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Evaluation of deploying data-driven predictive controls in buildings on a large scale for greenhouse gas emission reduction

Zhipeng Deng [a,c], Xuezheng Wang [a,c], Zixin Jiang [a,c], Nianxin Zhou [b,c], Haiwang Ge [b,c], Bing Dong [a,c,*]

[a] Department of Mechanical & Aerospace Engineering, Syracuse University, Syracuse, NY, 13244, USA
[b] School of Information Studies, Syracuse University, Syracuse, NY, 13244, USA
[c] Built Environment Science and Technology (BEST) Lab, Syracuse University, Syracuse, NY, 13244, USA

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ABSTRACT

Buildings consume more than 70% of electricity in the U.S. In order to reduce building energy consumption, advanced building controls have been developed. However, most building controls are using physics-based models and lack of scalability. Recent development of data-driven control models could overcome this challenge and be automatically developed and implemented on large scale. The purpose of this study was to evaluate the effectiveness, robustness, and scalability of automatic and systematic data-driven predictive control (DDPC) for a large-scale real-world deployment. We first used collected data from 78 buildings in RTEM database to train deep neural network models. Then we applied the models to optimize the HVAC control for energy savings. We focused on over 1000 HVAC units in five different commonly used types, including air handling units, rooftop units, variable air volume systems, fan coil units, and unit ventilators. Next, we evaluated the energy-saving potential and the reduction of greenhouse gas emissions of the proposed method. We found that DDPC was robust and scalable in buildings, with an average energy saving of 65% and peak load reduction of 15% compared to current control systems. The average reduction of GHG emissions for CO_2, CH_4, and N_2O was 15.18 kg, 5.76e-4 kg, and 5.48e-5 kg per m^2 per year, respectively. New York State can benefit 11% reduction in carbon emission from DDPC in buildings. For scalability, we also identified and categorized the challenging conditions when DDPC may not work properly and summarized the lessons learned from large-scale DDPC deployment.

1. Introduction

In accordance with the greenhouse gas (GHG) emission reduction requirements of New York State, the goals to combat climate change required to limit statewide GHG emissions to 60% of 1990 levels by 2030 and 15% by 2050 [1]. According to the 2021 Statewide GHG Emissions Report of the Department of Environmental Conservation in New York [2], the largest source of GHG was buildings which accounted for 32%. Moreover, space heating and cooling in residential and commercial sectors accounted for 38% and 10% of building energy usage, respectively [3]. Hence, it is necessary to develop a scalable smart control for building energy efficiency and GHG emission reduction.

New York State Energy Research and Development Authority (NYSERDA) supported a Real Time Energy Management (RTEM) Incentive Program [4] throughout the New York State. Among these buildings in the database, most were equipped with various HVAC systems for space heating and cooling. Therefore, we could develop and validate the smart building controls by using the database.

1.1. Data-driven model predictive control

Complex heat transfer and the lagging effects were existing in buildings due to the thermal mass of building envelopes and changeable complex indoor and outdoor environments. Model predictive control (MPC) derived from advanced process control could capture the dynamics of the building systems. Nowadays, it got more attention in the HVAC field [5] and played an important role in sustainable building energy systems [6]. Drgoňa et al. [7] and Mariano et al. [8] presented reviews of MPC in building operation and management. It was also found that MPC could save building energy use by 15–40% [5,9]. Meanwhile, MPC has been tested and deployed in field implementations in different buildings in various studies [10–12]. However, traditional

* Corresponding author. Department of Mechanical & Aerospace Engineering, Syracuse University, Syracuse, NY, 13244, USA.
E-mail address: bidong@syr.edu (B. Dong).

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physics-based MPC relied on the building thermodynamic model, so it required significant time and expert knowledge for model development and calibration. It was reported that developing and calibrating satisfactory models was one of the main obstacles and accounted for 70% of the total effort [13]. Additionally, they must be developed on a specific basis, as every building and HVAC application was different. The customized approach made it difficult for automatic development and implementation in multiple buildings in practice. As a result, the physics-based controls limited the large-scale deployment of decarbonization of buildings and the power grid.

In recent years, researchers have also developed data-driven model predictive control to overcome these challenges of traditional physics-based MPC [14,15]. Data-driven models such as deep neural networks (DNNs) could be developed with limited knowledge of building physics but utilizing sufficient historical time-series data [13]. And a single model architecture could be applied in multiple application cases to improve building energy efficiency [16] and energy flexibility [14]. Data-driven models could learn the complex and non-linear building properties, which was very difficult for physics-based models [17]. Many studies have used DNNs for building energy modeling [18], temperature control [19], and thermal behavior modeling [20,21]. DNN-based building control has become popular in the literature in both commercial buildings [22,23] and residential buildings [24]. Specifically, for example, to improve the development and solution of DDPC, Kusiak et al. [25] presented a data-driven approach for the multi-objective optimization of an HVAC system in an office building by the particle swarm algorithm. Ferreira et al. [26] implemented neural network predictive control for thermal comfort and energy savings in public buildings. The energy saving could be 50% in university as experimental results showed. Macarulla et al. [22] implemented neural network predictive control in a commercial building energy management system. The energy saving was nearly 20% and while ensuring building thermal comfort. Smarra et al. [27] used a random forest model for building energy optimization and climate control, achieving energy saving up to 49.2%. Jain et al. [28] used data-driven regression trees to represent building dynamics, and solved them in a real-time closed loop to reduce peak power in buildings. The peak load was reduced by 8.6%. Lee and Heo [29] proposed data-driven models for residential buildings and the case study achieved heating energy of 12% compared to traditional on/off control. Mugnini et al. [30] assessed the performance of data-driven and physical-based models and found that the energy cost savings was about 16% compared to a set-point control. We also found one study used the DNN-based model to study the energy flexibility potential of the building [31]. Winkler et al. [32] presented a data-driven MPC framework for smart building HVAC control. The optimization framework could minimize energy costs while maintaining comfort bounds for the building users based on real-time feedback. Drgoňa et al. [33] developed DNN models for the reduction of error and low computational demands. Chen et al. [34] also used transfer learning for the target building without enough operational data available. Additionally, researchers have conducted experiments and field implementations to evaluate the performance of data-driven controls in various buildings. For instance, Yang et al. [35] conducted an experimental study of machine-learning-based MPC and achieved up to 52% reduction in cooling energy. The proposed control was faster than the common MPC. Furthermore, experiments on the DDPC of a hospital HVAC system by Maddalena et al. [36] provided recommendations for managing the online optimization solver.

