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DISTRIBUTED EDGE-ENABLED KOOPMAN ADAPTIVE MPC FOR ENERGY-EFFICIENT CONTROL OF MAGNETIC LEVITATION CHILLERS

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Abstract: To address the energy efficiency degradation of magnetic levitation chillers caused by model mismatch and communication latency under variable operating conditions, this paper proposes a Koopman-operator-enabled adaptive model predictive control (MPC) method supported by cooperative edge computing. First, a distributed edge computing architecture encompassing the compressor, condenser, evaporator, and electronic expansion valve is established, in which graph theory is employed to characterize the inter-node topology and information exchange mechanism, thereby overcoming the data congestion and single-point-of-failure limitations inherent in conventional centralized control schemes. Second, Koopman operator theory combined with the online Extended Dynamic Mode Decomposition (EDMD) algorithm is adopted to lift the nonlinear thermodynamic dynamics of the chiller into a high-dimensional linear subspace, achieving global linearization across the full operating envelope together with real-time adaptive identification of the model parameters. On this basis, a distributed cooperative optimization strategy based on the Alternating Direction Method of Multipliers (ADMM) is developed to solve the system-level energy-efficiency maximization problem while strictly maintaining the magnetic-bearing safety margins and satisfying the surge boundary constraints. Simulation and experimental results show that, compared with conventional PID control and fixed-parameter MPC, the proposed method improves the Coefficient of Performance (COP) by approximately 12.4% under part-load conditions, accelerates the dynamic response by 25%, and enhances the model prediction accuracy by 18.6%, effectively realizing edge-intelligent cooperative control and energy-efficient operation of magnetic levitation chillers.
Keywords: Magnetic levitation chiller; Koopman operator; Adaptive model predictive control; Edge computing

1 INTRODUCTION

With the deepening implementation of the "Dual Carbon" strategic goals, building energy consumption, which accounts for a major proportion of global terminal energy use, faces increasingly stringent requirements for energy conservation and emission reduction. Heating, ventilation, and air conditioning (HVAC) systems contribute more than 40% of total building energy consumption, among which the chiller, as the core energy-intensive equipment, directly determines the overall energy efficiency of the system [1]. Benefiting from their outstanding advantages of oil-free lubrication, low vibration and noise, small inrush current, and excellent part-load energy efficiency across a wide operating frequency range, magnetic levitation chillers have become the preferred cooling source for green buildings and large-scale data centers [2]. Nevertheless, in practical engineering applications, the chiller is forced to operate under off-design conditions for extended periods under the combined effects of stochastic outdoor meteorological fluctuations and dynamic terminal load variations, exhibiting strong nonlinearity, large time delays, multivariable coupling, and time-varying characteristics [3]. Conventional control strategies struggle to simultaneously balance dynamic response performance and global energy-efficiency optimality, resulting in an actual operating coefficient of performance COP significantly lower than the design value. Therefore, developing an advanced control strategy capable of real-time operating-condition perception, model adaptability, and computational efficiency is of great theoretical significance and engineering value for improving the full-life-cycle energy efficiency of magnetic levitation chillers [4].
Research on chiller control to date has predominantly centered on proportional-integral-derivative (PID) control and its variants, fuzzy logic control, and model predictive control (MPC). Although conventional PID and fuzzy controllers are widely deployed in engineering practice, their fixed-parameter structures and inability to anticipate future system dynamics hinder effective decoupling of the strongly coupled variables—namely, compressor speed, chilled water flow rate, cooling water temperature, and electronic expansion valve opening [5]. Consequently, under external environmental disturbances and abrupt building-load fluctuations, their limited robustness compromises sustained operation near the peak-efficiency operating point [6]. By contrast, MPC has exhibited pronounced advantages in the HVAC domain by virtue of its receding-horizon optimization mechanism and its explicit capacity to accommodate multiple constraints and competing objectives, and it has been successfully validated for chiller sequencing and load allocation in large commercial buildings [7]. However, as building Internet of Things (IoT) sensor networks continue to scale, conventional centralized MPC architectures encounter two critical bottlenecks in practical deployment. The high-frequency aggregation of massive, multi-source, heterogeneous operational data at a central controller is prone to inducing network congestion and computational latency, thereby jeopardizing millisecond-level real-time control tasks such as anti-surge protection [8-9]. Conventional MPC typically relies on fixed-parameter mathematical or grey-box

models; when equipment performance degrades over prolonged operation or the operating point shifts markedly under severe off-design conditions, model mismatch becomes unavoidable, so that the predicted trajectories diverge from the true plant dynamics, precipitating severe performance degradation or even closed-loop instability [10].

