

Received 4 August 2026, accepted 26 August 2026, date of publication 2 September 2026, date of current version 11 September 2026.

Digital Object Identifier 10.1109/ACCESS.2026.3729760

RESEARCH ARTICLE

Development and Demonstration of an Integrated Energy Management System for Energy-Efficient Cold-Chain Logistics Centers

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This work was supported by the Technology Innovation Program (AI-Based Pre-Spark Detection Sensor System for Fire Prevention in Power Facilities) funded by the Ministry of Trade, Industry and Resources (MOTIR), South Korea, under Grant RS-2026-25563747.

ABSTRACT With the rapid expansion of the cold-chain logistics industry, energy consumption in low-temperature logistics centers has increased significantly due to the growing number and scale of refrigeration facilities. In particular, refrigeration and cooling systems account for approximately 60–70% of the total electricity consumption in cold storage facilities. As a result, they are major contributors to rising operational costs and greenhouse gas emissions. Accordingly, the development of an energy management system (EMS) specifically tailored to cold-chain logistics centers has become increasingly important to mitigate rising operational costs and greenhouse gas emissions. This study presents a cold-chain-specialized energy management system, referred to as the cold-chain EMS (CEMS), which integrates real-time energy monitoring with an AI-driven framework that combines three-dimensional (3D) temperature mapping, deep reinforcement learning-based unit cooler control, intelligent defrost initiation, and a digital twin-based energy management system. The proposed CEMS enables coordinated control of refrigeration equipment while maintaining strict temperature requirements for product quality preservation. Experimental testbed and field demonstration results show that the proposed integrated framework improves energy efficiency while maintaining temperature stability in cold-chain logistics centers. Furthermore, this study discusses future research directions for next-generation cold-chain energy management systems leveraging artificial intelligence and digital twin technologies.

INDEX TERMS Cold-chain logistics, deep reinforcement learning, digital twin, energy management system, intelligent defrost, 3-D temperature mapping, unit cooler control.

I. INTRODUCTION

The demand for temperature-controlled logistics environments has increased rapidly with the growth of global distribution networks for food, pharmaceuticals, and other perishable products. In the post-pandemic era, the reliable

maintenance of low-temperature conditions for high-value products such as vaccines, biopharmaceuticals, and frozen foods has emerged as a critical factor influencing national industrial competitiveness and supply chain resilience. As a result, cold-chain logistics centers have become essential infrastructure for modern logistics systems.

Unlike conventional logistics facilities, cold-chain logistics centers are required to maintain strictly controlled

The associate editor coordinating the review of this manuscript and approving it for publication was Ali Raza¹.

low-temperature environments on a continuous basis, operating 24 hours a day, 365 days a year. This operational characteristic leads to exceptionally high electricity demand compared to general commercial buildings, and cold-chain logistics centers are therefore widely regarded as representative energy-intensive facilities [1]. Previous studies have consistently reported that refrigeration and cooling systems alone account for more than 60–70% of the total energy consumption in cold storage warehouses [2], [3]. Continuous operation of refrigeration equipment not only increases operational and energy costs but also results in substantial greenhouse gas emissions, thereby imposing additional environmental burdens across the industrial sector.

In parallel with these challenges, macro-level energy issues have further intensified the need for demand-side energy efficiency improvements. According to the International Energy Agency, global electricity demand is projected to grow by an average of 3.4% annually through 2026, placing increasing structural pressure on energy supply and demand worldwide [4]. Under such conditions, improving energy efficiency in highly energy-intensive sectors, including cold-chain logistics, has become a key policy and industrial concern. This trend is further reinforced by rising global energy prices and the implementation of carbon neutrality policies [5].

In the building sector, energy-saving technologies and management systems have been actively promoted through national policies such as the Energy Use Rationalization Act and the Fifth Basic Energy Plan [6], [7]. These initiatives have accelerated the adoption of energy management systems (EMS) across various domains. However, despite their high energy consumption, cold-chain logistics centers remain relatively underserved in terms of systematic global and national policies, as well as technical standards specifically addressing energy demand management and efficiency improvement.

Conventional building energy management systems (BEMS) are primarily designed to improve energy efficiency while maintaining human comfort. The control objectives of BEMS focus on regulating indoor temperature, humidity, lighting, and ventilation conditions to ensure occupant satisfaction. In contrast, the primary control objective of EMS for cold-chain logistics centers is not human comfort but the preservation of stored refrigerated and frozen products. Consequently, temperature control requirements in cold-chain facilities are extremely stringent, often requiring precision within $\pm 0.5^\circ\text{C}$ for certain products. This fundamental difference in control objectives limits the applicability of conventional BEMS technologies to cold-chain logistics environments.

Deep reinforcement learning (DRL) [8], [9], [10], [11], [12], [13] has emerged as a promising, model-free approach for energy management, learning optimal policies through environmental interaction. For discrete state-action spaces, deep Q-network (DQN) methods are widely used for hybrid energy scheduling [8], [9]. Conversely, for continuous spaces,

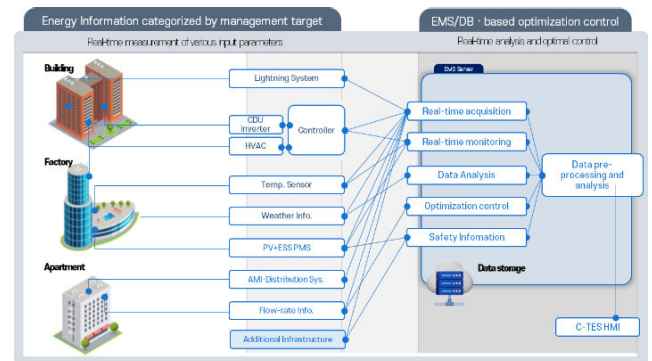


FIGURE 1. General functional framework of an energy management system applicable to buildings and industrial facilities.

the deep deterministic policy gradient (DDPG) algorithm is frequently employed in simulated environments and renewable energy scenarios [10], [11]. Additionally, hierarchical and hybrid DRL frameworks have been introduced to further improve system adaptability [12], [13]. In parallel, DRL has been actively applied to HVAC and building thermal control, where continuous-action methods such as DDPG regulate setpoints and airflow to reduce energy consumption while maintaining comfort constraints [14], [15]. However, as recent reviews point out, the majority of these studies remain at the simulation stage, and deployments that learn directly on live physical systems are still rare [16]. Despite these advances, most DRL-based energy research focuses on conventional buildings or microgrids, leaving a notable gap in cold-chain applications. Cold chains present unique challenges, including highly dynamic thermal behaviors and strict temperature constraints for product safety. To safely address these complexities, digital twin (DT) technology has gained significant traction [17], [18]. By creating high-fidelity virtual replicas, DTs enable the extensive testing of diverse operational scenarios, allowing DRL agents to learn complex thermal dynamics without risking physical assets. However, while DTs and simulations provide robust training platforms, they often fail to fully capture real-world uncertainties and hardware-control discrepancies. Practical integrated energy management for cold chains requires coordinated control across refrigeration, energy storage, and renewable subsystems. Consequently, this study validates the proposed DRL-driven framework through physical experiments in a live, real-world environment, demonstrating its practical feasibility for comprehensive cold-chain energy optimization.