At the community or urban scale, developing detailed physics-based building models become too time-consuming and impractical. To address this, researchers have developed data-driven models, which were more effective. For the state-of-the-art methodology for large-scale deployment, some research utilized the data-driven method to study the electricity demand under different scenarios based on measured historical data at the community [37] and district level [38]. Moreover, Ke et. al. [39] presented an innovative study on a data-driven predictive control for building energy management under the Internet of Things architecture. The cloud-based building energy management system framework was demonstrated in both residential and office buildings. Zhang [40] also developed a framework for building energy modeling for data predictive control. It provided an automatic workflow that started with raw data from building automation systems to the establishment of data-driven energy models for controllers. Darivianakis et al. [41] exploited the load shifting capabilities of the cooperative buildings and districts by data-driven robust predictive control. The methods could be utilized for more equipment such as heat pumps and batteries. However, these data-driven models were typically "black-box". It was very difficult to interpret the underlying physical meaning behind the model parameters, thus it led to some errors in the prediction results. Therefore, we need to conduct large-scale testing and verification for the scalability and robustness of the data-driven models. However, there were no examples of implementation of DDPC in a large number of building HVAC systems at the urban scale.

1.2. Scalability of building control

For large-scale applications, scalability of the model indicated both the crucial performance and scaling characteristics [42]. The model needed to be parametric and validated against a variety of different systems and cases showing high accuracy. There were several previous studies developing and evaluating scalable models for building control and simulation. For instance, Wang et al. [43] proposed a generic process framework for integrating all the solutions in building information modeling and simulation-based design cycle. Darivianakis et al. [44] proposed a highly scalable decentralized control scheme to address privacy concerns of the building occupants. It only required the individual buildings to communicate bounds on their energy demands and did not reveal the exact characteristics of the energy usage within each building. The demonstration through numerical studies of up to 12 buildings showed the efficacy of the proposed approach. Sahlin et al. [45] compared the equation-based building simulation models with Modelica. They observed radical differences in the scalability of mainstream Modelica models. Wang et al. [46] compared four machine learning algorithms and implemented three buildings to verify the feasibility and scalability of the DDPC. They found that DDPC achieved comparable performance to the grey-box model-based MPC. Reinbold et al. [47] assessed scalability of a low-voltage distribution grid co-simulation and found that it could run much faster than the integrated simulation for 24 buildings. Deng and Chen [48] used transfer learning to transfer the occupant behavior model to 5 other office buildings with good scalability and without the need for data collection. Therefore, most previous studies have explored the model scalability for numerous buildings. For building control, the key performance metrics included energy efficiency, carbon emission, environmental quality, and comfort. To evaluate the scalability of building control, only a few cases may not give a full understanding of scaling characteristics. To truly evaluate the scalability of the model, we need to validate the model performance including prediction accuracy and reduction of energy and GHG emission in large-scale applications.

The purpose of the present study was to evaluate the performance, robustness, and scalability of DDPC for real-world large-scale deployment. For this purpose, we first used the collected data from the RTEM database to build deep neural network models to predict space air temperature. Then we used these developed models to optimize the control system for energy savings. Next, we evaluated the energy-saving potential and reduction of GHG emissions of the proposed algorithm. Finally, we analyzed the robustness and scalability of the models.

The current study made several important contributions, including.

- We have evaluated the scalability of DDPC for a large number of HVAC systems across different types of buildings.

- We have validated the fully automatic and systematic implementations of DDPC for a large number of HVAC systems and buildings.
- We have verified the effectiveness of DDPC on energy saving and reduction of GHG emissions for various HVAC systems and buildings.
- We have learned valuable lessons on deploying data-driven predictive controls from a large-scale study.

2. Methods

2.1. Data preprocessing and descriptive statistics of data

Fig. 1 shows the overall approach for this paper. At first, we extracted the metadata from the RTEM database and conducted the data cleaning in the preprocessing step. The database contained data from over 200 buildings. The data in individual buildings were collected in different time periods from October 2016 to October 2021. However, for each specific building, the amount of data collection period and the start and end time were varied. Not all the buildings included complete HVAC energy-related data. We avoided using the time periods when the data recording was incomplete. As for the frequency of data recording, most building management systems (BMS) used 15 min. Some buildings were using 5 min, 30 min, or 1 h. To align with the frequency of control operations and the difficulty of solving the optimization problem, we used the frequency of time-series data in 15 min, which was suitable for DDPC. High-frequency data were resampled into 15 min. Since the database only contained the data collected from the BMS, but the outdoor air temperature was also an important factor for building energy prediction and control. So we also used the easily accessible outdoor weather data from the nearest airport in each city in New York State. The climate region in New York State was cold according to International Energy Conservation Code.

The metadata of the RTEM database provided descriptive information about the database, such as building ID, building area, building customer type, geographic city and address, number of equipment, number of data points, type and description of data points, logging time, and tags. According to the metadata, the most tags on HVAC system types were air handling units (AHUs), fan coil units (FCUs), rooftop units (RTUs), unit ventilators (UVs), and variable air volume (VAV) systems. Therefore, in this study, we applied the DDPC to these five most used HVAC systems. Through the data preprocessing, we found a total of 1017 HVAC units in 78 buildings in the database with complete air temperature and energy-related data, such as supply air temperature and airflow rate. Thus we used these data from the 78 buildings, and Table 1 lists the number of units and buildings for training and testing the DDPC in this study for various HVAC systems (in some buildings, there was more than one type of HVAC system).

We also obtained the information on the buildings which we used for analyzing DDPC in this study. Fig. 2 shows the statistical description of the data. We found that the areas of most buildings were less than 1000 000 ft^2 (92 903 m^2). The average building area was 360 000 ft^2 (33 445 m^2). There were totally eight types of buildings in the present study. The majority of the buildings for which we developed DDPC were commercial retail and commercial offices. They made up half of all the buildings. Fig. 3 shows the main distribution of 78 buildings in the RTEM database in New York State for evaluating DDPC in the present study. About one-third of the buildings were located in New York City.

2.2. Data-driven models of HVAC systems for predicting air temperature

After obtaining the data, we used them to develop data-driven models. In buildings, if the temperature in two adjacent zones are different, there is heat transfer through the walls. Heat also transfers through external walls between the building and the ambient environment. The temperature difference also causes infiltration. Additionally, the HVAC system also regulates the airflow within the building. For physics-based MPC, a state-space model was primarily used to describe the building thermodynamics. The state of the building typically included air temperature and wall temperature. However, physics-based state-space models required a significant amount of time and expertise

Table 1
Number of units and buildings for testing the DDPC in this study.