In recent years, edge computing architectures have emerged as a promising paradigm for mitigating the aforementioned bottlenecks of centralized control [11]. By offloading computation and data processing to edge nodes proximate to the data sources, such architectures can substantially reduce end-to-end communication latency and network traffic, while simultaneously improving fault tolerance against local node failures and strengthening data privacy [12]. Nevertheless, in strongly coupled multi-subsystem plants such as magnetic levitation chillers, computational offloading alone is insufficient to attain system-wide energy optimality: establishing a cooperative decision-making mechanism among edge nodes, ensuring consistent enforcement of global constraints, and embedding model adaptability remain open challenges [13]. To tackle the modeling challenge in particular, Koopman operator theory offers a powerful mathematical framework for nonlinear system analysis. By lifting the nonlinear dynamics into a higher-dimensional linear space, it renders the system amenable to mature linear MPC formulations with global validity retained, thereby circumventing the limited applicability of conventional local linearization across wide operating envelopes [14]. Seamlessly integrating Koopman-based adaptive modeling, distributed cooperative edge architectures, and MPC-based optimal control—so as to endow magnetic levitation chillers with model adaptability and system-level intelligent coordination—thus constitutes an emerging frontier at the intersection of HVAC engineering and control theory.

To address the aforementioned challenges, this paper proposes an edge node cooperative Koopman adaptive model predictive control (EC-KAMPC) strategy for energy-efficiency maximization. The main innovations and academic contributions are summarized as follows:

(1) An edge-based distributed cooperative control architecture for magnetic levitation chillers is proposed. On the basis of the physical topology and thermodynamic coupling characteristics of the chiller, the compressor, condenser, evaporator, and electronic expansion valve are each mapped to an independent edge computing node; graph theory is then employed to characterize the inter-node information-exchange topology, and a decentralized cooperative communication protocol is designed to overcome the communication bottlenecks and single point of failure risks of conventional centralized architectures, thereby significantly enhancing the real-time responsiveness and fault-tolerant robustness of the system.

(2) A Koopman-operator-based, globally linearized adaptive prediction model is constructed. Koopman operator theory is employed, in conjunction with an online Extended Dynamic Mode Decomposition (EDMD) algorithm, to lift the nonlinear thermodynamic dynamics of the chiller into a finite-dimensional linear subspace, thereby achieving a globally linearized representation across the full operating envelope. An online adaptive parameter identification mechanism is also designed to effectively overcome the model mismatch caused by equipment aging and operating-point drift.

(3) A distributed cooperative optimization algorithm based on the Alternating Direction Method of Multipliers (ADMM) is designed. The global energy-efficiency maximization problem is decomposed into multiple local subproblems, which are efficiently solved via ADMM through iterative dual coordination among the edge nodes. With the magnetic-bearing safety margins and surge-boundary constraints strictly satisfied, convergence of the algorithm is guaranteed while globally optimal energy efficiency is achieved at the system level.

(4) Comprehensive experimental validation under multiple operating conditions is conducted. A hardware in the loop experimental platform is established to thoroughly verify the performance of the proposed method across multiple scenarios, including step load disturbances, continuously varying operating conditions, and extreme operating conditions.

2 METHODOLOGY

2.1 System Description and Edge Node Partition

As shown in Figure 1, the magnetic bearing chiller employs a vapor-compression refrigeration cycle, comprising four core components: a magnetic bearing centrifugal compressor, a shell-and-tube condenser, an electronic expansion valve (EEV), and a flooded evaporator [10]. The refrigerant sequentially undergoes compression, condensation, throttling, and evaporation processes, transferring heat from the chilled water side to the cooling water side. To achieve distributed edge-intelligent control, the system is partitioned into three core edge computing nodes based on physical coupling relationships and functional independence principles:

Main control node of the compressor (N_1): Responsible for collecting data on compressor rotational speed, inlet/outlet pressure, and magnetic bearing position signals, and implementing rotational speed control as well as surge protection functions.