For the aforementioned reasons, it is insufficient to simply extend existing BEMS or generalized xEMS platforms to cold-chain logistics centers. Cold-chain-specific technological elements, including product-centered control logic, high-precision temperature maintenance algorithms, intelligent defrost strategies, and load forecasting functions, are essential for achieving both energy efficiency and product quality assurance. Therefore, a specialized EMS framework

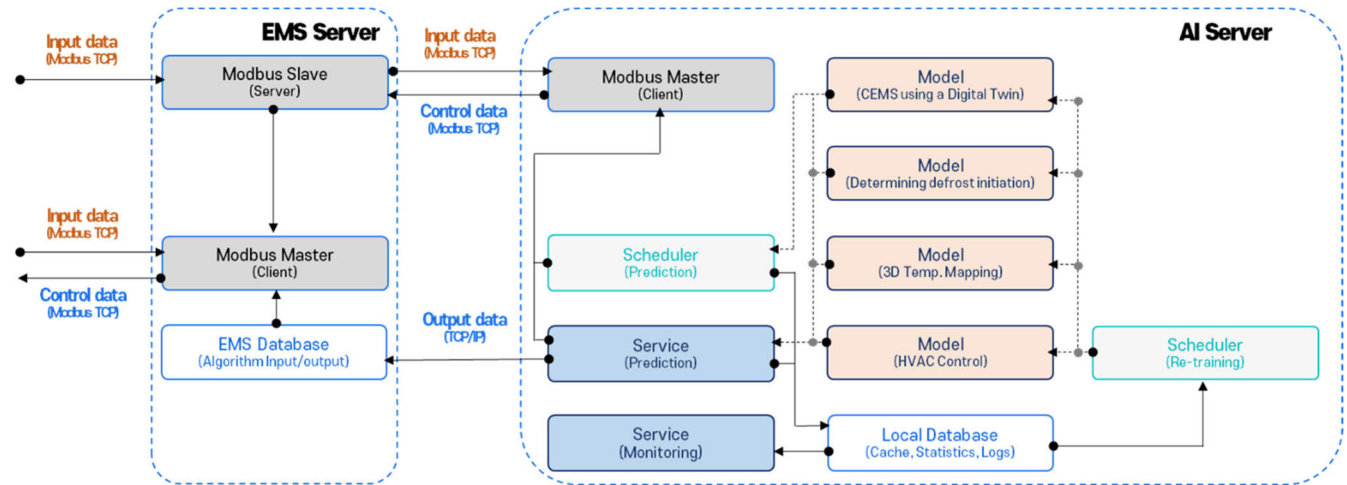


FIGURE 2. Service architecture and data flow of the integrated CEMS for Cold-Chain logistics centers.

is required to address the unique operational characteristics of cold-chain logistics facilities.

To address these challenges, this study proposes a CEMS that integrates four core technologies within an artificial-intelligence (AI)-based framework: 1) CNN-based 3D temperature mapping that reconstructs the full volumetric temperature field of a sub-zero warehouse from sparse sensor measurements using a CFD-informed training dataset, enabling facility-wide thermal monitoring without dense sensor deployment; 2) deep reinforcement learning-based unit cooler (UC) control, in which — unlike most existing DRL-based HVAC studies that remain at the simulation stage [16] — the controller is trained online within the live facility, converging within approximately two hours and achieving up to 27.3% energy reduction over conventional PID control; 3) LSTM-based intelligent defrost initiation that diagnoses the frost state from time-series temperature profiles to replace fixed-interval defrosting, eliminating unnecessary defrost operations and their high re-cooling power peaks; and 4) a digital twin-based EMS in which the DRL agent is pre-verified on a high-fidelity digital twin before physical deployment and coordinates ESS/PV operation against time-of-use tariffs, achieving a 10.58% reduction in monthly electricity cost while maintaining peak demand below the demand-charge baseline. The novelty of this work lies not in each learning algorithm in isolation, but in the integration of these AI modules into a single operational system and its long-term field demonstration at an operating cold-chain logistics center across multiple seasons and two facility scales — which, to the best of the authors' knowledge, has not previously been reported. Through experimental validation and field demonstrations, the proposed CEMS simultaneously reduces energy consumption and maintains strict temperature stability in cold-chain logistics centers. Furthermore, this study discusses future development directions for next-generation EMS tailored to cold-chain logistics centers.

II. FUNDAMENTALS OF ENERGY MANAGEMENT SYSTEMS

As global energy consumption and greenhouse gas emissions continue to increase, the need for efficient energy management has become increasingly critical. Governments worldwide have established carbon neutrality targets and are implementing various policies to achieve these goals, in which EMS has emerged as a key enabling technology. EMS is an integrated system that monitors and analyzes energy usage in real time across diverse environments such as buildings, factories, residential facilities, and logistics centers and optimizes energy consumption through intelligent control of equipment and systems (Fig. 1). The EMS collects data on multiple energy sources, including electricity, heating and cooling, gas, steam, and renewable energy through metering devices and information and communication technology (ICT) infrastructure. These data are stored in databases and analyzed using AI-based algorithms to enable predictive analysis and automated control, thereby improving overall energy efficiency.

Traditionally, energy management relied on passive monitoring and manual operation, with system control largely dependent on the experience and subjective judgment of facility managers. However, energy management has transitioned to a data-driven, real-time control paradigm. This transition enables various advanced functions, such as energy cost reduction, stable equipment operation, greenhouse gas emission mitigation, early detection of equipment abnormalities, and the generation of quantitative performance reports. As a result, EMS has become a core technology for improving energy efficiency. EMS can be categorized according to their application domains and operational objectives into BEMS, factory energy management system (FEMS), and home energy management system (HEMS). Each type of EMS is optimized to meet the specific energy management requirements of its respective domain. Nevertheless, all EMS share common functionalities, including real-time

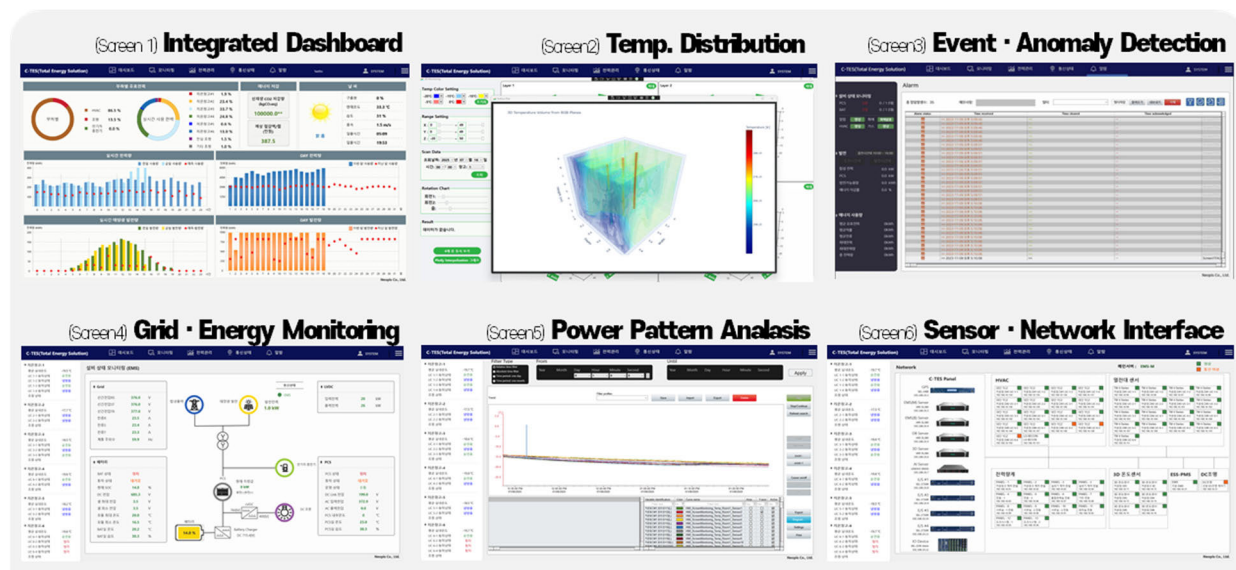


FIGURE 3. Integrated HMI of the CEMS for monitoring and control of cold-chain logistics centers.

monitoring of energy flows and intelligent control of energy consumption equipment and devices.

III. DEVELOPMENT OF ENERGY REDUCTION TECHNOLOGIES FOR COLD-CHAIN LOGISTICS CENTERS

A. INTEGRATED ENERGY MANAGEMENT SYSTEM FOR COLD-CHAIN LOGISTICS CENTERS (CEMS)

The service architecture of the integrated EMS for cold-chain logistics centers, referred to as CEMS, is illustrated in Fig. 2. The CEMS platform is structured around an EMS and database (DB) server, with input data including various sensor measurements and equipment status information and an AI server operating in coordination with the EMS. The AI server exchanges data with both the EMS and DB server, and performs multiple predictive and analytical functions such as temperature prediction, electricity consumption forecasting, defrost initiation prediction, and photovoltaic (PV) generation forecasting. Some data required for weather forecasting are collected directly through external API services. The primary operational data are stored in the central DB server, whereas the local database of the AI server is utilized as a temporary data repository for algorithm execution and statistical analysis. The AI server's local DB is designed to retain data only for the minimum period required for model operation and analysis.

