Energy Proceedings
Vol 60, 2025
ISSN 2004-2965

Iterative Machine-Learning-Based Model Predictive Control for Split Air Conditioners: A Cloud-Based Field Demonstration

Li Wei[1], Dong Suning [2,3], Li Kun[1], Jia Qiwei[1], Liu Shiyong[1], Zheng Wei[2,3], Wan Man Pun[2,3], Xu Mingjun[2,3], Yang Shiyu[2,4*]

1 Qingdao Haier Air Conditioner Gen. Co., Ltd., Qingdao, China, 266101

2 Hefei Xingyue Intelligent Control Technology Co., Ltd., Hefei, China, 230601

3 School of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore, 639798

4 State Key Laboratory of Electrical Insulation and Power Equipment, Xi'an Jiaotong University, Xi'an, China, 710049

(Corresponding Author: yangshiyu@xjtu.edu.cn)

ABSTRACT

In recent years, the Model Predictive Control (MPC) for building systems has received extensive attention, but few studies have applied machine learning (ML)-based MPC to split air conditioners. This paper presents a field implementation of an iterative ML-based MPC with a cloud-based framework to demonstrate its feasibility and energy-saving potential for split air conditioners. The measured results show that, compared with conventional PID control, MPC achieved an average energy-saving rate of 22.9%. In addition, iteratively updating the predictive model enables MPC to achieve enhanced thermal comfort. Hence, this paper demonstrates the energy-saving capability of ML-MPC for split air conditioners and potential scalable cloud-based deployment in residential buildings.

Keywords: Split Air Conditioner, Model Predictive Control (MPC), Machine Learning (ML), Energy Efficiency

1. INTRODUCTION

Energy consumption in buildings represents 20–40% of the total energy use in developed countries, with residential air conditioning contributing a substantial share of this demand [1]. This has motivated extensive research on intelligent control strategies aimed at improving indoor thermal comfort while reducing energy use, with particular attention given to model predictive control (MPC) [2].

MPC has been widely investigated in commercial buildings for its ability to anticipate future thermal loads and optimize control actions under system constraints [3]. Numerous studies have confirmed its effectiveness in intelligent building Heating, Ventilation, and Air Conditioning (HVAC) control, achieving notable energy savings while improving thermal comfort [4]. For example, in a GEOTABS office building in Belgium, high-fidelity physical modeling combined with cloud-based MPC demonstrated advantages in both energy savings and thermal comfort [5]. Similarly, Yang et al. applied MPC systems in an office [6] and a lecture theatre [7], achieving higher energy savings compared to conventional building management systems (BMSs) in both buildings.

Machine learning (ML) models, particularly Recurrent Neural Networks (RNNs), have emerged as powerful tools for capturing the nonlinear and time-dependent nature [8]. ML-Based MPC frameworks that integrate RNN have shown promising results, achieving superior temperature regulation and energy performance compared to traditional rule-based or PID control strategies [9]. However, most existing studies have concentrated on commercial buildings with centralized HVAC systems.

Despite the growing interest in intelligent control, there is still limited research on the deployment of ML-based MPC in residential air conditioning, especially for common household split air conditioners. These systems lack integrated BMSs and have limited sensing and computational capabilities, making on-site MPC deployment with real-time predictive model iteration more challenging. This gap presents a clear opportunity for exploring ML-based MPC integration in household settings, particularly under real-world conditions and using cost-effective hardware.

This study investigates the feasibility of applying an ML-based MPC framework to household split air conditioners, which are widely used in residential buildings. A control system combining Iterative Recurrent Neural Network with Model Predictive Control (IRNN-MPC) was developed and tested in real-world scenario. The field demonstration evaluates its performance and underscores its potential value in practical applications.

This is a paper for the 5th Applied Energy Symposium and Forum: Renewable Energy Matrix (REM2025), Oct. 29-31, 2025, Yancheng, China.

The main contributions of this paper are as follows: (1) To the best of the authors' knowledge, this is the first field demonstration of ML-based MPC for split air conditioners, with its control performance and energy consumption benchmarked against mainstream PID control. (2) To continuously enhance the fidelity of the predictive model, Iterative Recurrent Neural Network was employed as the core predictor within the MPC framework. (3) Given the limited local computing capacity of split air conditioners, predictive model iteration and control command execution were designed to operate within a cloud-based framework.