HVAC systems	Number of units	Number of buildings
AHU	256	42
FCU	178	8
RTU	163	44
UV	145	3
VAV	275	6

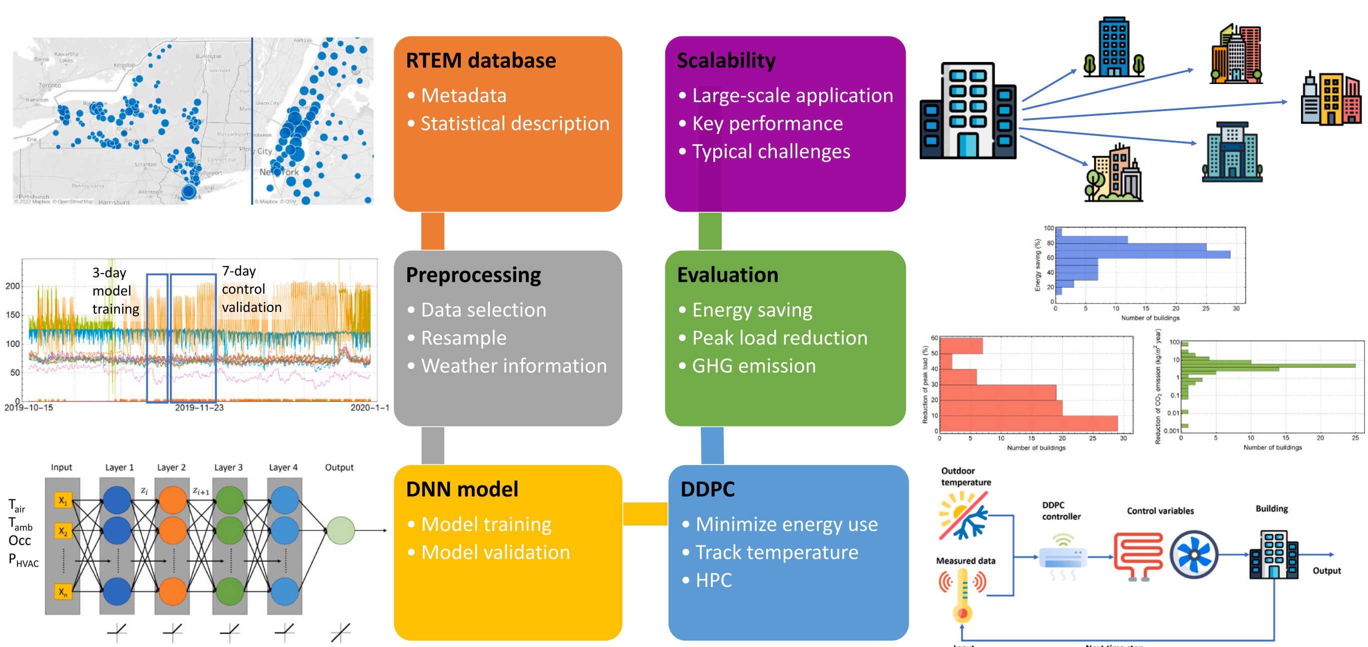

Fig. 1. The overall approach for this paper.

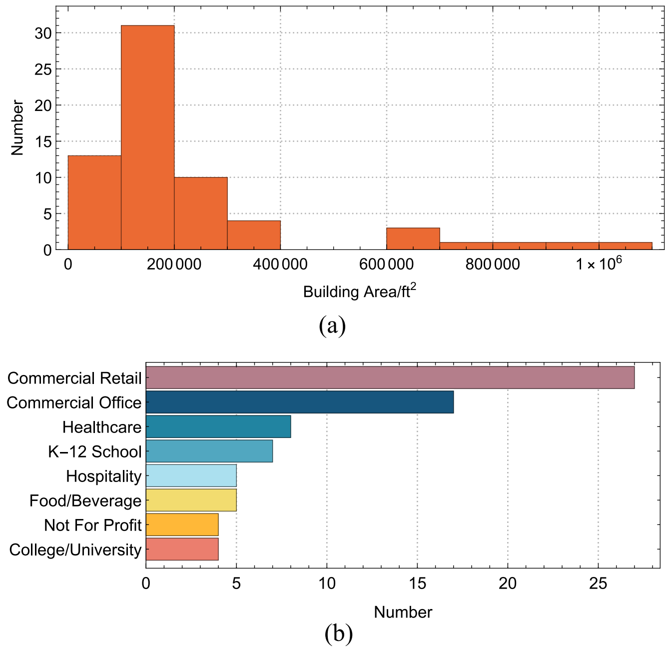

Fig. 2. Statistical description of the data: (a) distribution of building area; (b) distribution of building customer type.

for development and calibration. In this study, we used a data-driven model, which was built using historical time-series data, instead of the state-space model. Therefore, after data preprocessing, we built data-driven DNN models for zone air temperature prediction. DNN model was a powerful machine learning method that used multiple layers in the neural network model to learn the relationship between the input parameters and the output [49]. We used the collected data in the RTEM database to train the DNN model. The input parameters were space air temperature, outdoor air temperature, room occupancy, and heating or cooling load of the HVAC system. These parameters were usually recorded by the BMS. However, for a large number of existing buildings, the structure information on building envelope, window-wall ratio, external and internal wall layers, property on insulation and glass material, and floor plan was un available and hard to collect. Different from white-box and grey-box physics-based models, data-driven models could be built without this detailed information about the building. Meanwhile, wall temperature, solar radiation, number of occupants, internal heat gain, and heat transfer among different zones were also important for building thermodynamics. Most physics-based models required these data for model development. But collecting these parameters required specific sensors, making it very hard to collect automatically in most existing buildings. The RTEM database did not contain the relevant information, either. To be scalable, these parameters were not conducive to large-scale automatic deployment, thus we did not consider them as input parameters in the data-driven control. The relationship of these parameters could be learned from the historical data by the DNN models. The output of the DNN model was zone air temperature for the next time step. The DNN model could be written as

$$T_{air}(t+1) = f[T_{air}(t), T_{amb}(t), Occ(t), P_{HVAC}(t)] \tag{1}$$

Where f is the trained DNN model, including multi-layer network structure and activation functions. We assumed the load of the HVAC system for the space heating/cooling was proportional to the supply airflow rate and the temperature difference between supply and return air as

$$P_{HVAC}(t) \propto Q(t)\cdot\left[T_{supply}(t) - T_{return}(t)\right] \tag{2}$$