Table 1 and Fig. 3 present the core service components and the human-machine interface (HMI) of the CEMS platform. Unlike conventional facility monitoring systems, CEMS is an integrated management system capable of simultaneously coordinating multiple facilities, forecasting and analysis of real-time power demand, communication status monitoring, and product quality assurance. In particular, key functionalities such as three-dimensional warehouse temperature analysis for refrigerated and frozen storage areas, defrost

initiation prediction, and AI-based UC control are significantly more advanced than those of conventional BEMS or general xEMS platforms. Therefore, CEMS can serve as a core operational platform specifically tailored to the management of cold-chain logistics centers. Representative HMI screen configurations of the CEMS platform are described below:

- 1) Screen 1: Real-time power consumption, photovoltaic (PV) generation output, carbon emission reduction and estimated monthly energy cost savings
- 2) Screen 2: Status monitoring of the Condensing Unit (CDU) compressors, cooling water systems, abnormal signals and real-time three-dimensional (3D) warehouse temperature visualization
- 3) Screen 3: Monitoring of HVAC, power conditioning system (PCS) and battery status as well as fire and gas alarm systems.
- 4) Screen 4: EMS status monitoring of the grid, battery, LVDC and PCS
- 5) Screen 5: Monitoring of input data from various sensors and load-specific measurements
- 6) Screen 6: Status monitoring of servers, data acquisition (DAQ) system, I/O devices and GPS modules.

B. 3D TEMPERATURE MAPPING AND UNIT-COOLER CONTROL TECHNOLOGY

Cold-chain logistics centers exhibit non-uniform thermal distribution within the storage space due to various complex factors such as structural characteristics, external heat loads, door operations, and loading patterns. Such heterogeneous thermal distribution can induce localized overheating or overcooling zones, thereby compromising the quality and stability of stored products. When facility managers operate equipment excessively to prevent these issues,

TABLE 1. Core functional components of the proposed CEMS.

Category	Sub-function	Description
3D Temperature Analysis	Precision temperature measurement	Analysis of 3D volumetric temperature distribution
Unit-Cooler Control	Unit cooler temperature control	AI-based unit cooler temperature control technology
Defrost Optimization	Frost formation prediction	Prediction of optimal defrost initiation
Power Consumption Analysis	Distribution power optimization	Load-specific power consumption and pattern analysis
Peak Power Optimization	Peak demand prediction and control	Optimization of AC/DC load distribution
DC Smart Lighting	Lighting layout and design	Digital twin-based power optimization
Alarm System	Communication status alerts	Administrator notification and corrective action guidance
Database	Data logging	Data analysis and visualization

this leads to unnecessary increases in energy consumption. Consequently, the need for analytical tools capable of quantitatively analyzing thermal behavior throughout the entire space has emerged. Simultaneously, control technologies that optimize actual equipment operation have become increasingly important [19], [20]. The 3D temperature mapping algorithm can be utilized as a key tool for diagnosing temperature non-uniformity by visually reconstructing temperature distribution within storage spaces. In this study, a deep learning-based 3D temperature mapping technique was developed using data collected from actual sensor networks. To achieve this, a training dataset was constructed by combining Computational Fluid Dynamics (CFD) simulation results with measured data. The CFD simulations provided dense spatial temperature distributions under various operating conditions, while sensor measurements were used for model calibration and validation.

Fig. 4 shows the overall structure and conceptual framework of the proposed 3D temperature mapping algorithm, which adopts an encoder-decoder architecture. The sparse sensor temperatures, together with their spatial gradient information, are fed into a fully connected (dense) encoder that expands the input through three dense layers ($300 \rightarrow 3000 \rightarrow 20,000$ units) and reshapes it into a $25 \times 25 \times 32$ latent feature map. This representation is then passed to four parallel CNN decoder branches, each corresponding to one horizontal measurement plane ($z = 2, 4, 6, 8.5$ m). Each branch first up-samples the latent map ($25 \times 25 \times 32 \rightarrow 50 \times 50 \times 32$) and then applies four successive 4×4 convolutional layers with 16, 16, 8, and 3 filters ($50 \times 50 \times 32 \rightarrow 50 \times 50 \times 16 \rightarrow 50 \times 50 \times 16 \rightarrow 50 \times 50 \times 8 \rightarrow 50 \times 50 \times 3$), reconstructing a full-field 2D temperature distribution encoded as a normalized three-channel (RGB) image.

The training dataset comprised approximately 5,000 samples constructed by combining CFD simulation results with

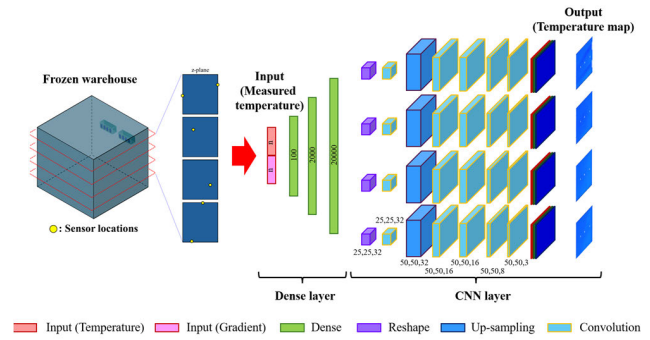


FIGURE 4. Architecture of the CNN-based 3D temperature mapping algorithm: sparse sensor temperatures and their spatial gradients are encoded by dense layers and decoded by four parallel CNN branches into RGB-encoded temperature fields at four horizontal planes ($z = 2, 4, 6, 8.5$ m).

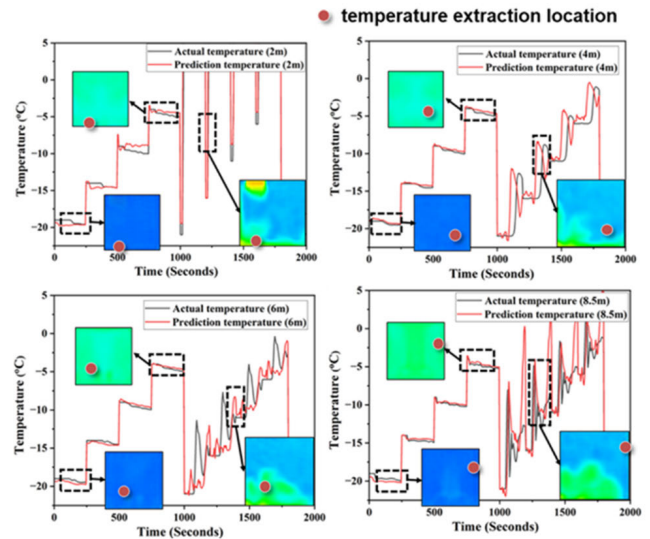


FIGURE 5. Prediction accuracy of the 3D temperature mapping algorithm at four height levels ($z = 2, 4, 6, 8.5$ m), with mean prediction error within ± 2 °C for both steady-state and transient conditions.

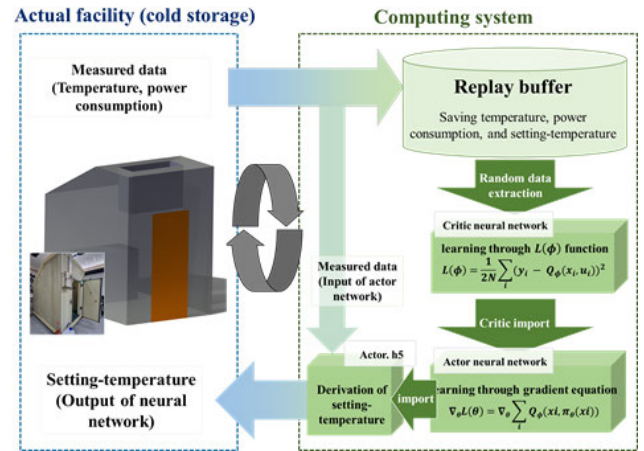
field measurements. CFD analyses were performed under varying operating conditions such as unit-cooler inlet temperature and door-opening events. Field measurements were collected from 16 temperature sensors distributed across the four horizontal planes (four points per plane) and were used for calibration and validation. The measured sensor temperatures and their spatial gradients were min-max normalized to the $[0,1]$ range over an operating span of $[-25, 0]$ °C, and the target full-field temperature distributions were encoded as normalized three-channel (RGB) images using a fixed colormap. The dataset was partitioned into training, validation, and test subsets at a ratio of 8: 1: 1. The model was trained using the Adam optimizer with a learning rate of 1×10^{-3} and a batch size of 32 for 100 epochs, minimizing a binary cross-entropy loss over the normalized RGB temperature maps. The complete architecture and training configuration are summarized in Table 2.