2. METHODOLOGY

2.1 Overview

Figure 1 shows the overview of the cloud-based field demonstration with IRNN-MPC system. The MPC system is deployed on the cloud and controls the local air conditioner remotely. Communication with the units is established through an Internet of Things (IoT) gateway, while real-time weather data are retrieved via APIs from open-source platforms. The cloud MPC contains three functional modules: the MPC module, the ML-based predictive model iteration module, and the database module. The MPC module computes and issues the optimal compressor frequency command in real time. The ML-based predictive model iteration module trains and updates models that capture the thermal dynamics of the room. The database module stores operational data, control commands, and weather information.

To ensure both intelligent optimization through MPC and operational reliability on the local side, the control system supports switching between AI and non-AI mode. In AI mode, the local controller executes compressor frequencies generated by the MPC. In non-AI mode, or if the cloud server connection is lost for more than 3-min, the controller automatically reverts to the original PID control. For short-term signal loss, the local controller continues to use the last control command from MPC.

To leverage the continuously expanding dataset and enhance predictive model fidelity, the ML-based model is iterated during online operation. As illustrated in Figure 2, operational data from the indoor and outdoor units, together with real-time weather information, are collected via the IoT gateway and uploaded to the cloud

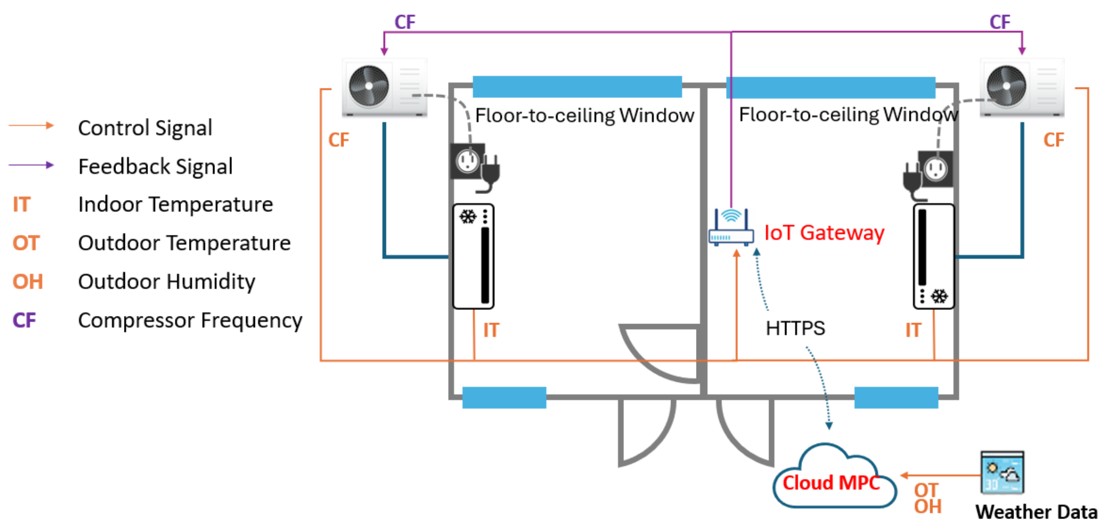


Fig. 1 Overview diagram of the cloud-based field demonstration with IRNN-MPC system