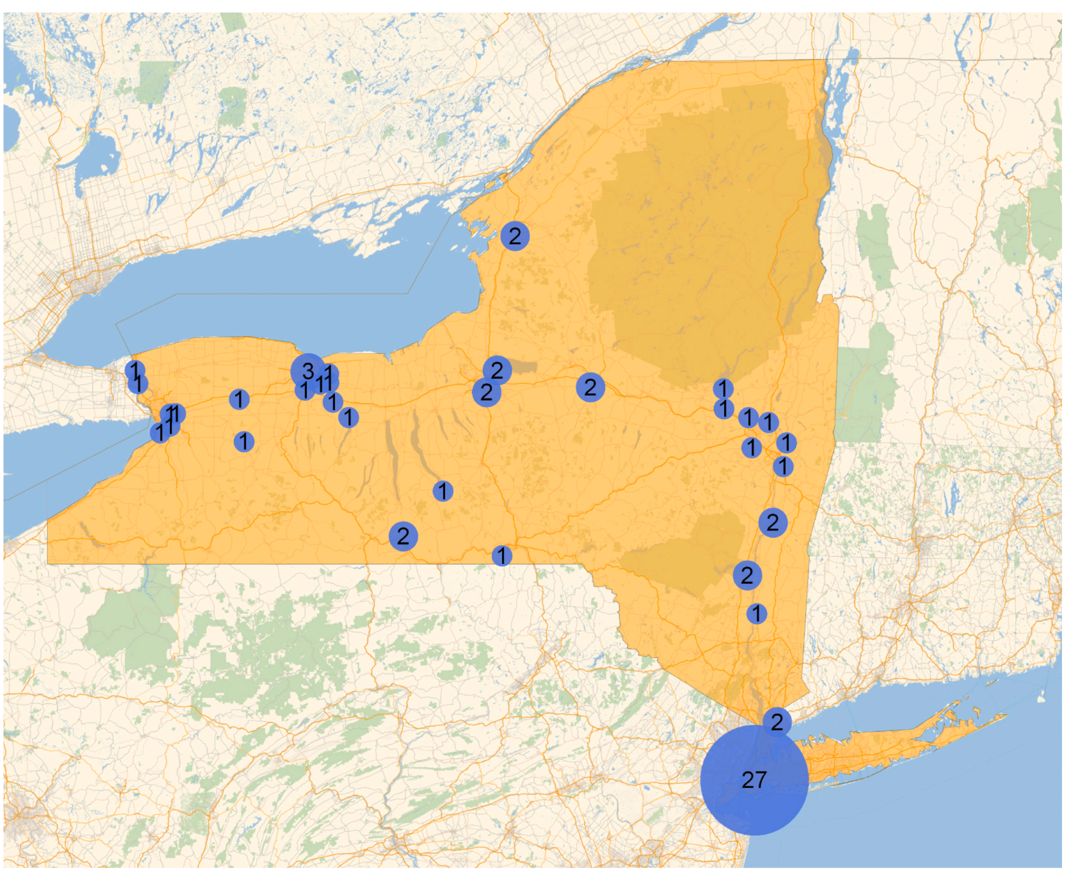

Fig. 3. The distribution of buildings in the RTEM project in New York State for evaluating DDPC in the present study.

However, we did not consider the energy consumption by dehumidification, fan, and reheating. Since the building envelope and heat transfer in each thermal zone varied in different buildings, we built and trained different models for all the HVAC systems using the collected data. We only used the data from the HVAC system to train the DNN model so that the trained model could automatically learn the relationship from the data. We assumed that the each HVAC system worked for a single thermal zone. For each HVAC system of the buildings in New York State, we trained two models for both heating season (winter from October to March) and cooling season (summer from June to August), respectively. We randomly selected the historical data in 3 consecutive days for training, and used the data in 7 consecutive days to evaluate the model performance, energy efficiency, and reduction of GHG emission. And random selection could ensure that the results were unbiased in the evaluation of energy consumption, and the results could represent the typical conditions in New York State in winter and summer. As for the shoulder seasons, we found that the energy consumption of most buildings and zones was minimal or even zero. As the HVAC load was not significant during this time period, we focused on the winter and summer seasons when the DDPC had greatest energy-saving potential.

2.3. Model training and control development

For model training, we first used min-max normalization on all the input data. Then, we used the grid search method to obtain the values of hyperparameters of the DNN models. We found that for optimal model performance, the appropriate number of neurons was 50; the number of hidden layers was 4; the learning rate was 0.001; the training method was ADAM (Adaptive Moment Estimation) optimization algorithm; the number of training episodes was 10 000. We used rectified linear unit (ReLU) as the activation function and 64 as the batch size. We also split the training data randomly and used 20% of the data as the validation set during the training process. We used mean absolute percentage error (MAPE) to evaluate the model performance of accuracy as

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{3}$$

Where A_t and F_t were the actual values and predicted values, respectively.

After developing the DNN models, we used them for smart data-driven predictive control (DDPC). The purpose of DDPC was to minimize the total energy use during the prediction horizon while maintaining the room air temperature at a comfortable level. The control variables were the heating or cooling load of the HVAC systems. The air temperature was controlled to track the collected actual air temperature or set point in each space at a difference less than 0.5 °C. We set the prediction horizon as 3 h for all the buildings in this study. The control time step was 15 min. The DDPC could be written as

$$\begin{aligned} &\min_{P_{HVAC}(t)} \sum_{t=0}^{N-1} P_{HVAC}(t) \\ &s.t. \\ &T_{air}(t+1) = f[T_{air}(t), T_{amb}(t), Occ(t), P_{HVAC}(t)] \\ &T_{actual}(t) - 0.5 \le T_{air}(t) \le T_{actual}(t) + 0.5 \end{aligned} \tag{4}$$

Where $T_{air}(t)$ was the predicted space air temperature in each time step, and $T_{actual}(t)$ was the collected air temperature.

We utilized Python to process the data, train the DNN model, and develop the data-driven control. Since the number of HVAC units to be studied was large, we used high-performance computer with 80 cores and 176 GB memory to perform the model training and validate the DDPC. In actual deployment, the related calculation would be distributed to local computers of BMS in each building.

2.4. Evaluate the performance of energy saving, GHG emissions, and model scalability

To evaluate the reduction of energy use of the developed DDPC for each HVAC system, we simulated the energy usage with DDPC for each space in all the buildings for 7 days in both heating and cooling seasons. Then we compared the results with the baseline control, which was the current control strategies and collected energy use for all the buildings. We found that almost all the buildings used simple set point or schedule control for air temperature. The energy efficiency was defined as energy reduction over the actual energy usage by baseline control, as

$$\eta = \frac{P_{HVAC\_DDPC} - P_{HVAC\_actual}}{P_{HVAC\_actual}} \tag{5}$$

Then we used GHG Emissions Calculator from the United States Environmental Protection Agency [50] to evaluate the reduction of GHG emissions. EPA GHG calculator is a Microsoft Excel tool that can be used to calculate the GHG emissions from various sources, such as combustion, fuel, vehicles, electricity, steam, heat, waste generated and refrigerants. Some of the factors used in the calculation are specific to certain locations. It can calculate emissions for CO_2, CH_4 and N_2O, which are the most common greenhouse gases. Thus, this calculator was a useful tool for estimating the energy and GHG of various energy conservation measures for commercial buildings. In different locations, the emission factors varied. In this study, the data were collected in New York State, thus we used the information of emission factors from Upstate New York, New York City, and Long Island. We assessed the emission reduction of CO_2, CH_4, and N_2O, which were top contributors to GHG. Table 2 shows the emission factors for these gases in New York State.