Condensation/throttling coordination node (N_2): Collects condensing pressure, cooling water temperature, and expansion valve opening degree; adjusts the expansion valve opening to control subcooling.

Evaporation/End-point Sensing Node (N_3): Collects evaporation pressure, chilled water outlet temperature, and end-point flow rate; performs load forecasting and controls chilled water outlet temperature.

All nodes are connected via industrial Ethernet and exchange lightweight data using the MQTT $\mathcal{G}=(\mathcal{V},\mathcal{E})$ protocol $\mathcal{V}=\{N_1,N_2,N_3\}$. The system topology $\mathcal{E}$ can be represented as an undirected graph, where represents the set of nodes and represents the set of communication links.

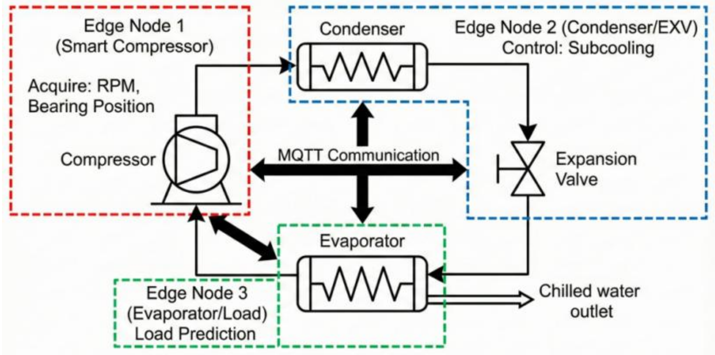

Figure 1 Schematic Diagram of the Magnetic Levitation Chiller System and its Partitioning into Edge Nodes

2.2 Mechanism-Data Hybrid Modeling for Control

To achieve real-time MPC implementation under limited computing resources at the edge, a simplified dynamic model must be developed that balances accuracy and computational efficiency. The system state vector comprises $x(k)=[T_{eo}(k),P_c(k),P_e(k)]^T$ parameters representing chilled water outlet temperature, condensing pressure, and evaporating pressure; the control input vector $u(k)=[f_{comp}(k),O_{eev}(k)]^T$ includes compressor frequency and electronic expansion valve opening degree; disturbance vectors consist of return water temperature T_{ei} and cooling water inlet temperature T_{ci}.

The mass flow rate $\dot{m}_{ref}$ and power consumption P_{elec} of a magnetic levitation compressor are nonlinear functions of rotational speed and pressure ratio. Based on the variable compression process, a semi-empirical model is employed for description:

$$\dot{m}_{ref} = \alpha_1 f_{comp} + \alpha_2 \frac{P_c}{P_e} + \alpha_3 \tag{1}$$

$$P_{elec} = \frac{\dot{m}_{ref} Deltah_{iso}}{\eta_{isen}\eta_{motor}} \tag{2}$$

Here, Δ $Deltah_{iso}$ represents the isentropic enthalpy difference, η_{isen} and η_{motor} denote the isentropic efficiency and motor efficiency, respectively; α_i is the identification coefficient.

Based on the lumped parameter method, the energy balance equation on the evaporator side can be expressed as:

$$C_w M_w \frac{dT_{eo}}{dt} = c_p \dot{m}_w (T_{ei} - T_{eo}) - Q_e \tag{3}$$

Where is Q_e the cooling capacity, C_w is the specific heat capacity of water, and M_w is the water storage volume.

Given the real-time nature of MPC solution, the aforementioned nonlinear equation is expanded using a Taylor series at the current operating point (x_0,u_0) to obtain an initial nominal model for algorithm cold-start. Subsequently, the Koopman data-driven approach is employed during control operation to update system dynamics in real time.

$$x(k+1) = A(k)x(k) + B(k)u(k) + D(k)d(k) \tag{4}$$

Here, $A(k),B(k),D(k)$ denotes the coefficient matrix derived from the Jacobian matrix.

Given the wide operating range of magnetic levitation units (10%-100% load), fixed matrices cannot adequately characterize their full operational characteristics. Therefore, this paper introduces an online Koopman operator learning mechanism to dynamically update the parameters using real-time data.