TABLE 2. Implementation configuration of the CNN-based 3D temperature mapping model.

Category	type	value
Neural Network	Architecture (conv/pool/FC layers)	3 dense-layer encoder + 4 parallel CNN decoder branches
	Input channels	2 (temperature + spatial gradient)
	Filters/kernel size	16 / 16 / 8 / 3 filters (per decoder branch), 4 × 4 kernel
	Activation	Dense: ReLU/ReLU/ReLU, Conv: ReLU/ReLU/ReLU/Sigmoid
Learning Process	Optimizer	Adam
	Learning rate	0.001
	Batch size	32
	Epochs	100
	Loss function	Binary cross entropy for normalized RGB temperature-map reconstruction
Convergence criteria	Max epochs	100

The mean prediction error of the proposed algorithm converged to within ± 2 °C, indicating that temperatures in regions without installed sensors can be accurately estimated. Fig. 5 presents the prediction accuracy of the 3D temperature mapping algorithm at four different height levels ($z = 2, 4, 6, 8.5$ m), demonstrating that the model successfully captures both steady-state temperatures and transient thermal events across all measurement positions. Using this system, facility managers can intuitively identify spatial temperature non-uniformity through visualized temperature distributions rather than simple numerical data. This information can serve as a basis for quality management and operational strategy development in logistics centers. Early detection of repetitive temperature deviation patterns at specific locations can support managerial decision-making, such as determining equipment maintenance timing and improving loading methods. It should be noted that the mapping model complements, rather than replaces, the physical sensor network: at product-critical locations, temperatures are monitored directly by installed sensors, while the reconstructed field identifies non-uniformity in regions without sensors, guiding sensor deployment and operational improvements.

UC control in cold-chain logistics centers is a highly demanding control task that must simultaneously achieve energy efficiency and stored product quality assurance. Conventional Proportional-Integral-Derivative (PID) control methods offer advantages in simplicity and universality. However, they require repeated parameter optimization due to outdoor temperature variations and the highly nonlinear characteristics of refrigeration systems [21]. In actual warehouse operating environments, unpredictable disturbances such as door operations, outdoor air infiltration, and loading density changes occur frequently. Under these conditions, fixed parameter-based PID control alone is insufficient to achieve stable and efficient operation. To overcome these limitations, this study applied the Deep Deterministic

**FIGURE 6. Conceptual diagram of the modified DDPG-based UC control algorithm, showing the closed loop between the cold-storage facility and the actor-critic networks with the UC setpoint action bounded to $[-15, -5]$ °C.**

Policy Gradient (DDPG), a deep reinforcement learning-based control algorithm. DDPG is a representative model-free reinforcement learning algorithm based on the actor-critic architecture, capable of handling both continuous state spaces and continuous action spaces [22]. The actor network receives current state information as input and outputs continuous control actions, while the critic network evaluates Q-values for state-action pairs to continuously improve the policy generated by the actor. To mitigate instabilities during the training process, this study applied experience replay (replay buffer) and target networks. The replay buffer stores experience data up to a specified capacity and utilizes random sampling for training, thereby reducing correlation among time-series data and enhancing learning stability. Target networks suppress oscillations during training by applying delayed parameter updates (soft update, $\tau = 0.001$) to the actor and critic networks. Additionally, Ornstein-Uhlenbeck noise was added to action values for exploration, reflecting continuous noise characteristics observed in actual physical systems [23].

Fig. 6 illustrates the conceptual diagram of the modified DDPG-based UC control algorithm. The left side shows the actual cold storage facility where measured data, including temperature and power consumption are collected. The right side depicts the computing system architecture, featuring the replay buffer for experience storage and the actor-critic neural networks for policy optimization. In this framework, the state consists of real-time temperature and power consumption data within the cold storage facility, normalized to the $[-1, 1]$ range for neural network input. The action is defined as the UC setpoint temperature, where the actor network output of $[-1, 1]$ is linearly transformed to the actual control range $[-15, -5]$ °C. Furthermore, the reward function was designed to reflect the balance between power consumption reduction and temperature stability [24], [25]:

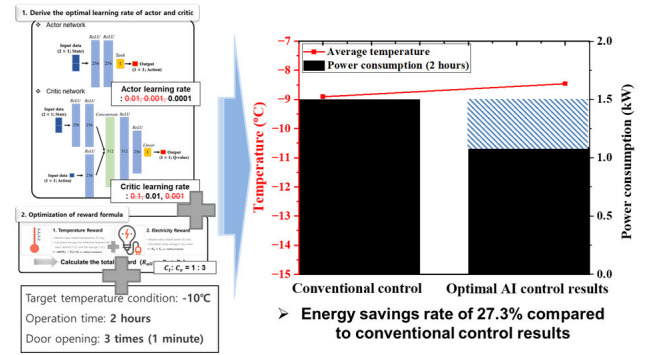
$$R = -C_t \cdot |T - T_{set}| - C_e \cdot E \quad (1)$$

TABLE 3. Implementation and training configuration of the DDPG-based UC controller.

Category	type	value
Neural Network	Actor architecture	3 hidden layers (state $\rightarrow$ action)
	Critic architecture	state in 1st layer, action concat in 2nd layer $\rightarrow$ Q
	Activation	ReLU (hidden) / tanh (output)
	L2 regularization	1.0×10^{-4} (all hidden layers)
Training	Actor learning rate	1.0×10^{-4}
	Critic learning rate	1.0×10^{-2}
	Optimizer	Adam
	Batch size	128
	Epoch (per update)	1
	Discount factor γ	0.95
	Soft-update τ	0.001
	Replay buffer size	10,000
	Convergence criteria	Reward plateau
	Learning mode	Online (live facility), then autonomous deployment
	Data acquisition interval	5 s
	Training duration	≈ 2 h (until reward convergence)
	OU noise (θ, μ, σ)	$\theta = 0.15, \mu = 0, \sigma = 0.2$
Exploration	OU noise (θ, μ, σ)	$\theta = 0.15, \mu = 0, \sigma = 0.2$

where T is the actual temperature, T_{set} is the target temperature (-10°C), E is power consumption and C_t and C_e are weighting coefficients for temperature stability and energy efficiency, respectively. In this study, multiple weight ratios (1:1, 1:3, 1:5) were established to simultaneously consider temperature deviation and power consumption, and learning performance was compared for each ratio. This design ensures that the algorithm considers both energy consumption reduction and temperature stability of stored products, rather than focusing solely on energy minimization.

The actor network is designed with three fully connected hidden layers, taking the normalized state as input and producing a continuous action, while the critic network processes the state in its first hidden layer and concatenates the action in the second layer before outputting the Q-value. ReLU activations are used in the hidden layers, with a tanh output for the actor, and an L2 regularization penalty (1.0×10^{-4}) is applied to all hidden layers. The learning rates are set to 1.0×10^{-4} for the actor and 1.0×10^{-2} for the critic, with a soft-update coefficient τ of 0.001 and a discount factor γ of 0.95. A replay buffer with a capacity of 10,000 samples is used, and networks are updated with a batch size of 128. Unlike the digital-twin-based ESS agent, the UC controller was trained online within the live cold-storage facility: temperature and power-consumption data were acquired at 5-second intervals, and the policy converged after approximately 2 hours of real-time training, after which the learned controller was deployed for autonomous operation. The AI-based UC controller is implemented using Python 3.11 and trained on a computing system equipped with an Intel

**FIGURE 7.** Application results of the DDPG-based UC control: (left) optimization of learning rates and reward weight ratio ($C_t: C_e = 1:3$); (right) power consumption comparison with PID control, showing up to 27.3% average reduction.

Core i9-10900X CPU, four NVIDIA TITAN RTX GPUs, and 192 GB of RAM. The complete set of network architectures and training hyperparameters is summarized in Table 3.

In this initial learning stage, experiments were conducted on a small-scale freezer, and policies were improved based on real-time temperature and power consumption data. Fig. 7 presents the application results of the UC control algorithm. The left panel shows the optimization process for deriving optimal learning rates for both actor and critic networks, along with the reward formula optimization with a $C_t: C_e = 1:3$. The right panel compares the performance between conventional control and optimal AI control results. Under the 1:3 weight ratio condition, the comparison was conducted under identical operating conditions: a target temperature of -10°C , a 2-hour operation period, and three door-opening disturbance events — and average power consumption was reduced by up to 27.3% compared with conventional PID control [24]. Furthermore, even in disturbance situations such as external heat load changes or door operations, the controller showed fast response characteristics and returned to a stable state, effectively suppressing energy waste due to excessive operation. When the same algorithm was applied to extended-scale demonstration centers, the energy reduction rate averaged over 20%, and control efficiency was observed to vary depending on sensor placement locations [25]. This suggests that sensor network design may be a critical factor in determining control performance for future applications in large-scale logistics centers.