As for the performance metrics of model scalability, we focused on the results of prediction accuracy and energy saving for different HVAC systems, which were important metrics for DDPC. Good scalability indicated that DDPC could achieve similar results when applying to various systems in large-scale deployment. Thus we compared the performance of DDPC across various buildings and systems to evaluate the scalability. At last, we also analyzed and categorized the conditions when the DDPC could not perform properly at scale, including model training, model validation, and control deployment. The feasible solutions were provided to enhance the scalability.

3. Results

3.1. Training and testing of DNN models

Fig. 4 shows the training and testing results of DNN models for air temperature prediction of one AHU in a school gymnasium in Guilderland, NY. We found that the difference between time-series air temperature prediction and measurement was mostly within 0.5 °C. The average difference was 0.05 °C for testing. The MAPE of training result by the DNN model for this AHU was 0.2% and 0.3% for the heating and cooling seasons, respectively. And the MAPE of testing result was 1.0% and 1.6% for the heating and cooling seasons, respectively. The training results were very good. Similar results could be found for other HVAC systems. But we still found for some HVAC units, there were cumulative errors that the prediction in the first few days was very good. Once the model prediction error was large, the following forecast would be worse and worse. Therefore, to address this issue, dynamic correction every

Table 2
Total emission factors in New York State [50].

Location	CO_2 (lb/MWh)	CH_4 (lb/MWh)	N_2O (lb/MWh)
Upstate New York	232.3	0.017	0.002
New York City	553.8	0.021	0.002
Long Island	1209.0	0.157	0.020

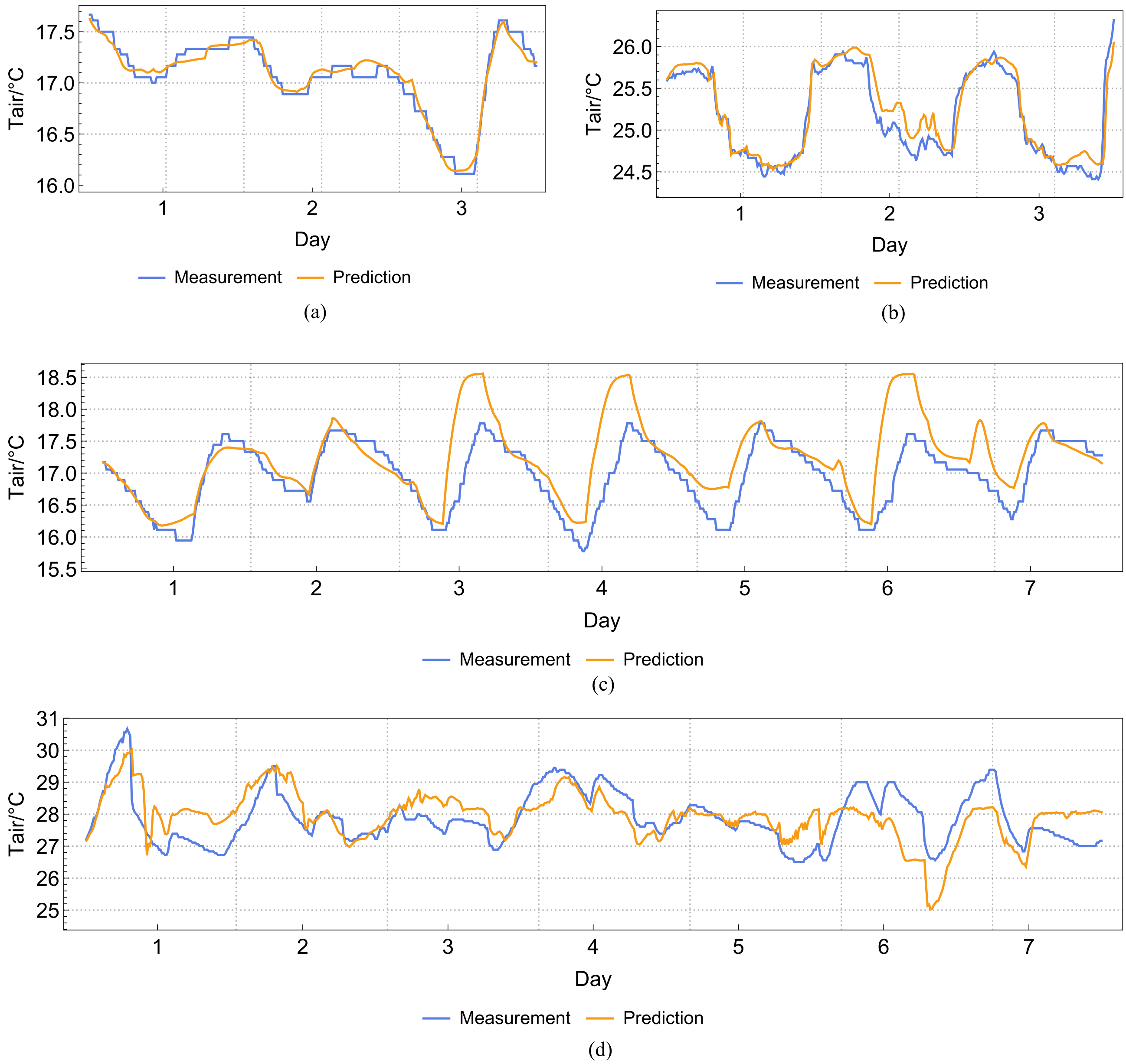

Fig. 4. Results of DNN models for air temperature prediction of one AHU in a school gymnasium located in Guilderland, NY: (a) training results in three heating days; (b) training results in three cooling days; (c) testing results in seven heating days; (d) testing results in seven cooling days.

day or every few days was necessary for data-driven models. The process of dynamic correction was to retrain the model on new data in order to improve the accuracy. Additionally, dynamic correction was also to eliminate the accumulated errors and use new data as the initial value for optimization when the error was large.