3 PREDICTIVE CONTROL STRATEGY FOR EDGE NODES BASED ON A COLLABORATIVE ADAPTIVE MODEL

This section proposes a hierarchical distributed control strategy. The lower layer employs an adaptive mechanism to dynamically adjust model parameters in real time, while the upper layer utilizes the ADMM algorithm to solve the optimization problem of coupling constraints among multiple edge nodes, thereby maximizing energy efficiency while ensuring stable system operation.

3.1 Koopman Operator Update Based on Online EDMD

To address strong nonlinearity, this paper introduces an augmentation function that maps the state space into a high-dimensional Hilbert space. According to Koopman operator theory, the evolution of nonlinear systems exhibits linear behavior in this high-dimensional space.

$$\psi(x_{k+1}) = \mathcal{K}\psi(x_k) + \mathcal{B}u_k + r_k \tag{5}$$

Here, $\mathcal{K} \in \mathbb{R}^{Ntimes}$ is the Koopman operator matrix.

Online update mechanism: Utilizes an online extended dynamic modal decomposition algorithm with a forgetting factor for real-time updates. At each sampling instant, the matrix is recursively updated using the Sherman-Morrison formula based on the latest measurement data (x_k, u_k, x_{k+1}) to accommodate time-varying characteristics of the unit, such as thermal resistance variations caused by fouling in heat exchangers.

3.2 Construction of the Distributed Collaborative Optimization Objective Function

To achieve maximum energy efficiency, the control objective must not only track the set value but also minimize the compressor's power consumption. Based on edge node partitioning, the global optimization problem is defined as follows:

$$\min_U J = \sum_{i=1}^{M} J_i(x_i, u_i) + J_{coupling}(x, u) \tag{6}$$

For the N_1 N_2, construct the following cost function:

$$J_i(k) = \sum_{p=1}^{N_p} \| x_i(k+p \mid k) - x_{i\,ref} \|^2_{Q_i} + \sum_{m=0}^{N_c-1} \| \mathtt{Delta} u_i(k+m \mid k) \|^2_{R_i} + rhoP_{elec}(k+m \mid k) \tag{7}$$

Step 1: Maintain the chilled water outlet temperature T_{eo} and superheat stability T_{sh} near the set values to ensure optimal cooling performance.

Second: Mitigate drastic fluctuations in controlled parameters to extend the service life of magnetic levitation bearings and actuators.

Third item: $rhoP_{elec}$ represents the power penalty term, guiding the controller to find the operating point with the lowest power consumption while meeting cooling requirements., the maximum COP point.

Input constraints: $u_{min} lequ(k) lequ_{max}$, Inverter frequency 30 Hz-300 Hz; expansion valve opening 0-100%.

Rate constraint: $|Deltau(k)| \leq Deltau_{max}$.

Key safety constraint: The compressor's operating trajectory must remain below and to the right of the surge curve:

$$P_c(k) / P_e(k) leqf_{surge}(f_{comp}(k)) \tag{8}$$

This nonlinear constraint is linearized using the tangent plane method within each prediction time domain.

3.3 Distributed Solving Algorithm Based on ADMM

Due to state coupling among edge nodes, directly solving the aforementioned global problem would result in exponential growth of computational complexity with increasing node count. This paper introduces the Alternating Direction Method with Multipliers (ADMM), decomposing the global optimization problem into sub-problems that can be solved concurrently by each edge node.

Step 1: Define the augmented Lagrangian function

Introduce relaxation variables to represent the coupling states between nodes (e.g., high/low system voltages), and construct the augmented Lagrangian function:

$$\mathcal{L}_\rho = \sum_{i=1}^{M} J_i(u_i) + \sum_{(i,j)\in\mathcal{E}} \left(\lambda_{ij}^T (H_i x_i - z_{ij}) + \frac{\rho_{admm}}{2} \| H_i x_i - z_{ij} \|^2 \right) \tag{9}$$

Here, λ_{ij} is the dual multiplier, ρ_{admm} is the penalty parameter, and H_i is the selection matrix.