In summary, the reinforcement learning-based UC control technology proposed in this study achieves both superior energy savings and high temperature stability compared to conventional control methods, as verified through field tests. By adapting the DDPG algorithm to actual cold-chain environments, a stable framework that enables simultaneous learning and control was successfully implemented. In particular, the model-free controller maintained stable operation under real disturbances such as door operations, outdoor-air infiltration, and external heat-load variations,

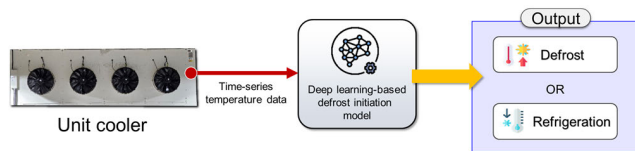


FIGURE 8. Schematic of the AI-driven defrost initiation model, which uses time-series temperature data to determine whether defrost initiation is required.

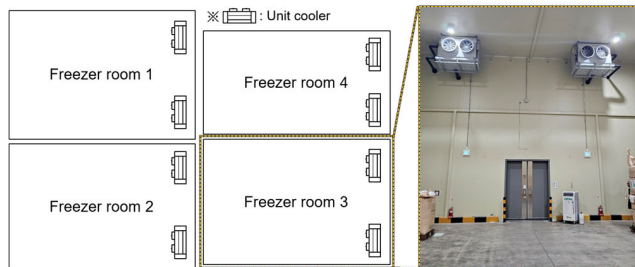


FIGURE 9. Four freezer rooms used for evaluation of the AI-driven defrost initiation model at an industrial cold storage facility. Each freezer room is equipped with two unit coolers, and four rooms share a single screw compressor and a centralized defrost water tank.

returning rapidly to the target temperature band without manual retuning, while the CNN-based mapping model was trained across various CFD operating conditions covering the principal sources of thermal variability encountered in practice. This indicates that the proposed method is a practical control technology applicable to real cold-chain logistics center operations, beyond the theoretical level. Moreover, because the framework requires no facility-specific physical model and converges within approximately two hours of online training, as demonstrated by its transfer from a small-scale freezer to an extended-scale demonstration center while retaining average energy savings above 20% [24], [25], it can potentially be extended to efficient control and optimized operation of other energy-intensive facilities, such as large-scale logistics centers, data centers, and HVAC systems with continuous setpoint control. Nevertheless, control efficiency was observed to depend on sensor placement, and the demonstration was conducted at a single site; validating the framework across facilities with different structural and climatic conditions remains a subject of future work.

C. STRATEGY FOR DETERMINING DEFROST INITIATION

Continuous heat exchange between the evaporators in the UCs and the air is essential to stably maintain the target low-temperature environment in cold storage systems. However, operating evaporators under low-temperature conditions inevitably induces the nucleation and subsequent accretion of frost on the heat exchanger surfaces [26], [27], [28], [29]. As the frost layer grows, it increases the thermal resistance and obstructs the air flow passages, causing a rapid increase in the air-side pressure drop. Consequently, frost accumulation degrades the overall heat transfer coefficient,

reduces the performance of the UC, and increases the power consumption of the refrigeration system.

Since performance degradation due to frost formation is thermodynamically inevitable, defrosting is necessary to recover system efficiency. However, the defrosting process introduces a significant energy penalty, necessitating substantial energy input for melting the accumulated frost. Furthermore, it imposes an additional thermal load on the refrigerated space, which subsequently increases the compressor work required for the temperature recovery process to the target temperature [30], [31], [32]. Therefore, an optimal control strategy is necessary to balance the trade-off between restoring the cooling capacity of the heat exchanger and minimizing the peak power consumption induced by the defrosting process.

Conventionally, time-based periodic defrosting has been widely adopted in industrial cold storage systems [33], [34]. However, real-world cold storage systems are subject to significant stochasticity in operating conditions caused by external environmental changes. Since frost growth varies depending on the properties of the airflow, the periodic control strategy may lead to inefficient defrosting. Under high-humidity conditions, rapid frost growth may degrade the heat transfer rate before the scheduled defrosting interval, leading to severe energy efficiency deterioration of the refrigeration system. Conversely, under low-humidity conditions, the system is prone to executing premature defrosting on heat exchangers with negligible frost accumulation. This results in energy waste, particularly due to the increase in air temperature and the subsequent energy-intensive re-cooling process required to restore the target temperature.

To overcome these limitations, a demand-defrost control strategy based on real-time diagnosis of the frost state is imperative. Fig. 8 illustrates the schematic of the proposed deep learning-based defrost initiation model. The proposed model employs a Long Short-Term Memory (LSTM) network, an architecture adept at capturing temporal dependencies in time-series data, to determine the precise defrosting timing; the specific network architecture and hyper-parameters are detailed in Tables 4 and 5. The model utilizes time-series air temperature profiles acquired from the upstream side (air inlet) of the evaporator in the UC as input parameters. By directly sensing localized parameter variations within the unit cooler rather than relying on indirect measurements from other system components (e.g., the compressor or condenser), the proposed model minimizes its dependence on the configuration of the cold storage facility. Experimental observations revealed that the temperature at the upstream side of the heat exchanger remains stable during the initial stages of frost formation but exhibits a distinct temperature profile when the frost layer reaches a critical thickness. This thickness corresponds to a blockage ratio of 70-80%, a regime characterized by a sharp decline in the heat transfer rate [35]. Accordingly, this inflection point in the temperature profile was established as the

TABLE 4. Architectures of the defrost initiation model.

Layer	Type	Size	Activation function
Input layer	Sequence input	15	
Hidden layer 1	LSTM	256	
Hidden layer 2	LSTM	256	
Hidden layer 3	LSTM	128	
Hidden layer 4	LSTM	64	
Hidden layer 5	FCNN	64	ReLU
Hidden layer 6	FCNN	32	ReLU
Output layer	FCNN	1	sigmoid

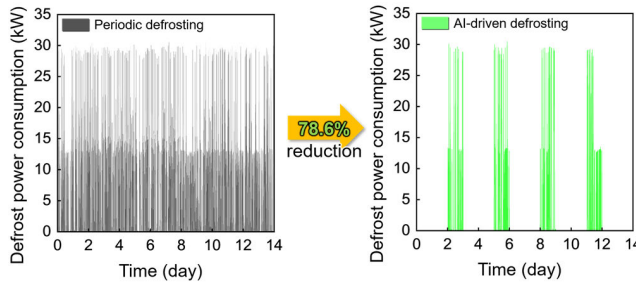


FIGURE 10. Comparison of energy consumption of defrosting system under periodic and AI-driven defrost control over a 2-week period. The system consists of a defrost water pump and an electric heater.

criterion for initiating the defrost. The dataset was collected over 30 days under varying environmental conditions, with ambient temperatures and relative humidities ranging from 7.6 °C to 18.3 °C and from 45% RH to 91% RH, respectively. The status of the evaporators was formulated as a binary classification problem to determine whether a defrosting operation is required. Data preprocessing involved labeling, min-max normalization, and a sliding window to generate the dataset from the experimental data. Specifically, the ground-truth labels for defrost initiation were derived from the gradients of the temperature profiles, which exhibit distinct variations under severe frosting conditions. The dataset was split into training and validation subsets with an 8:2 ratio. The model achieved prediction accuracies of 97.3% and 96.3% for the training and validation subsets, respectively, demonstrating robustness without overfitting.

The performance of the deep learning-based defrost initiation model was preliminarily evaluated in an industrial cold storage facility comprising four freezer rooms with footprints of 308.3, 304.2, 304.2, and 251.9 m² and a ceiling height of 8 m (Fig. 9). The internal temperature of the testbed was regulated at −20 °C. The system performance was compared against a conventional periodic defrosting strategy set at 6-hour intervals [36], [37].

The environmental conditions for both defrost control methods were maintained comparably; specifically, the average ambient temperatures and relative humidities were 21.1 °C and 75.6% RH during the periodic defrost control, and 22.1 °C and 73.2% RH during the AI-based defrost control.