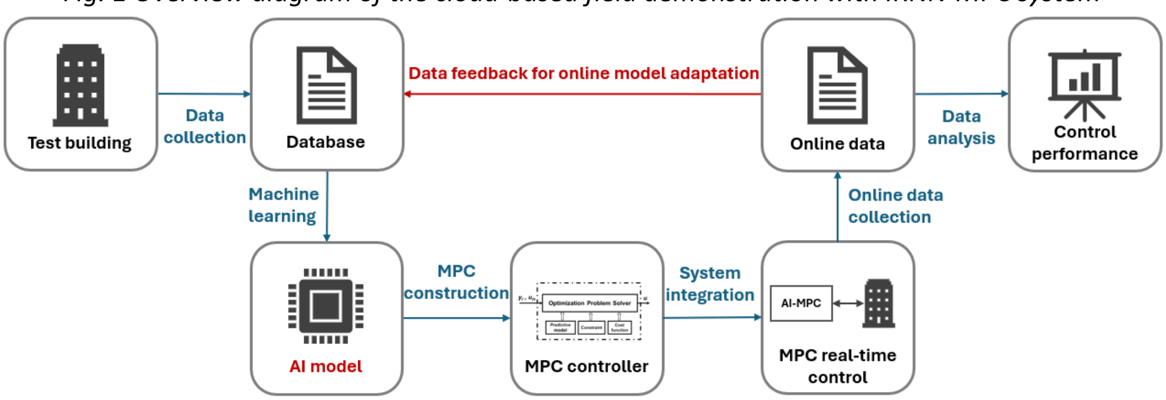


Fig. 2 An overview of the ML-based predictive model iteration

database for model training and iteration. Each iteration uses all the accumulated data in the database. Since RNN-based MPC has demonstrated effectiveness in numerous studies, this work adopts an RNN as the predictive model (Section 2.4). The model is designed to predict indoor temperature dynamics over a 16-minute horizon, with a temporal resolution of 2 minutes and an MPC prediction horizon of eight.

2.2 Testbed

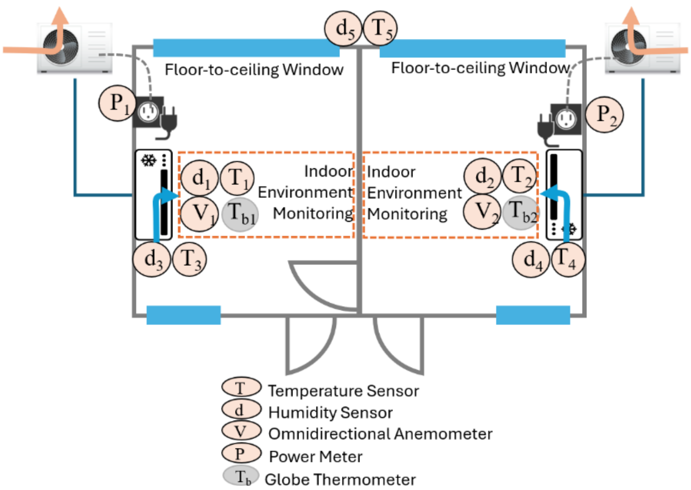
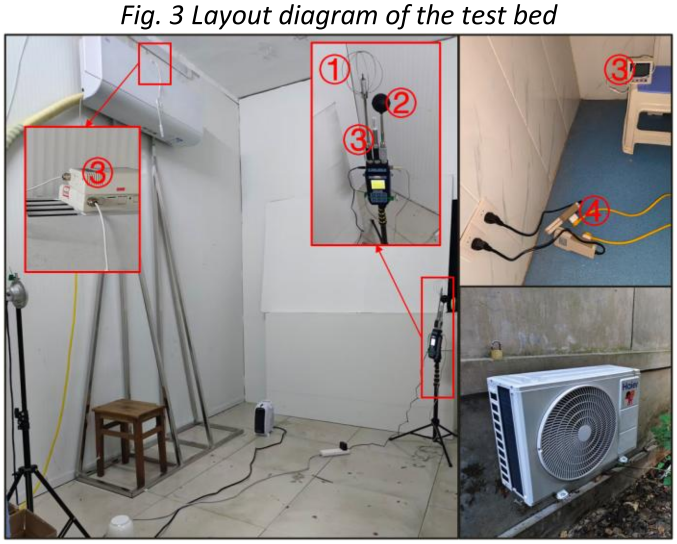


Fig. 3 Layout diagram of the test bed



①Air speed ②Globe temp sensor ③temp & humidity sensor ④Power meter

Fig. 4 Internal view & external components of testbed

Indoor thermal comfort is evaluated using the Predicted Mean Vote (PMV) index [10], which is derived from air temperature, humidity, air velocity, and mean radiant temperature. These variables were measured by instruments installed in the test rooms, temperature sensor, humidity sensor, anemometers and globe thermometers, as shown in Figure 3. The complete PMV model involves nonlinear iterative computations, particularly for estimating clothing surface temperature, which can impose a high computational burden for real-time optimization. To address this, a simplified approach is adopted by mapping the PMV target (i.e. PMV=0 indicating the thermally neutral state) into a reference indoor temperature T_{ref} . Two of the PMV input parameters, indoor air temperature and radiant temperature, were directly obtained from the return air outlet of the indoor unit. Relative humidity was also measured in real time. Clothing insulation and metabolic rate are assumed to be 1.25 clo and 1.0 met, respectively.