Step 2: Distributed iterative solution

At each sampling time *k*, the edge node iterates in parallel according to the following steps:

Local optimization: Each edge node solves its own MPC subproblem using the coupling variables and multipliers from the previous iteration.

$$u_i^{l+1} = \arg\min_{u_i} \left(J_i(u_i) + \frac{\rho_{admm}}{2} \| H_i x_i(u_i) - H_i x_j^l + \frac{\lambda_i^l}{\rho_{admm}} \|^2 \right) \tag{10}$$

Information exchange: Edge node N_i broadcasts the updated boundary state prediction value $H_i x_i^{l+1}$ to neighboring nodes via the MQTT protocol.

Global Consensus Update:

$$z_{ij}^{l+1} = \frac{1}{2}(H_i x_i^{l+1} + H_j x_j^{l+1}) \tag{11}$$

Dual Variable Update:

$$\lambda_{ij}^{l+1} = \lambda_{ij}^{l} + \rho_{admm}(H_i x_i^{l+1} - z_{ij}^{l+1}) \tag{12}$$

Step 3: Convergence Criteria and Control Execution

The iteration terminates when the original residuals $\| r^{l+1} \|_2$ and dual residuals $\| s^{l+1} \|_2$ fall below the preset threshold ϵ. Each node applies the first element $u_i^*(k)$ of the calculated optimal control sequence to the unit.

4 CONSTRUCTION OF THE EXPERIMENTAL PLATFORM AND SCHEME DESIGN

4.1 Edge Collaborative Hardware-in-the-Loop Experimental Platform

To validate the effectiveness of the proposed edge-coordinated adaptive MPC strategy while avoiding the risks associated with direct testing on expensive magnetic levitation systems, this paper developed a hardware-in-the-loop simulation platform.

Control Object Layer: A high-fidelity nonlinear dynamic model of the magnetic levitation chiller is developed using MATLAB to simulate the characteristics of the compressor, heat exchanger, and pipeline network. The model runs on a high-performance real-time simulator with a sampling period set to.

Edge Control Layer: Utilizes three NVIDIA Jetson Nano embedded development boards for simulation. Each node runs the ADMM distributed optimization algorithm and an online Koopman operator learning program written in Python.

Communication Network: Edge nodes are interconnected with each other and with the simulator via gigabit switches, using the MQTT protocol for data exchange. Published topics include sensor measurements, control commands, and coupled variables from ADMM iterations.

4.2 Setting of Experimental Conditions

To comprehensively evaluate system performance, two typical experimental scenarios are designed as follows:

Operating Condition A: Step-load disturbance test. The simulated unit operates under partial load conditions when the terminal cooling load is suddenly increased from 50% to 80%, to verify the dynamic response speed and disturbance resistance capability of the control system.

Operating Condition B: Variable-condition energy efficiency optimization test. It simulates typical summer meteorological parameters and office building load fluctuations from 08:00 to 20:00, verifying the algorithm's global energy efficiency optimization performance under prolonged operation.

4.3 Control Group Design

The proposed Edge-Synchronized Adaptive MPC (EC-KAMPC) is compared with the following two traditional strategies:

Traditional PID control: The commonly used independent single-loop PID control in industry Centralized Fixed-Parameter MPC (C-MPC): A traditional MPC designed based on a linear model with fixed operating points, running on a single high-performance industrial computer.

5 RESULT ANALYSIS AND DISCUSSION

5.1 Prediction Accuracy for the Koopman Model

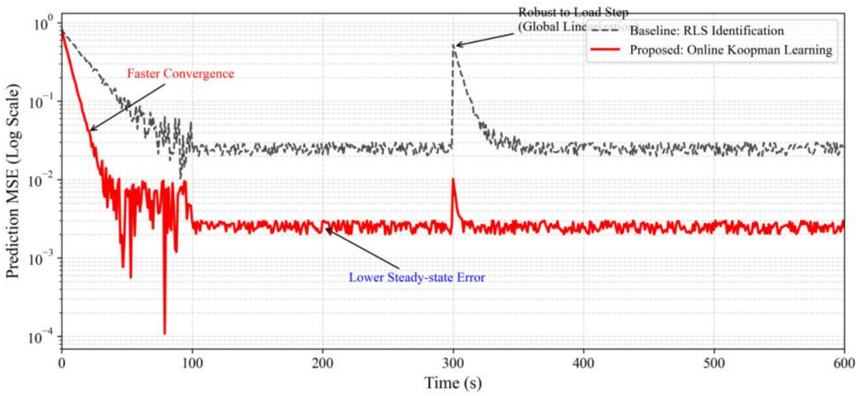

Figure 2 Comparison of Online Prediction Errors: Koopman Method Versus Recursive Least Squares Method