TABLE 5. Hyper-parameters of the defrost initiation model.

Hyper-parameter	Size
Initialization	Glorot uniform initialization
Optimizer	Adam optimizer
Learning rate	0.0005
Loss function	Binary cross entropy
Metric	Accuracy

TABLE 6. Energy consumption of refrigeration system.

Component	Periodic defrost	AI-driven defrost
CDU and UC	24.2 MWh	23.3 MWh
Defrosting system	2.8 MWh	0.6 MWh
Total refrigeration system	27.0 MWh	24.0 MWh

Under the periodic defrosting strategy, the system executed a defrost operation every 6 hours regardless of the actual frosting status, resulting in unnecessary defrosting even when frost accumulation was negligible. Consequently, as detailed in Table 6, the total energy consumption over the two-week period was 27.0 MWh. In contrast, the AI-driven defrost model correctly diagnosed the frost growth rate under similar operating conditions, thereby preventing unnecessary defrosting operations. The proposed model demonstrated robustness and low sensitivity to environmental fluctuations. Specifically, the AI-driven model demonstrated robust predictive performance in determining the optimal defrost initiation timing without false predictions, despite a 16 °C deviation from the ambient conditions during acquisition of the training dataset. Furthermore, the model exhibited low sensitivity to environmental fluctuations during the testing period, operating across ambient temperatures of 19.6 °C to 24.1 °C and relative humidities of 62% RH to 93% RH. Consequently, the AI-driven defrost model reduced the number of defrosting cycles by 91.7% over two weeks, achieving a 78.6% reduction in the energy consumption of the defrosting system (from 2.8 MWh to 0.6 MWh) as shown in Fig. 10. Furthermore, the total energy consumption of the entire refrigeration system was reduced to 24.0 MWh, yielding an 11.1% reduction compared to the periodic defrosting method. These substantial energy savings are primarily attributed to avoiding power consumption associated with defrosting operations.

Specifically, by eliminating unnecessary defrosting, the proposed model effectively prevented the excessive power consumption required to reheat the cooled defrost water drained from the unit cooler. These findings indicate that the proposed model accurately identifies the optimal defrosting timing, thereby maximizing the energy efficiency of the refrigeration system. During the two-week evaluation, the AI-driven model executed classifications at 5-second intervals, generating a total of 241,920 inference instances. The AI model correctly executed the initiation signal 16 times, which correspond to 16 true positive events. For the remaining

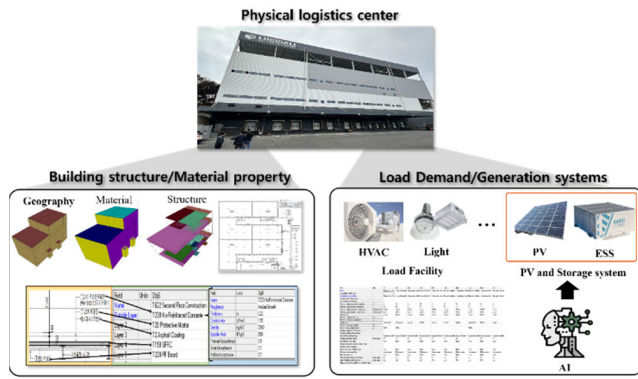


FIGURE 11. Digital twin system architecture of the cold-chain center.

241,904 timesteps, the model correctly maintained a non-trigger state, representing true negative events. Consequently, the model yielded zero false positives and false negatives. Although the AI-driven defrost model demonstrated robustness against environmental fluctuations (e.g., ambient temperature and relative humidity) and spatial variations among distinct freezer rooms, yielding no false predictions during the two-week testing period, the present investigation is constrained by its reliance on a single cold storage facility and an evaluation duration shorter than actual operational cycles. Consequently, subsequent studies are warranted to further validate the long-term reliability and generalizability across diverse cold storage facilities.

D. DEVELOPMENT OF AN AI-BASED EMS USING A DIGITAL TWIN

The digital twin system of temperature-controlled logistics centers refers to a virtual representation of the logistics facility that closely replicates the real operating environment [38]. This system enables quantitative estimation of temperature variations in the anterooms and internal storage areas, as well as the power consumption of individual components. The developed digital twin system provides a platform for systematically analyzing power consumption and temperature patterns under various operational scenarios. The generated datasets are then used to train AI-based EMS, allowing performance evaluation prior to deployment in the actual physical system. In particular, the digital twin enables simulation of electricity demand under extreme conditions, such as heat waves, with significantly increased electricity costs. Through this process, the AI-based EMS can be evaluated across a broader range of operating scenarios, improving reliability while reducing operational costs and risks, ultimately enhancing energy efficiency and cost-saving performance [39].

1) DIGITAL TWIN SYSTEM ARCHITECTURE AND CALIBRATION

The cold-chain digital twin system is designed using EnergyPlus, which specializes in building structure and energy

system modeling. Fig. 11 illustrates the architecture of the proposed cold-chain digital twin system. The developed digital twin system is broadly divided into building structure modeling and energy equipment modeling.

The building structure model is constructed based on the architectural drawings of the logistics centers and incorporates key material properties such as wall layer composition, thickness, surface temperature, thermal conductivity, density, and specific heat capacity. These parameters represent the static physical characteristics of the building and interact with external environmental conditions, such as ambient temperature, solar irradiance, and humidity, as well as HVAC operating states, thereby serving as critical factors for indoor temperature estimation. Consequently, this modeling enables the reproduction of the thermal inertia of logistics centers and supports accurate estimation of cooling loads and energy consumption associated with indoor temperature variations.

To ensure the high fidelity of these estimations and bridge the Sim-to-Real gap, key thermal and electrical parameters were strictly calibrated using empirical data collected from the physical facility. Based on thermodynamic models established in previous studies [40], the dynamic temperature variation within the cold-chain zone is governed by

$$C_Z \frac{dT_z}{dt} = Q_{inf} + Q_{others} + Q_{HVAC} \quad (2)$$

where C_Z represents the zone's thermal capacitance, T_z is the zone temperature, Q_{inf} denotes the heat gain from air infiltration, and Q_{HVAC} is the cooling energy provided by the HVAC system. Instead of employing a computationally heavy AirflowNetwork, air infiltration and door events were modeled using scheduled design flow rates (e.g., Zone-Infiltration:DesignFlowRate), aligning with practical calibration approaches [40]. The infiltration rate fluctuates based on the operational door-open schedule, transitioning between closed and open states to reflect actual logistics workflows.

Furthermore, the power consumption of the HVAC system, which constitutes the majority of the facility's energy use, was calibrated by identifying the performance curve of the compressor. Following established performance modeling methodologies [40], the compressor's power consumption P_{CP} is modeled as follows:

$$P_{CP} = C_1 + C_2 T_e + C_3 T_e + \dots + C_{10} T_c^3 \quad (3)$$

where C_1 to C_{10} are the coefficients of the empirical polynomial function, representing the compressor's power characteristics based on the evaporating temperature T_e and condensing temperature T_c .

These aforementioned parameters, including infiltration rates, thermal capacitance multipliers, and compressor power coefficients, were calibrated to fit the measured temperature and power profiles using heuristic optimization algorithms. For detailed mathematical formulations and the

comprehensive parameter identification procedure, readers are referred to [40].

In addition to thermal and HVAC modeling, the actual energy management and generation facilities, including an energy storage system (ESS) and photovoltaic (PV) generation, are incorporated into the digital twin system with the objective of reducing electricity costs via the AI-based EMS. The PV generation system derives power generation patterns based on temperature and solar irradiance using synoptic meteorological data provided by the Korea Meteorological Administration, and daily generation profiles are estimated under various weather-condition scenarios. Finally, the control of the ESS is performed by the proposed AI-based model, which determines the optimal charging and discharging power. Through this comprehensive design, the digital twin system effectively emulates both the thermodynamic behaviors and the renewable energy utilization strategies of the actual logistics center.

