medium, and low during the day. As a result, the proposed AI-based MPC strategy reduced the total operating cost by 9.06–14.56% compared to the RBC strategy. In addition, in the MPC strategy, different operation schedules were observed depending on the scale of the daily cooling load pattern.

In Chapter 7, the effectiveness of the above MPC strategy was further verified by comparing it with two different RBC strategies. Two RBC cases were collected from the experimental system that differed in the cooling operation with TES discharging priority. The case of RBC-1 commences the TES discharging operation as soon as the cooling mode commences. While the RBC-2 case begins the chiller cooling operation by itself, and the TES begins discharging when the electricity price is highest during the occupied hours. Based on the comparative analysis between the MPC strategy and two RBC strategies, the potential of cost savings of AI-based MPC strategy was further verified to reduce the operating costs by 9.7–22.5% compared to the RBC strategies.