In this study, to verify the effectiveness of IRNN-MPC for split air conditioners, a field demonstration was conducted on a dual-room test platform located in Changsha, Hunan. One room was controlled by a conventional PID controller, while the other was operated by the IRNN-MPC, as illustrated in Figure 3. The two adjacent rooms share identical configurations, are directly exposed to the outdoor environment, and each has a floor area of 7.7 m², making them suitable for comparative studies. For cross-validation, the PID and MPC controllers were periodically swapped between the two rooms. Figure 4 shows the on-site deployment in one of the rooms. The test air conditioner is a wall-mounted inverter heat pump split unit produced by Haier, consisting of the indoor unit KFR-35G/Z500-1Pro and the outdoor unit KFR-35W/D2-1.

2.3 MPC formulation

The objective of the MPC optimization problem in this study is to minimize energy consumption, thermal discomfort, and violations of soft constraints. Over a prediction horizon N, the cost function is formulated as follows, as shown in Eq. (1)

$$J = Minimize(\sum_{k=0}^{N} F_{i,t+k|t}^{2} + \sum_{k=0}^{N}(WT_{t+k|t} - T_{\mathrm{ref}})^{2} + \sum_{k=0}^{N} W_{\epsilon}(\epsilon_{t+k|t})^{2}), \tag{1}$$

Where J refers to the objective function; $F_{i,t+k|t}^{2}$ represents the proxy of energy consumption, expressed as the squared compressor frequency; W is the weight associated with temperature deviation, which balances energy saving and comfort; $T_{t+k|t}$ is the predicted indoor temperature, and T_{ref} is the thermally neutral reference temperature calculated from the PMV model; N is the prediction horizon, indicating the number of future steps considered in the optimization; and $\epsilon_{t+k|t}$ is the slack variable that allows limited violations of the thermal comfort bounds and is penalized in the cost function.

In addition to the cost function, the optimization problem is governed by several constraints and the predictive model. Indoor temperature is constrained within specified limits, and minor violations are tolerated through the slack variable with associated penalties. The compressor frequency, serving as the manipulated variable, is bound by both amplitude and rate-of-change constraints to guarantee safe and stable operation. The predictive dynamics are provided by a RNN [11] , which forecasts indoor temperature evolution using past states, control commands, and external disturbances, i.e., outdoor temperature [12]. The reference trajectory T_{ref} is continuously updated based on the PMV model, enabling the controller to capture variations in environmental conditions and occupant comfort requirements.

In this field demonstration, the sampling period is set to 1-min, the control interval is set to 2-min, the prediction horizon is set to 8, and the control horizon is set to 2 for reducing the dimensionality of the optimization problem. The compressor frequency setpoint serves as the manipulated variable of the MPC, with its upper and lower bounds specified by equipment constraints and its rate of change constrained to avoid rapid fluctuations. The weighting factors are tuned such that the energy term weight is set to 1, the comfort term weight W is set to 3, and the soft-constraint penalty weight W_{ϵ} is set to 10000, ensuring strict adherence to thermal comfort limits. This configuration guarantees real-time feasibility of optimization while effectively balancing the dual objectives of energy saving and thermal comfort. The Sequential Least Squares Programming (SLSQP) algorithm is employed in MPC module to solve this optimization problem.

2.4 Machine-learning model

A recurrent neural network (RNN) was employed to construct the temperature prediction model. The initial model was trained on initial data collected between February 24 and March 4. Key variables were normalized for numerical stability (compressor frequency divided by 100; outdoor and indoor temperatures divided by 50). The dataset was then randomly split into training and validation sets at an 8:2 ratio, with the training set used for parameter learning and the validation dataset for early stopping and model selection.