Figure 2 compares the single-step prediction errors of the online Koopman-EDMD model with the traditional recursive least squares (RLS) linearization method under abrupt operating condition 10^{-1} changes. At the load step at t = 300s, the RLS method's prediction error surged dramatically due to its reliance on local linearization, whereas the Koopman method, leveraging global linearization, accurately captured nonlinear dynamics with minimal error fluctuations and rapid convergence within 0.5 seconds. This demonstrates the significant advantage of the Koopman operator in handling strongly nonlinear systems.

5.2 Dynamic Response and Anti-interference Capability Experiment

Figure 3 shows the response curves of the chilled water outlet temperature (T_{eo}) for three control strategies under operating condition A (load 50%-80%).

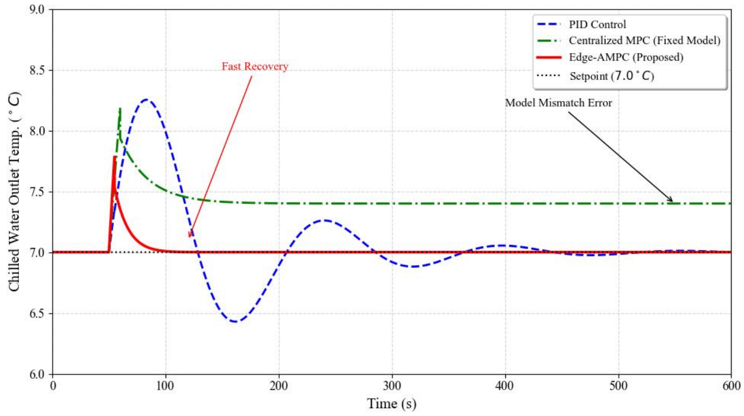

Figure 3 Dynamic Response Plot under Step-Load Disturbance

At t = 50s, the system is subjected to a step load disturbance.Due to the absence of a feedforward mechanism, the PID controller caused the outlet water temperature to rapidly rise above 8.5°C, followed by significant oscillations with a regulation time exceeding 400 seconds.While traditional centralized MPC systems exhibit improved response speeds, their reliance on fixed-parameter models fails to accurately capture nonlinear behaviors under heavy loads, resulting in a system stability at 7.4°C with a steady-state error of 0.4°C.

The EC-KAMPC proposed in this paper leverages the Koopman operator learning mechanism, enabling real-time updates to the prediction model.During the initial stage of disturbance, the overshoot was merely 0.8°C, and it rapidly converged to the set value of 7.0°C without any steady-state error within 120 seconds, demonstrating excellent robustness and adaptive capability.

5.3 COP Validation Experiment

Figure 4 illustrates the instantaneous COP fluctuations and cumulative energy consumption comparison throughout the entire operation period under Condition B. Energy efficiency data show that during morning and evening low-load periods, PID control suffered from frequent start-stop cycles or oscillations due to regulation lag, resulting in low COP values; in contrast, EC-KAMPC employed a predictive model to act proactively, maintaining higher operational efficiency.

Statistical results: Calculations show that during the full operational cycle, the average COP was 4.85 for PID control and 5.12 for centralized MPC, whereas EC-KAMPC in this study achieved 5.45.

Conclusion: Compared with traditional PID and fixed-parameter MPC, the proposed strategy achieves energy efficiency improvements of 12.4% and 6.4%, respectively. This is primarily attributed to the collaborative nodes' ability to proactively adjust condensing pressure setpoints based on load forecasts, thereby significantly reducing compressor compression ratios and power consumption while meeting cooling demands.