Fig. 5 shows the training and testing results of DNN models for indoor air temperature prediction for various HVAC systems. The MAPE of the prediction by the DNN model for 163 RTUs was 1.1% and 2.8% for training and testing, respectively. The training results were very good, as the training error was less than 5% for almost all the RTUs. The testing results were slightly worse than the training. Similar results could be found for other systems. The MAPE for training and testing of 275 VAVs was 1.0% and 3.0%, respectively. The MAPE for training and testing of 178 FCUs was 2.3% and 3.9%, respectively. The MAPE for training and testing of 145 UVs was 1.1% and 2.1%, respectively. The MAPE for training and testing of 256 AHUs was 1.0% and 2.3%, respectively. The prediction accuracy was similar for four HVAC systems except for FCU. We also calculated the root mean square error (RMSE) of the air temperature prediction for each HVAC system. The RMSE results were 0.68 °C, 0.73 °C, 0.91 °C, 0.54 °C, and 0.59 °C for RTU, VAV, FCU, UV, and AHU, respectively. For predicting indoor temperature as one of the key performance metrics, the DNN models performed well for different HVAC systems and buildings. So the DNN models showed good scalability preliminarily. Thus we could use the trained DNN model to predict the air temperature. Then we used the trained model for DDPC to reduce energy use in each zone.

3.2. Results of load reduction

After building and training the DNN models, we could use them for the data-driven predictive control. Fig. 6 shows the results of the tracked temperature and energy saving by DDPC for a UV in one building located in Hudson, NY on seven heating and cooling days. DDPC could control the predicted temperature to track the actual collected data within 0.5 °C most of the time, which ensured the thermal comfort in this zone was almost the same as actual condition. In the winter seasons, the

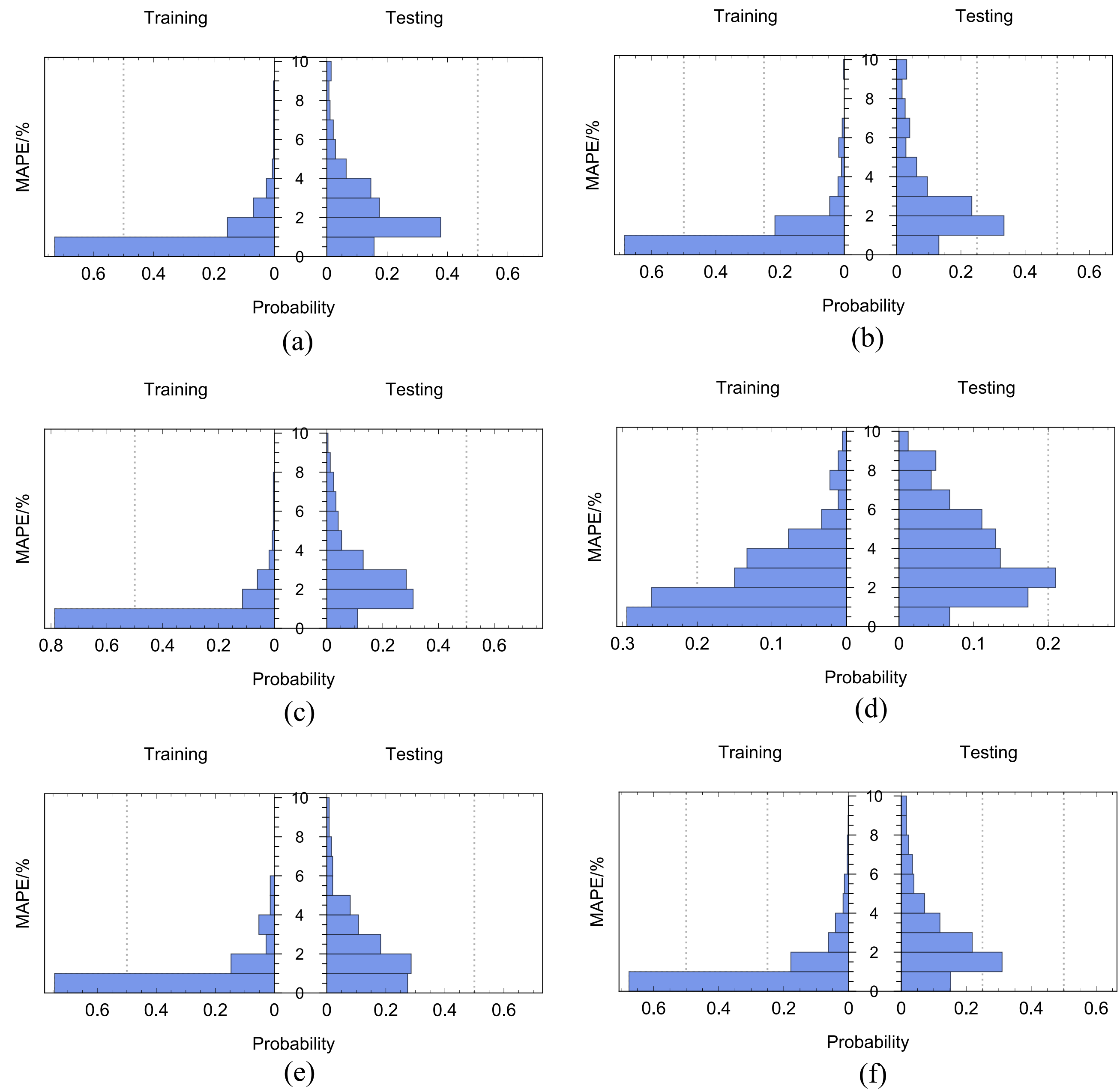

Fig. 5. Training and testing results of DNN models for indoor air temperature prediction for various HVAC systems: (a) RTU, (b) VAV, (c) AHU, (d) FCU, (e) UV, and (f) all the HVAC systems.

indoor air temperature during the daytime could be controlled around 21–22 °C. At night when unoccupied, the HVAC system did not provide load to save energy. During the weekend of the 7 consecutive days, there was no load and the air temperature was free to fluctuate and it may drop to 18–19 °C. Similarly, in summer, the indoor temperature was controlled at around 22 °C during the daytime. It could rise to 24 °C when the system was not working at night and on weekends. Fig. 6(a) and (c) also show that the heating and cooling load could be reduced by DDPC comparing with the current baseline control. Energy saving for heating and cooling load was 51% and 55% on seven days. Meanwhile, the peak load reduction was 6% and 28% for this UV in winter and summer. We also found that the actual measured load fluctuated violently, and especially cooling and heating load existed in the measurement at the same time. This rule-based baseline control led to very large energy consumption. As for DDPC, the fluctuation was much smaller, so it could save energy. On the other hand, part of the reason of strong fluctuation was from the accuracy of the prediction model. We found that the accuracy MAPE of the model was 4.3% in this case, which was above average as Fig. 5(e) shows.