Fig. 5 shows the schematic diagram of the RNN. The model takes the most recent 5 steps of three variables, which include compressor frequency, outdoor temperature, and indoor temperature, to predict the indoor temperature one step ahead. The time step of RNN is 2 minutes. The prediction process can be expressed as follows:

$$T_{in}(t+1) = RNN\left([f_{\text{comp}}, T_{out}, T_{in}]_{t-4:t}\right), \tag{2}$$

where $f_{comp}, T_{out}, T_{in}$ refer to compressor frequency, outdoor air temperature (℃) and indoor air temperature (℃)

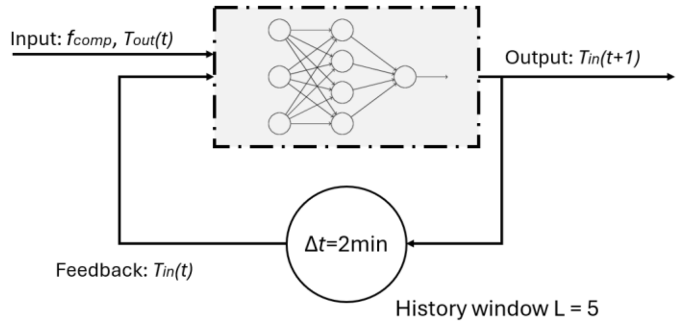


Fig. 5 Structure of the RNN predictor for MPC

The model was trained using the Adam optimizer with a mean absolute error (MAE) loss, together with an early-stop strategy constrained by patience of 16. To improve robustness, five independent runs with different initializations were conducted, and the model achieving the lowest validation error was selected for deployment in the MPC framework.

2.5 Experimental arrangements

Table 1
Model Iteration Schedule

Cases	Model	Training Dataset
1-4	Initial Model (Model_v0)	Initial Data
5-7	1st Iteration (Model_v1)	Data from Cases 1-4
8-10	2nd Iteration (Model_v2)	Data from Cases 5-7
11-13	3rd Iteration (Model_v3)	Data from Cases 8-10
14-16	4th Iteration (Model_v4)	Data from Cases 11-13
17-19	5th Iteration (Model_v5)	Data from Cases 14-16
20-21	6th Iteration (Model_v6)	Data from Cases 17-19

For comparison, the left and right rooms alternately adopt different control strategies: one room uses the existing PID control, while the other room operates under the proposed IRNN-MPC control strategy. A total of 21 experiment cases were conducted, with 11 cases assigning IRNN-MPC to control the right room and PID for the left room, and the remaining 10 experiments configured in the opposite way. Each case lasted for 6 hours, with at least 30-min natural ventilation between 2 cases to set up the initial condition of each case. As the outdoor temperatures were relatively high during the testing period in March, fresh air was introduced at a flow rate of 400 m³/h to increase the cooling load. The detailed experiment schedule and the model Iteration table are presented in Table 1.

3. RESULTS

3.1 Energy consumption performance

Due to the failure of the PID controller to reach the setpoint on case 16, data from this case was excluded for analysis. Based on the measurements from laboratory power meters, the MPC system demonstrated significant energy-saving potential compared to the conventional PID control. Statistical results show that, in nearly all cases, the energy consumption of MPC is significantly lower than that of PID. This highlights that MPC consistently outperformed PID in terms of energy efficiency, regardless of which room it was applied to. Overall, the average energy savings of the MPC controller against PID controller is 22.9%, confirming its superior capability for energy reductio.

