Experimental Verification of Adaptive Multirate Model Predictive Control in Industrial Freezer

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***Abstract*—Industrial freezers consume a substantial amount of electricity. However, conventional refrigeration systems are typically operated using simple on–off control based solely on upper and lower temperature thresholds. The aim of this paper is to develop an energy management system for commercial and industrial large-scale refrigeration facilities by constructing a real-time optimal control method that achieves significant reductions in electricity costs. The temperature dynamics and electricity consumption of refrigerated warehouses are modelled by considering ambient temperature conditions and the number of active cooling units. An optimisation problem is formulated to minimise electricity costs while maintaining the temperature of each room within the required bounds. Simulation results demonstrate that the proposed method improves energy efficiency without violating temperature constraints. Based on these findings, a 24-hour field experiment was conducted in an operational industrial freezer. The adaptive multirate model predictive control is employed to an industrial freezer, enabling the control model to be continuously updated through online learning during the experiment. The results indicate that the proposed system can effectively handle unpredictable temperature disturbances while simultaneously reducing electricity costs, demonstrating its practical applicability to real refrigerated warehouse operations. More accurate temperature control could unlock additional cost savings by making better use of electricity markets and could also reduce CO_2 emissions by increasing the use of renewable electricity.**

***Index Terms*—Freezer, Heat, Energy Management, Optimisation, Model Predictive Control**

I. Introduction

Refrigeration systems are essential equipment for keeping stored goods such as food within specified temperature ranges, and their operation can be adjusted within an allowable temperature tolerance. In warehouse applications, storage temperature bands are specified by regulations and industry standards, and warehouse operation is required to comply with these ranges [1]. This gives refrigeration systems a certain degree of operational flexibility.

In typical refrigerated warehouses, a simple ON/OFF strategy is widely used: cooling starts when the storage temperature reaches the upper limit and stops when it reaches the lower limit. In practice, each room is usually controlled independently, without sufficient consideration of disturbances caused by warehouse activities, such as door opening and closing, or external factors such as electricity prices and grid conditions. By contrast, if the allowable temperature range is actively utilised, the timing of cooling can be shifted. As a result, a cold storage warehouse can exhibit behaviour analogous to thermal energy storage [2], [3].

Large-scale refrigeration systems, in particular, consume substantial electrical power and account for a major share of operating costs in cold storage facilities. In frozen warehouses in Japan, refrigeration and freezing equipment accounts for nearly 80% of total electricity consumption [4]. Therefore, enhancing the operation of large refrigeration systems and exploiting them to reduce electricity costs is highly significant. These points suggest a need for a control method that goes beyond simple ON/OFF control and adjusts operating timing while meeting temperature constraints and accounting for warehouse operations.

For the control of large refrigeration systems, methods have been proposed to manage the overall power peak of supermarkets by assessing the controllability of refrigeration demand and adjusting short-term electricity consumption while respecting temperature constraints for both air and stored products [5]. In addition, [6] investigates the demand-side flexibility that thermostatically controlled loads (TCLs) can provide in Denmark, comparing the attractiveness of Manual Frequency Restoration Reserve and load shifting. Using supermarket refrigeration systems as TCLs, the study models temperature dynamics and proposes a stochastic mixed-integer linear programming approach that accounts for electricity prices and demand variability.

Real-world deployment also requires that the optimisation be solved within a short time at each update, so computational efficiency becomes important. Related work on thermally flexible loads has therefore discussed ways to reduce the computational burden of optimisation. For example, [7] compares a complete optimisation approach with a two-step method that decouples equipment sizing and operation for heat pumps in low-voltage feeders, achieving a substantial reduction in computation time with only a small loss in optimality.

Despite these progresses, few publicly available studies (i) optimise the operation of an entire large-scale refrigerated warehouse by coordinating multiple rooms and cooling units, or (ii) validate such an approach in a real warehouse with online model updates. Bridging this gap requires combining adaptive, multirate, and Model Predictive Control (MPC).

Multirate output controllers with online identification are

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applied to temperature regulation in greenhouses [8] and can be extended to also non-minimum-phase mechanical systems [9]. Robust adaptive MPC with feasibility and stability guarantees is developed [10], whilst a data-driven multi-step predictor is shown to reduce conservativeness in multirate constraint tightening [11]. Online model identification has also been integrated with adaptive MPC to compensate for time-varying plant dynamics in real-time applications [12], and reinforcement learning has been employed to adapt all components of a parameterised MPC scheme, achieving substantial reductions in computational complexity [13]. They are extended to nonlinear systems with heterogeneous sampling rates [14] and to online optimisation-based planning under hard constraints [15].