Then we evaluated the energy saving of the DDPC across all HVAC systems in the 78 buildings. Fig. 7 shows the reduction of heating and cooling load by the DDPC for all AHUs, RTUs, VAVs, FCUs, and UVs in buildings. We found that it could save 64% on the heating load and 60% on the cooling load of the AHUs on average. For RTUs, 69% on the heating load and 68% on the cooling load could be saved. For VAVs, FCUs, and UVs, the energy saving was 64%, 67%, and 69%, respectively. The overall energy saving was 65% on heating and cooling load. For different HVAC systems and buildings, DDPC has achieved similar energy-saving goals. It showed that the scalability of DDPC was very good. Fig. 8 shows the distribution of reduction of peak load by DDPC for all buildings. The average peak load reduction was 15.4% for all 78 buildings. Therefore, data-driven predictive control demonstrated huge

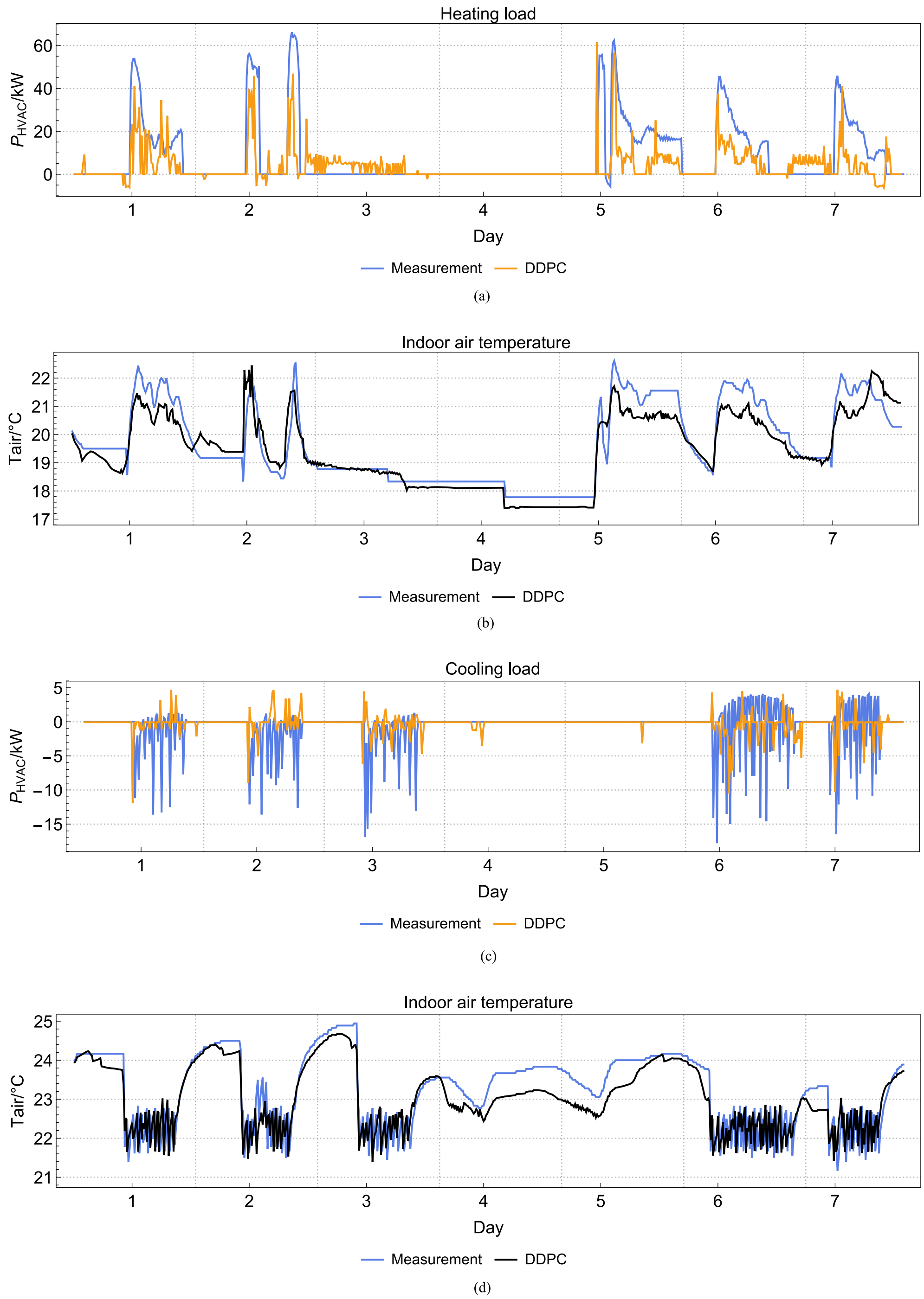

Fig. 6. Energy and air temperature results of the DDPC for a UV in one building located in Hudson, NY: (a) heating load in seven days; (b) air temperature in seven heating days; (c) cooling load in seven days; (d) air temperature in seven cooling days.

potential for energy saving and reduction of peak load in New York State.

3.3. Reduction of GHG emission for DDPC

At last, we did the GHG emission analysis for the DDPC with the results of energy reduction of 78 buildings. Fig. 9 shows the distribution of reduction of CO_2 emission among all the buildings. We found that DDPC could reduce the emission of CO_2 by an average of 15.18 (1.88e-3–72.30) kg per m^2 per year. The distribution of other GHG was similar since the GHG emission was calculated based on energy reduction and emission factors. The results on the reduction of CH_4 and N_2O emission were 5.76e-4 (7.11e-8–2.74e-3) and 5.48e-5 (6.77e-9–2.61e-4) kg per m^2 per year, respectively. For different buildings, the results varied a lot, as Fig. 9 shows. The possible reasons could be that the HVAC systems which we analyzed in different buildings may not represent all the systems inside the building, since the data of some systems were missing or not accessed. Besides, the building area shown in the database may be different from the conditioned area. Considering these possible reasons, the resulting reduction of GHG emissions could be more in some buildings.

There are more than 2 million buildings in New York State. As buildings accounted for 32% of total GHG emissions, and space heating and cooling accounted for about 50% of total energy usage. If assuming