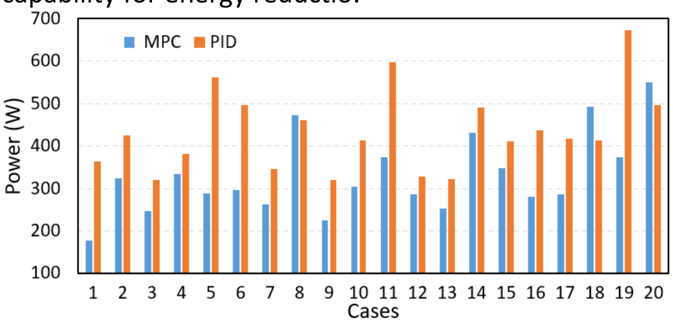


Fig. 6 Average power of each case: MPC vs PID

3.2 Indoor temperature performance

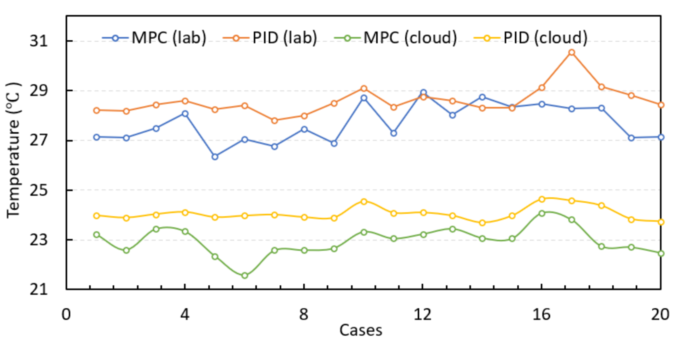


Fig. 7 Average Indoor Temperature: MPC vs PID

According to the laboratory measurements, the average of the standard deviations (STD) of indoor temperature across multiple cases under MPC control was 1.19, while it was 0.91 under PID control. This increase in variation can be attributed to two main factors: the temperature discrepancy between the cloud-received value and the real-time measured room temperature in the laboratory due to communication latency, and the fact that the MPC controller targets the PMV index instead of temperature directly. Specifically, the average indoor temperature across all cases with MPC is 27.72 °C, while it is 28.56 °C with the PID controller.

3.3 Predictive model iteration

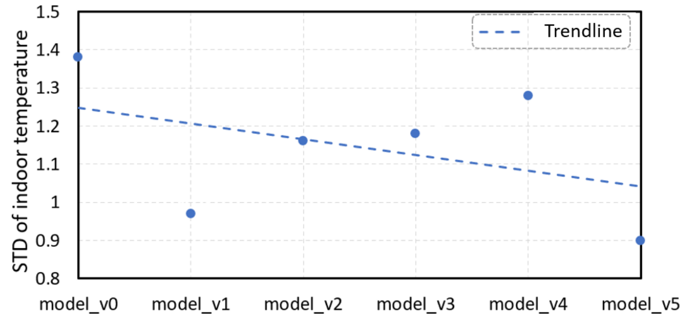
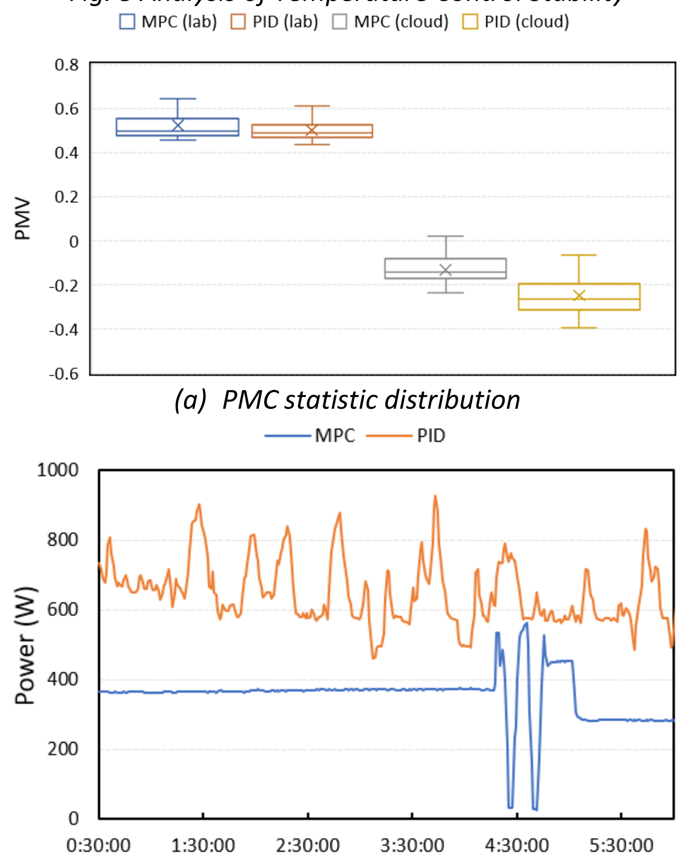


Fig. 8 Analysis of Temperature Control Stability



(a) PMC statistic distribution

(b) Power curve of air conditioners

Fig. 9 Comparison in Case 20: MPC-controlled room vs PID-controlled room

To evaluate the adaptation progress during predictive model iteration, the standard deviation of indoor temperature was averaged across cases controlled with the same predictive model, as shown in Figure 8. Since the last three cases were conducted one week later as supplementary experiments, only the first five iterative predictive models are analyzed. Compared with the initial model, the iterated model gradually improved the stability of temperature control, indicating an enhancement in prediction accuracy and effectiveness of model iteration.