2) DESIGN OF THE AI-BASED ENERGY MANAGEMENT ALGORITHM

Based on the designed digital twin system, the AI-based EMS system was developed to perform optimal EMS control using an RL algorithm. The reinforcement learning problem is generally formulated as a Markov decision process (MDP) [39], which consists of a state space, an action space, state transition dynamics, and a discount factor. The agent observes the power consumption state of the virtual digital twin system and selects an action according to the given policy. Subsequently, a reward is returned based on the observed next state. The objective of the reinforcement learning algorithm is to maximize the expected cumulative reward, which is defined as follows:

$$J(\pi) = E_{\pi} \left[\sum_{t=0}^{\infty} \gamma^t r_t \right] \quad (4)$$

In this study, the DDPG algorithm [22], which is capable of handling continuous state and action spaces, is employed. DDPG is based on an actor-critic architecture, where the actor network determines a continuous action given a state s , while the critic network $Q(s, a|\theta^Q)$ approximates the state-action value function (Q-value). The critic network is trained based on the Bellman equation, and its loss function is defined as follows:

$$L(\theta) = E(s, a, r, s') [(Q(s, a|\theta^Q) - y)^2] \quad (5)$$

$$y = r + \gamma Q'(s', \mu'(s'|\theta^{\mu'}) | \theta^Q) \quad (6)$$

where Q' and μ' denote the target networks used to ensure stable learning. The actor parameters are updated according to the gradient of the Q-value output by the critic, thereby gradually improving the policy performance. Accordingly, the proposed AI-based EMS can efficiently address continuous control problems, such as ESS charging and discharging control, by employing the DDPG algorithm.

TABLE 7. Hyperparameter configuration for training of AI-EMS.

Category	type	value
Neural Network	Actor Network	[256, 400]
	Actor Target Network	[256, 400]
	Critic Network	[256, 256, 400]
	Critic Target Network	[256, 256, 400]
Learning Process	Actor Learning Rate	5.0×10^{-5}
	Critic Learning Rate	5.0×10^{-6}
	Soft Update	0.005
	Buffer Size	10,000
Convergence criteria	Max Episodes	2,000

3) DESIGN OF THE REINFORCEMENT LEARNING REWARD FUNCTION AND INPUTS/OUTPUTS

The RL algorithm is trained to maximize the expected cumulative reward. In this study, the proposed AI-based EMS is designed with the objectives of electricity cost reduction and peak load mitigation. Accordingly, the reward function is formulated by considering electricity pricing, peak load occurrence, and the operational constraints of the ESS, and is defined as follows:

$$r_{total} = \alpha r_{price} + \beta r_{soc} + \omega r_{load} \quad (7)$$

where α , β , and ω are weighting coefficients used to balance the relative magnitudes of the reward components. The defined reward function is designed to encourage ESS discharging during peak load periods and charging during off-peak periods. In addition, even outside peak load intervals, the reward structure considers scenarios in which charging may be performed to prevent electricity costs from exceeding predefined pricing thresholds. Furthermore, a reward or penalty associated with the state of charge (SOC) is incorporated to induce appropriate charging and discharging decisions when SOC reaches upper or lower limits.

The input state of the proposed DRL-based AI-EMS consists of the 6-minute averaged grid power consumption, the ESS charging/discharging power, and the estimated electricity price. The control action corresponds to the charging and discharging power command of the ESS. To account for inherent communication latency between field devices and the central control server, the operational time-step for both state observation and action execution is set to a one-minute interval. During operation, real-time measurements are continuously acquired through the AMI system and battery management system. To mitigate the impact of instantaneous sensor noise and enhance data reliability, the input state variables provided to the DDPG agent are not based on instantaneous values but are instead computed using a one-minute average of the collected data. This preprocessing step improves the robustness of the learning process by filtering high-frequency fluctuations. Furthermore, the use of averaged grid power over a 6-minute window enables the agent to capture short-term load trends while maintaining

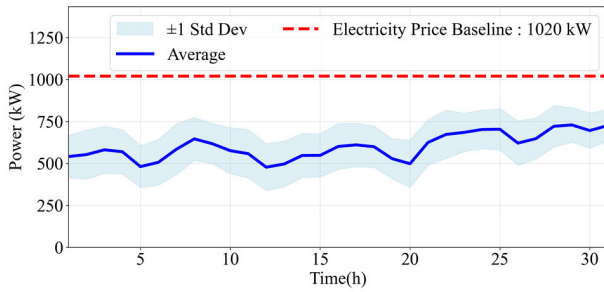


FIGURE 12. Average daily building power consumption profile during July 2025 with the ± 1 standard deviation range and the 1020 kW electricity demand charge baseline for peak demand analysis.

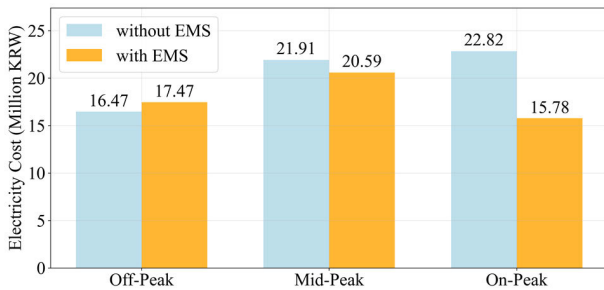


FIGURE 13. Comparison of electricity costs by TOU period before and after EMS operation, demonstrating the reduction in on-peak electricity cost through AI-based EMS coordinated control strategy.

TABLE 8. Electricity cost reduction achieved by the ai algorithm at the temperature-controlled logistics center in july.

Category	Electricity cost (KRW)	Cost Savings (KRW)	Reduction Rate (%)
Without AI Control	69,690,279	7,373,130	10.58%
With AI Control	62,317,149		

computational efficiency, which is critical for real-time EMS operation under practical deployment conditions.

4) HYPERPARAMETER CONFIGURATION AND TRAINING SETUP OF THE DRL FRAMEWORK

In the AI-EMS study, the hyperparameters of the DRL framework are categorized into three groups: neural network architecture, training procedure, and convergence criteria, as summarized in Table 7. The proposed algorithm is based on DDPG, which follows an actor–critic structure. The framework consists of two types of networks: the primary networks used for learning (actor and critic) and the corresponding target networks used for stable policy updates. The target networks share the same architecture as the primary networks to ensure consistency during training.

The actor network is designed as a two-layer fully connected neural network with hidden layer sizes of [256, 400]. Similarly, the critic network adopts a deeper structure with hidden layers of [256, 256, 400]. The learning rates are set to 5.0×10^{-5} for the actor and 5.0×10^{-6} for the critic, enabling stable convergence of both policy and value functions. For the training process, a replay buffer with a capacity of 10,000 samples is used. Considering that the system operates with a 1-minute time resolution, this buffer size corresponds to approximately one week of historical data, allowing the agent to learn from sufficiently diverse experiences. A soft update coefficient of 0.005 is applied to gradually update the target networks, improving training stability. Regarding convergence criteria, the training is conducted over 2,000 episodes. The final model parameters are selected based on the maximum cumulative reward achieved during training, ensuring optimal policy performance.

The AI-based EMS is implemented using PyTorch 2.2 and trained on a high-performance computing system equipped with an Intel(R) Core(TM) i9-10900X CPU, 192 GB RAM, and four NVIDIA GeForce RTX 3090 GPUs.

5) VERIFICATION OF THE AI-BASED ENERGY MANAGEMENT ALGORITHM AND COST SAVINGS ANALYSIS

The AI-based EMS trained using the digital twin system was deployed at an actual logistics center to analyze its energy-saving performance. The developed algorithm was evaluated from July 1 to July 31, during the summer season, when electricity consumption is highest. The cost savings were calculated based on the electricity tariff regulations of KEPCO. As shown in Fig. 12, the applied power did not exceed 1,020 kW, which corresponds to the minimum billing demand of the logistics center. This indicates that no peak power demand occurred during the test period, and consequently, no increase in electricity charges was incurred. These results demonstrate that the AI-based EMS effectively suppressed peak demand by discharging the ESS in accordance with the designed peak-related reward function.

Fig. 13 presents the converted electricity costs under KEPCO's tariff structure for off-peak, mid-peak, and peak load periods. During off-peak periods, the ESS performs charging operations, resulting in a slight increase in electricity costs compared to the case without AI-based control. However, during peak load periods, ESS discharging significantly reduces the overall electricity cost. Table 8 summarizes the electricity cost reduction results for the month of July, showing total cost savings of KRW 7,373,130 and a reduction rate of 10.58%. Therefore, the results verify that applying the AI-based EMS designed and developed using the digital twin system to an actual logistics center yields a meaningful reduction in electricity costs.