The aim of this paper is to develop an energy management system for large-scale commercial and industrial refrigeration facilities by developing a real-time optimal control method that delivers significant electricity cost savings, and to validate the proposed approach in an operational industrial freezer.

The contributions of the paper are as follows:

- The temperature control of the industrial freezer is optimised by the energy consumption model based on the number of active coolers.
- The performance of the temperature control using the Adaptive Multirate Model Predictive Control (AMMPC) is experimentally validated in the industrial freezer.

The outline is as follows. In Section II, the problem that is considered in this paper is formulated. In Section III, the developed approach is presented. In Section IV, the performance improvement with the developed approach is validated. In Section V, conclusions are presented.

II. Problem formulation

This paper formulates a mixed-integer linear programming to realise an energy management system (EMS) for commercial refrigerated warehouses, with the objective of reducing electricity costs. Implementing the optimisation requires a model that adequately represents the operating state of the facility; in particular, (i) prediction of room temperature trajectories and (ii) prediction of electricity consumption are essential prerequisites.

With the cooperation of a logistics company, we obtained detailed operational data from an in-service commercial refrigerated warehouse. The facility is a four-storey warehouse equipped with NewTon compressors manufactured by Mayekawa. In this paper, we focus on modelling and formulating the problem for a single compressor group. The compressor serves five cooling units for room temperature control. In general, each cooling unit serves a single room; however, one room on the 1st floor is exceptionally cooled by two cooling units. Fig. 1 shows the system structure of the target warehouse. Room temperatures are measured at a one-minute interval. Under current operation, a simple ON/OFF control strategy is employed: a cooling unit is activated when the room temperature exceeds $-20\,^\circ\mathrm{C}$ and is deactivated when it decreases to $-22\,^\circ\mathrm{C}$. In this paper, we treat this allowable temperature band as a hard constraint and formulate a control problem that optimises operating timing while keeping temperatures within the specified range.

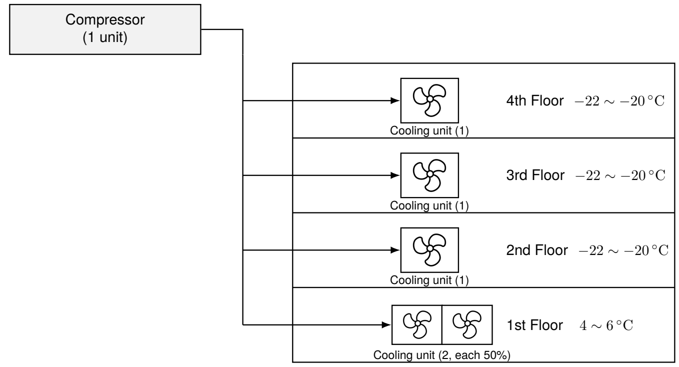

Fig. 1. System structure of the industrial freezer.

Room temperature is affected not only by the ON/OFF state of the cooling units but also by several disturbances. Typical examples include outdoor temperature changes, warehouse operations such as door opening and closing, inbound/outbound handling, product type and quantity, and defrost cycles that cause temporary temperature rises.

In the target facility, however, door-opening events are not recorded. In addition, although inbound/outbound quantities and product categories are available, the exact timing of handling events is not logged. For this reason, we start by building a temperature prediction model that uses only outdoor temperature as an exogenous input, since it can be observed reliably in real time.

III. Approach

A. Temperature prediction model

Heat transfer in a refrigerated warehouse can be represented by an equivalent thermal circuit consisting of thermal resistance and thermal capacitance [16]. With a time step Δt, the indoor temperature $T_{\mathrm{in}}(t+\Delta t)$ is written as

$$T_{\mathrm{in}}(t+\Delta t) = T_{\mathrm{in}}(t) + \frac{\Delta t}{C}\left(\frac{T_{\mathrm{out}}(t) - T_{\mathrm{in}}(t)}{R} + Q(t)\right), \tag{1}$$

where C is the thermal capacitance of the room air and stored goods, $T_{\mathrm{out}}(t)$ is the outdoor temperature at time t, R is the thermal resistance to the ambient environment, and $Q(t)$ is the heat removed by the cooling unit, a constant negative value when ON and zero when OFF.