As shown in Fig. 9, after multiple iterations, the MPC achieved a stable state ensuring significant energy savings without compromising thermal comfort, as evidenced by the comparable PMV levels under MPC and PID. The first 30 minutes of data are excluded due to the warm-up period needed for indoor temperature stabilization.

CONCLUSIONS

This paper demonstrates a cloud-based field application of iterative ML-Based MPC for split air conditioners. Experimental results show that under MPC control, the average energy saving rate against PID reaches 22.9%. As the predictive model iterated, the temperature stability of MPC keeps improving, showing good adaptive and self-learning ability of predictive model iteration. The results confirm that MPC brings clear improvements in energy saving without compromising the comfort of residents, demonstrating strong potential in terms of intelligence and adaptability. Nevertheless, several limitations remain. First, the performance of the RNN model relies heavily on the quality of historical and real-time data. Inaccurate sensors or delays in cloud communication may negatively impact prediction accuracy and control stability. Second, hardware constraints should be considered (i.e., insufficient compressor performance at low-frequency operations, which may hinder the execution of optimized control actions). In the future, if improvements can be made in model generalization and cloud-edge protocol efficiency, this method is expected to be applied in a wider range of household and building energy-saving scenarios.

REFERENCE

[1] Pérez-Lombard L, Ortiz J, Pout C. A review on buildings energy consumption information. Energy and Buildings 2008;40:394–8. https://doi.org/10.1016/j.enbuild.2007.03.007.

[2] Hilliard T, Swan L, Qin Z. Experimental implementation of whole building MPC with zone based thermal comfort adjustments. Building and Environment 2017;125:326–38. https://doi.org/10.1016/j.buildenv.2017.09.003.

[3] Bird M, Daveau C, O’Dwyer E, Acha S, Shah N. Real-world implementation and cost of a cloud-based MPC retrofit for HVAC control systems in commercial buildings. Energy and Buildings 2022;270:112269.

[4] Yang S, Wan MP, Ng BF, Zhang T, Babu S, Zhang Z, et al. A state-space thermal model incorporating humidity and thermal comfort for model predictive control in buildings. Energy and Buildings 2018;170:25–39.

[5] Drgoňa J, Picard D, Helsen L. Cloud-based implementation of white-box model predictive control for a GEOTABS office building: A field test demonstration. Journal of Process Control 2020;88:63–77. https://doi.org/10.1016/j.jprocont.2020.02.007.

[6] Yang S, Wan MP, Ng BF, Dubey S, Henze GP, Rai SK, et al. Experimental study of a model predictive control system for active chilled beam (ACB) air-conditioning system. Energy and Buildings 2019;203:109451. https://doi.org/10.1016/j.enbuild.2019.109451.

[7] Yang S, Wan MP, Ng BF, Dubey S, Henze GP, Chen W, et al. Experimental study of model predictive control for an air-conditioning system with dedicated outdoor air system. Applied Energy 2020;257:113920. https://doi.org/10.1016/j.apenergy.2019.113920.

[8] Shakhovska N, Mochurad L, Caro R, Argyroudis S. Innovative machine learning approaches for indoor air temperature forecasting in smart infrastructure. Sci Rep 2025;15:47. https://doi.org/10.1038/s41598-024-85026-3.

[9] Hamayat F, Ullah MO, Zubair S, Anwar SM. An Indoor Air Temperature Prediction Framework for Model Predictive Control in HVAC Systems. 2022 27th International Conference on Automation and Computing (ICAC), 2022, p. 1–6. https://doi.org/10.1109/ICAC55051.2022.9911173.

[10] Fanger PO. Thermal Comfort: Analysis and Applications in Environmental Engineering. R.E. Krieger Publishing Company; 1982.

[11] Medsker L, Jain LC. Recurrent Neural Networks: Design and Applications. CRC Press; 1999.

[12] Yang S, Wan MP, Chen W, Ng BF, Dubey S. Model predictive control with adaptive machine-learning-based model for building energy efficiency and comfort optimization. Applied Energy 2020;271:115147. https://doi.org/10.1016/j.apenergy.2020.115147.