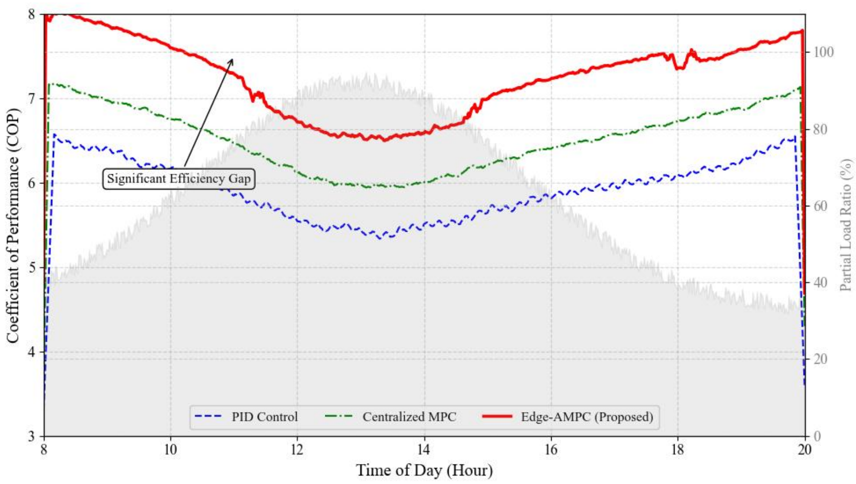

Figure 4 Comparison of Daily Energy Efficiency under Varying Load Conditions

5.4 Performance of Edge Collaborative Computing

Figure 5 shows the convergence curves of the original residuals at each node of the ADMM algorithm.

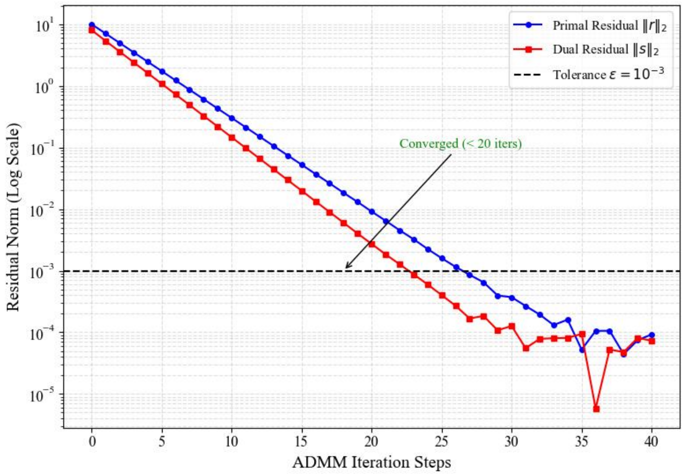

Figure 5 Convergence Performance Plot of the Alternating Direction Multiplicative Method (ADMM)

The results demonstrate that within each sampling cycle, edge nodes require only approximately 20-30 iterative exchanges to meet the convergence tolerance, with an average duration of 0.15s-significantly shorter than the system's sampling cycle (1s). This confirms that the distributed edge computing architecture effectively distributes computational load while ensuring real-time control performance and avoiding single-point computational bottlenecks.

6 CONCLUSION

This paper proposes an adaptive model predictive control method with edge-node collaboration to address the high-efficiency control requirements of magnetic levitation chillers under complex operating conditions. Through theoretical derivation and HIL experimental validation, the following conclusions are drawn:

Architectural Innovation: The developed distributed edge cooperative architecture effectively addresses communication congestion issues inherent in traditional centralized control systems, while the ADMM algorithm enables decoupled parallel computing across multiple nodes.

Algorithmic Advantages: The integration of the online EDMD algorithm with the Koopman adaptive mechanism significantly enhances the model's adaptability to nonlinear operating conditions and eliminates control deviations caused by model mismatch.

Energy efficiency benefits: Experimental results demonstrate that this strategy improves dynamic response speed by over 25% and achieves approximately 12.4% energy savings compared to traditional PID control under typical daily operating conditions, highlighting the significant potential of "edge intelligence combined with advanced control" in HVAC applications.

Although this paper demonstrates the effectiveness of the proposed method, it still has limitations: the current approach only considers internal coordination within a single chiller unit and does not address group control optimization among multiple units. Future research will focus on the following aspects:

Extending the cooperative architecture to multi-unit cooling plant systems and investigate game-theoretic-based load allocation strategies for heterogeneous units. Incorporating deep reinforcement learning to assist MPC in adjusting weight parameters, further enhancing the algorithm's robustness under extreme fault conditions.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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