Let $u(t) \in \{0, 1\}$ be the ON/OFF state of the cooling unit (ON: 1, OFF: 0). With $Q(t) = Q_{\mathrm{cool}} u(t)$, where Q_{cool} is the cooling capacity, (1) can be rewritten in the linear form

$$T_{\mathrm{in}}(t+\Delta t) = aT_{\mathrm{in}}(t) + bT_{\mathrm{out}}(t) + du(t) + e, \tag{2}$$

with $a = 1 - \frac{\Delta t}{CR}$, $b = \frac{\Delta t}{CR}$, and $d = \frac{Q_{\mathrm{cool}}\Delta t}{C}$.

Using measured data, we estimate a, b, and d by linear regression, together with a constant term e. The term e is included to account for unmodelled residual components

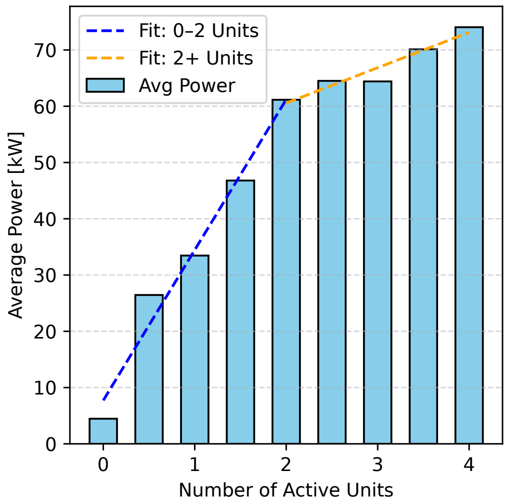

Fig. 2. Power consumption model of the industrial freezer based on the number of active coolers.

such as internal heat gains and small equipment-related heat flows. To smooth short-term fluctuations, we apply a centred 5-minute moving average to the data. Linear regression is performed using scikit-learn [17] in Python. The model is trained using data from the four days immediately before the optimisation period described in Subsection III-C. The model is applied to rooms on the 2nd to 4th floors. The room on the 1st floor is a chilled handling area with larger temperature fluctuations, and is therefore excluded from this paper.

With these parameters, we compute the temperature trajectory recursively from the initial value $T_{\text{in}}(0)$, the outdoor temperature $T_{\text{out}}(t)$, and the cooling-unit ON/OFF signal $u(t)$, and evaluate the model.

B. Power consumption model

The cooling units on the 1st floor have approximately half the rated capacity of those installed on the second to fourth floors. Accordingly, we count each 1st-floor cooling unit as 0.5 unit.

Analysis of measured current data indicates a clear correlation between the number of operating cooling units and compressor power. Furthermore, during periods in which the number of operating cooling units remains unchanged, compressor power is observed to be nearly constant. We therefore compute the average compressor power for each operating-unit count and summarise the relationship.

The variation in compressor power with respect to the number of operating cooling units is shown in Fig. 2. Fig. 2 shows that compressor power increases with the number of operating cooling units, but the relationship is not uniform. When two or fewer units are operating, power rises steeply as additional units are switched on. When more than two units are operating, the increase becomes much smaller, indicating different operating regimes. Based on this behaviour, we define $m(t)$ as the effective number of operating cooling units at time t and model the compressor power $W(t)$ [kW] using the piecewise-linear relations as follows.

$$W(t) = 26.7m(t) + 7.72 \qquad (m(t) \leq 2) \tag{3}$$
$$W(t) = 6.28m(t) + 48.0 \qquad (m(t) \geq 2) \tag{4}$$

C. Economic optimisation model

Using the room temperature model and the power consumption model for the refrigerated warehouse, we construct an optimisation model for the control of the large-scale refrigeration system. The objective function is shown in (5). We minimise the total electricity consumption [kWh] over the 24-hour evaluation period. The control interval is set to 15 minutes, and the 24-hour horizon is discretised into 96 time steps.

$$\text{Consumption} = \frac{15}{60} \times \sum_{t=1}^{96} W(t) \tag{5}$$

The one-minute temperature evolution in each room is approximated by (6). The allowable temperature range is enforced by (7). Although the nominal upper bound is $-20\,^\circ\text{C}$, we introduce a small margin and use $-20.3\,^\circ\text{C}$ as the upper bound to account for possible temperature oscillations.