IV. RESULTS AND DISCUSSION

In this study, we addressed the critical challenge of reducing energy consumption in cold-chain logistics centers while

maintaining strict temperature stability for product quality preservation. To this end, an integrated CEMS was developed by combining three-dimensional temperature mapping, deep reinforcement learning-based UC control, intelligent defrost initiation, and a digital twin-based energy optimization framework. Through experimental validation and field demonstrations, the proposed system was systematically evaluated in terms of energy reduction, peak demand mitigation, and electricity cost savings under realistic operating conditions.

The results are summarized as follows:

- 1) UC Control (DDPG-Based) - 27.3% Power Reduction: The DDPG-based UC control strategy achieved a maximum reduction of 27.3% in average power consumption compared with conventional PID control while maintaining temperature stability. In extended field demonstrations, an average energy reduction exceeding 20% was consistently observed, indicating that optimized refrigeration operation provides a key opportunity for energy savings in cold-chain logistics centers.
- 2) Intelligent Defrost Initiation - 11.1% Reduction in Energy Consumption: Compared with periodic defrosting at fixed 6-hour intervals, the AI-based defrost diagnosis method effectively suppressed unnecessary defrost operations, reducing the 2-week total energy consumption from 27.0 MWh to 24.0 MWh (11.1% reduction). Specifically, the proposed approach significantly reduced the defrosting frequency by 91.7%, consequently achieving 78.6% energy savings in the defrosting system. Although the AI-driven model accurately determined defrost demand with high accuracy, the model requires substantial human intervention for data labeling during the training phase. As the dataset grows, the time and cost increase rapidly due to this intervention. Therefore, future studies should explore strategies such as unsupervised learning to minimize human intervention in data labeling prior to model training.
- 3) Digital Twin-Based ESS Operation Optimization – 10.58% Electricity Cost Reduction: By applying the reinforcement learning-based control strategy trained on the digital twin platform, a 10.58% reduction in monthly electricity cost was achieved in July, corresponding to a total saving of KRW 7,373,130. Furthermore, the maximum demand was maintained below 1,020 kW, demonstrating that the proposed control framework effectively mitigated demand-charge risks and contributed to stable electricity cost management.

The developed integrated EMS for cold-chain logistics centers is expected to serve as a representative domestic model by demonstrating energy-reduction-oriented smart temperature-controlled logistics facilities. Through large-scale field validation and practical dissemination, the proposed system is anticipated to promote widespread adoption across the industry and accelerate the advancement and modernization of domestic cold-chain logistics technologies.

A. ROBUSTNESS AND GENERALIZATION UNDER VARYING ENVIRONMENTAL CONDITIONS

The developed integrated EMS was empirically validated at a LogisALL cold-chain center located in South Korea. South Korea exhibits four distinct seasons, presenting a rigorous testbed with a wide spectrum of ambient temperatures ranging from 5 °C to 20 °C in spring and autumn, 24 °C to 35 °C in summer, and –10 °C to 5 °C in winter. In sub-zero cold storage facilities, HVAC use and load variability are highly sensitive to these external conditions. During winter, the minimal temperature differential results in lower HVAC operation rates and stable load variability. Conversely, the extreme ambient temperatures in summer lead to peak power consumption and maximum load volatility to maintain the target internal temperature.

By successfully demonstrating substantial and consistent energy and cost savings across these diverse, year-round environmental extremes, the proposed framework demonstrates its robustness and adaptability to severe ambient temperature fluctuations and load variability. This multi-season validation indicates that the RL agent is not overfitted to a specific static environment but has learned the underlying thermodynamic dynamics across a broad operational spectrum. These results demonstrate robustness across the seasonal operating conditions encountered at the investigated site. While this suggests that the framework is transferable in principle, its extension to facilities with different geometries, sensor layouts, and climatic conditions requires further validation, as discussed in Section IV-B.

B. LIMITATIONS OF THE PROPOSED INTEGRATED ENERGY MANAGEMENT SYSTEM

1) LIMITATIONS OF THE AI-BASED EMS

Although the proposed AI-EMS has been successfully deployed with significant energy savings, practical limitations remain regarding further refinement and generalizability. First, control performance heavily depends on the accuracy of the digital twin. While initially well-fitted to empirical data, the physical system's thermodynamic characteristics will gradually shift over time due to equipment aging and mechanical wear. This inevitably creates a “Sim-to-Real gap.” Therefore, a single deployment cannot guarantee permanent optimization; it requires continuous data collection and periodic recalibration of the digital twin to maintain performance throughout the system's lifecycle. Second, real-time control faces hardware and communication latency. Although a 1-minute time-step was applied to mitigate network delays, the RL agent was trained assuming instantaneous control execution. In actual field operations, an unavoidable physical latency of 5 to 10 seconds occurs between the AI server and edge devices. Incorporating this short hardware delay into the dynamic model of the training environment in future studies will further enhance control precision and energy optimization.

2) LIMITATIONS OF 3D TEMPERATURE MAPPING AND UC CONTROL

Beyond the EMS-level constraints discussed above, two limitations were identified in the 3D temperature mapping and UC control modules. First, the online training of the DDPG-based UC controller inherently involves an exploration phase before policy convergence. In this study, the associated risk was bounded by physically constraining the action space to the admissible setpoint range of $[-15, -5]$ °C and by the short convergence time of approximately two hours; nevertheless, control performance during this initial period is not guaranteed to exceed that of the incumbent controller, and facilities with slower thermal dynamics may require longer convergence. Incorporating formal safe-exploration mechanisms, such as supervisory safety layers or constrained RL formulations, remains a direction for future work. Second, the scalability of the proposed modules is subject to site-specific factors. Control efficiency was observed to depend on sensor placement, and the CNN-based 3D mapping model is trained for a specific warehouse geometry and sensor configuration; deployment to a facility with a different layout requires reconstructing the CFD dataset and retraining the model. Moreover, while inference of the trained networks is lightweight, periodic retraining relies on workstation-class computing resources that may not be available on-site, suggesting the need for lightweight retraining strategies or cloud/edge-based training architectures. Validating the framework across facilities with different structural and climatic conditions therefore is the primary direction for future work.

C. FUTURE PERSPECTIVES ON INTEGRATED COLD-CHAIN EMS

Looking ahead, future EMS for cold-chain logistics centers should evolve beyond conventional energy and carbon reduction toward integrated intelligent operational platforms that combine EMS, warehouse management systems (WMS), and order management systems (OMS). Rather than functioning solely as energy monitoring tools, next-generation CEMS platforms should comprehensively address product quality preservation, inventory and cargo flow management, thermal capacity characteristics according to product type and quantity, energy efficiency optimization, carbon emission reduction, operational stability, and regulatory compliance.

With the implementation of such integrated intelligent operational platforms, cold-chain logistics centers can transition from fragmented management structures—where energy, storage, and order processing are operated independently—to unified systems that enable real-time coordination and optimization of energy use, storage conditions, and operational workflows. This transformation will allow operators to move beyond simple electricity cost reduction and adopt advanced operational strategies, including customized cooling operations based on product thermal characteristics, energy-efficient facility management linked

to optimized logistics flows, and automatic control of refrigeration operation patterns in response to fluctuations in order volume.

The realization of intelligent integrated EMS platforms is expected to play a critical role in enhancing the competitiveness of the cold-chain industry, strengthening the sustainability of global supply chains, and ensuring the safety and reliability of food and pharmaceutical products. Consequently, continuous research and development efforts in this direction will be essential for establishing next-generation cold-chain logistics infrastructures that are both energy-efficient and resilient.

V. CONCLUSION

This study presents an integrated CEMS for coordinated thermal monitoring, refrigeration control, and energy management in cold-chain logistics centers. In the UC evaluation, DRL-based control reduced average power consumption by up to 27.3% relative to conventional PID control while maintaining temperature stability. Intelligent defrost initiation reduced total energy consumption of the refrigeration system by 11.1% over the two-week evaluation relative to fixed-interval defrosting. DT-based energy management reduced electricity costs by 10.58% during the July evaluation. These findings support the practical feasibility of the proposed CEMS for energy and cost management in cold-chain facilities. Future work will focus on improving long-term operational reliability through periodic DT recalibration to account for equipment aging and explicit modeling of control delays in the training environment. Additional priorities include safety mechanisms for the initial exploration phase of online DRL and computationally efficient retraining strategies. Validation across facilities with different geometries, sensor configurations, and climatic conditions will further assess the applicability of the framework beyond the investigated site.

ACKNOWLEDGMENT

(Young-Min Ju, Hyeonho Lee, and Sanghyeob Kwon contributed equally to this work.)

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