$$T_{i,k+1} = a_i T_{i,k} + b_i T_k^{\text{out}} + d_i u_{i,k} + e_i \tag{6}$$
$$-22 \leq T_{i,k} \leq -20.3 \tag{7}$$

Here, $T_{i,k}$ denotes the room temperature [°C] of room i at minute-wise time step k, T_k^{out} is the outdoor temperature, $u_{i,k} \in \{0,1\}$ is the ON/OFF status of the cooling unit, and a_i, b_i, d_i, and e_i are coefficients estimated by regression.

The constraints associated with the power consumption model are given in (8)–(15).

$$W(t) \leq n_x \times m(t) + f_x + M \times z(t) \tag{8}$$
$$W(t) \geq n_x \times m(t) + f_x - M \times z(t) \tag{9}$$
$$W(t) \leq n_y \times m(t) + f_y + M \times (1 - z(t)) \tag{10}$$
$$W(t) \geq n_y \times m(t) + f_y - M \times (1 - z(t)) \tag{11}$$
$$m(t) - 2 \leq M \times z(t) \tag{12}$$
$$m(t) - 2 \geq \varepsilon - M \times (1 - z(t)) \tag{13}$$
$$m(t) = \sum_{i=1}^{4} u_{i,t} \tag{14}$$
$$W(t) \leq W_{\max} \tag{15}$$

In (14), $m(t)$ represents the number of cooling units operating simultaneously. The operating status of the cooling units on the 1st floor is categorized into two patterns based on the outdoor temperature conditions: an ON-dominant pattern and an OFF-dominant pattern. The binary variable $z(t)$ is introduced to switch between two linear regimes of the power model depending on the operating-unit count: (12) and (13) enforce $z(t) = 1$ when $m(t) \geq 3$ and $z(t) = 0$ when $m(t) \leq 2$. With a sufficiently large constant M and a sufficiently small positive

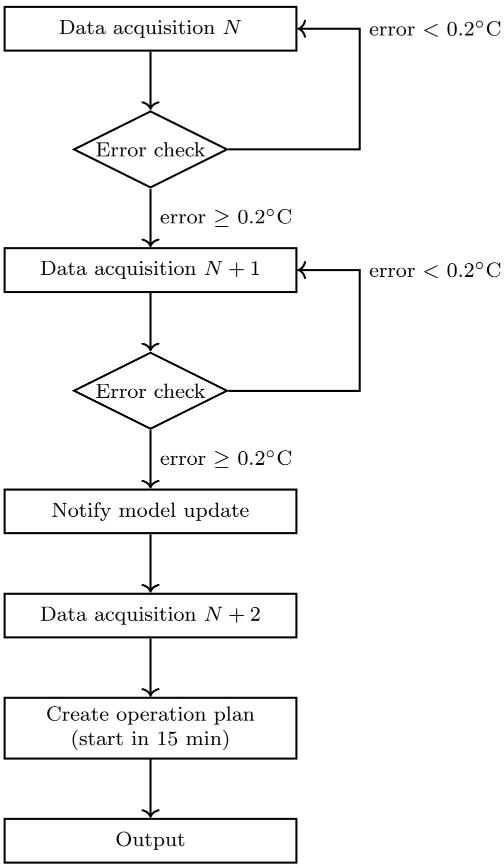

Fig. 3. Operation strategy of the industrial freezer using the adaptive multirate model predictive control.

constant ε, (8)–(11) ensure that $W(t) = n_x \times m(t) + f_x$ for $z(t) = 0$ and $W(t) = n_y \times m(t) + f_y$ for $z(t) = 1$. The parameters n_x, f_x, n_y, and f_y are estimated by regression.

D. Adaptive multirate model predictive control

To validate the proposed approach in an operational refrigerated warehouse, we designed control rules to ensure safe operation when applying optimisation-based control. We adopt Adaptive Multirate Model Predictive Control (AMMPC). This is the MPC-based approach that uses a model of the plant to predict future states and selects control inputs based on these predictions. It is effective when hard constraints must be satisfied, which is often difficult to guarantee with PID control. AMMPC extends standard MPC by updating model parameters online, so the controller can adapt to changes in operating conditions and system behaviour. Fig. 3 shows the AMMPC control rules used in this paper. Measured room temperatures are imported into our user interface every 30 minutes, and we monitor whether the deviation between the simulated and measured temperatures reaches or exceeds $0.2\,°\mathrm{C}$. If the deviation remains below the threshold, control is continued according to the pre-computed operating schedule. If the deviation reaches or exceeds the threshold for two consecutive checks, we judge that the model mismatch persists and recompute the temperature prediction model and the optimisation when the next measurement arrives. The operating schedule obtained from the recomputation is applied from the interval 15 minutes later.

IV. Experiment

A. Condition

The field demonstration was conducted at an operational refrigerated warehouse, with the cooperation of the logistics company which provided the dataset, for 24 continuous hours from 12:00 on Tuesday 25 November 2025 to 12:00 on Wednesday 26 November 2025.

The optimisation results display the ON/OFF decisions for each of the three cooling units in every 15-minute time slot. Here, the cooling units on the 1st floor were set to the OFF state, as the outdoor temperature was low. Based on this display, the operator at the partner company implemented the control actions via setpoint adjustments.

B. Experimental result

Fig. 4 shows the temperature trajectories during the field test. The solid lines are measured temperatures, and the dashed lines are the predicted temperatures from the optimisation model. The shaded regions indicate the ON periods of each cooling unit.

The room on the 4th floor is closer to ambient conditions and tends to warm up more easily due to larger heat gains. In contrast, rooms on the 2nd floor and the 3rd floor are sandwiched between other rooms, so they are less affected by outdoor conditions and their temperatures are easier to maintain. Because of this, during the first 12 hours, the behaviour of the room on the 4th floor led to longer ON times for the cooling units of rooms on the 2nd floor and the 3rd floor, mainly for better power efficiency. After sufficient cooling had been stored during this period, the ON times of rooms on the 2nd floor and the 3rd floor became shorter in the second 12 hours. This behaviour suggests that shifting operating timing within the allowable temperature range can make the warehouse act like thermal energy storage.

Over the 24-hour test, the AMMPC model was updated eight times, and the upper temperature limit ($-20\,°\mathrm{C}$) was reached five times. As shown in Fig. 4, the cooling units in rooms on the 2nd floor and the 3rd floor were sometimes forced ON from around 09:00 due to a temperature rise that the model did not fully capture. This may have been caused by the start of business hours, with extra heat gains from handling activities such as inbound and outbound operations.

Fig. 5 compares energy consumption. In addition to the 24-hour energy use on the test day, the figure also shows daily energy consumption averaged over seven days for the week before and the week after the test. This comparison reduces the effect of day-to-day variation and helps evaluate the change in energy use before and after applying the proposed method. The total energy consumption on the test day was about 2.4% lower than the seven-day average of the previous week, and about 20.3% lower than the seven-day average of the following

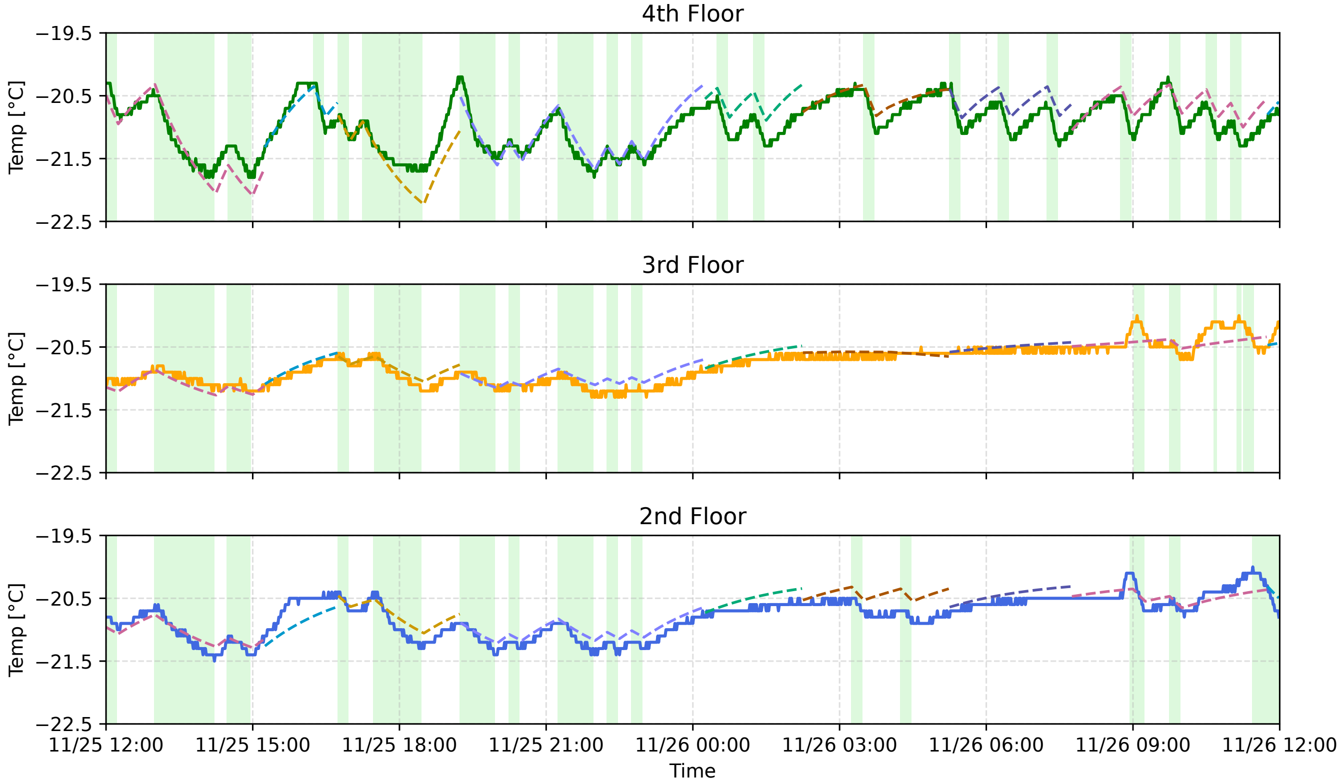

Fig. 4. Experimental results of the temperature control in the industrial Freezer. Solid line: measured temperature. Dotted line: estimation model. Colored area: cooler on-time.

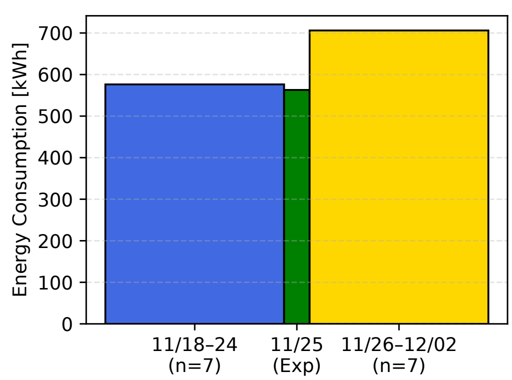

Fig. 5. Energy consumption of the industrial freezer. Data before and after the experiment are averaged over 7 days.

week. These results suggest that the proposed method can shift operating timing while meeting the temperature constraints and can reduce energy consumption.

V. Conclusion

In this paper, an energy management method for a refrigerated warehouse is proposed by combining mixed-integer linear programming based on a room temperature model and a power model with AMMPC-based operating rules, and a 24-hour field test is carried out in an operational warehouse. During the test, operating timing is adjusted while keeping the temperature constraints satisfied, and the total electricity consumption was lower than the weekly averages before and after the test. In addition, by running the system with model updates and safety rules, it is confirmed that the control approach can work under real operating conditions.

At the same time, what is directly confirmed in this test was a reduction in electricity consumption and electricity costs. This does not necessarily mean that the system became more energy-efficient or that the Coefficient Of Performance (COP) improved. For example, changes in outdoor conditions and internal load could mean that the electricity use per unit of cooling actually became worse. To judge whether the proposed method leads to more efficient operation, an evaluation based on indicators that include cooling capacity, such as COP is needed.

As future work, we plan to measure temperatures on the suction and discharge sides of the cooling unit and pressure if needed, and estimate cooling capacity so that COP can be calculated during operation. Our longer-term goal is to extend the control design to achieve both lower electricity costs and improved operating efficiency. More accurate temperature control may enable further cost savings through better use of electricity markets and may also reduce CO_2 emissions by supporting greater use of renewable electricity.

ACKNOWLEDGMENT

The authors sincerely appreciate the support provided by Freezo Co., Ltd. (https://www.freezo.jp) and the collaborating cold storage company in the experimental verification.

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