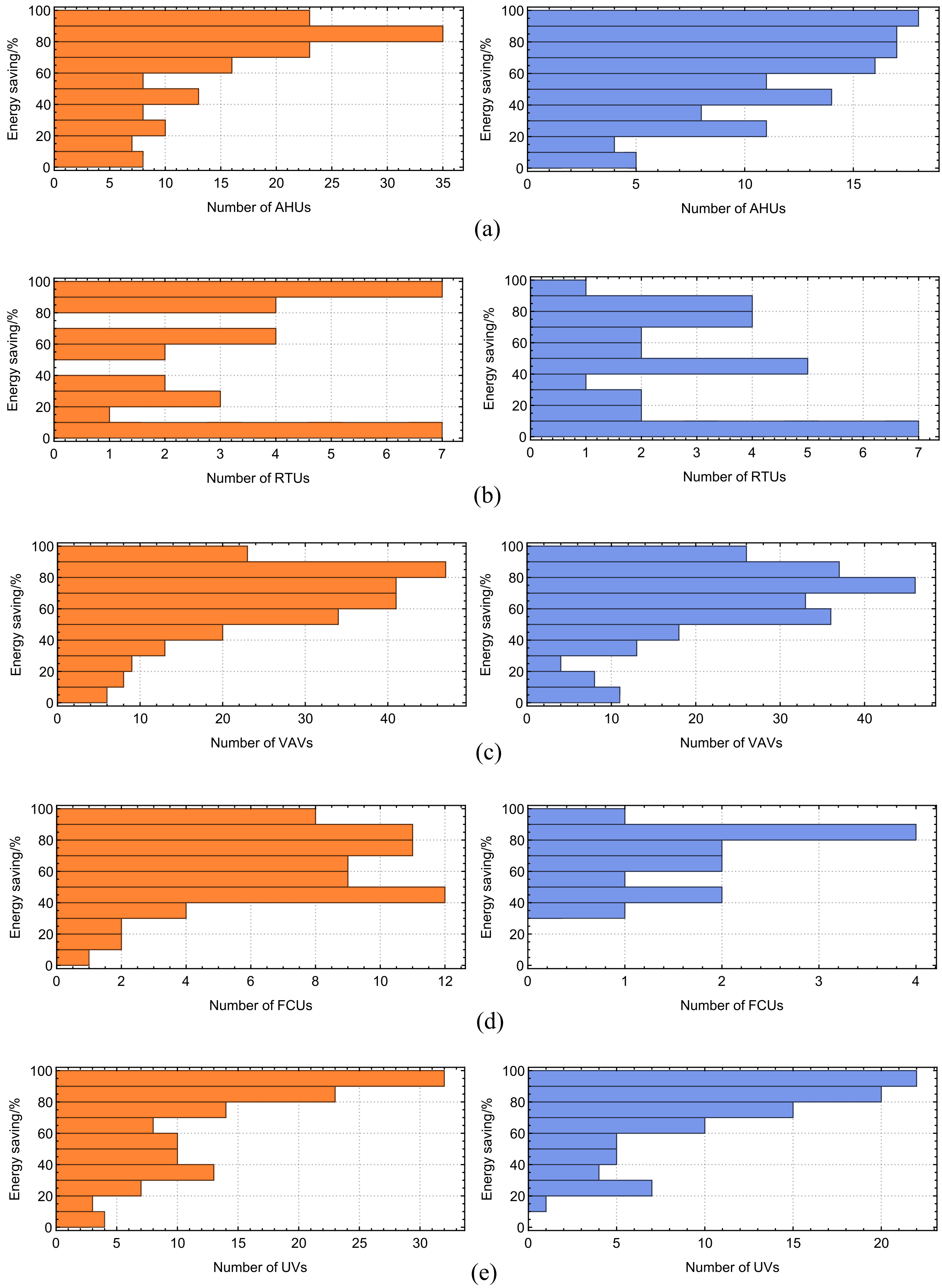

Fig. 7. Results of the DDPC on energy saving (heating on the left and cooling on the right) for (a) AHUs, (b) RTUs, (c) VAVs, (d) FCUs, (e) UVs, (f) all kinds of HVAC systems, and (g) all the buildings.

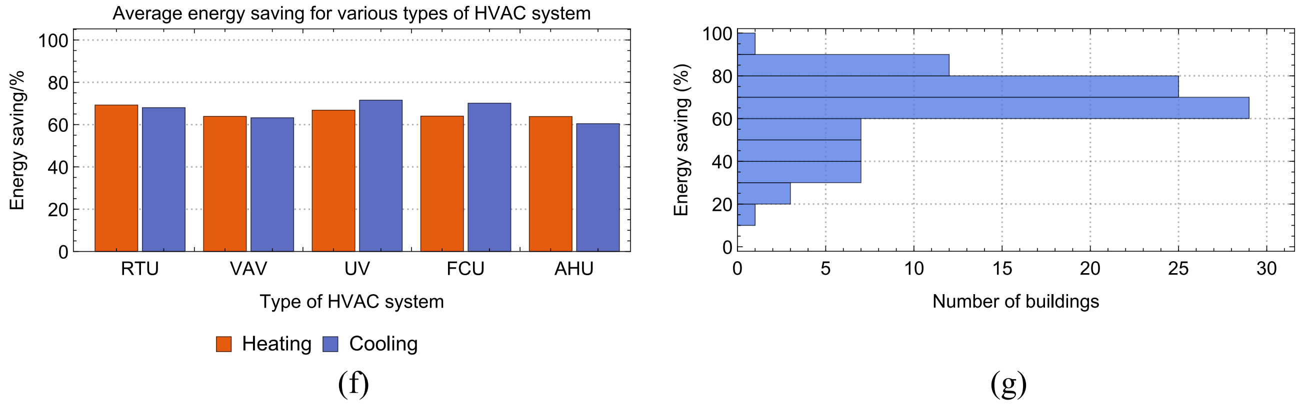

Fig. 7. (*continued*).

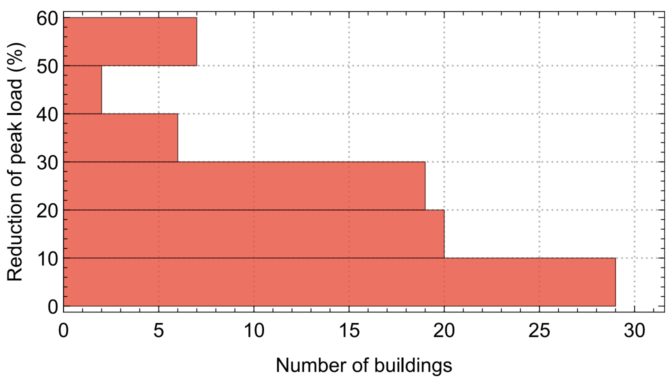

Fig. 8. Distribution of reduction of peak load for all buildings by DDPC.

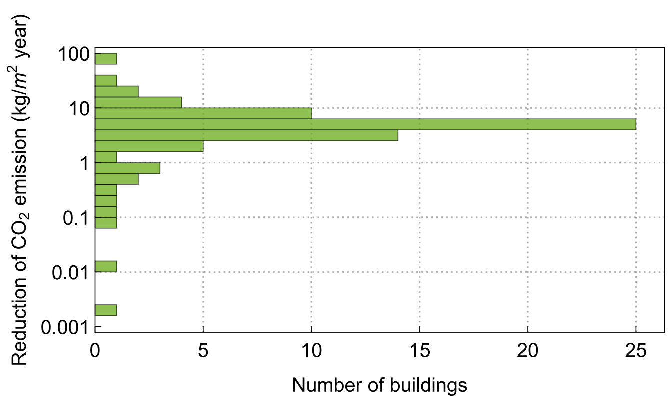

Fig. 9. Distribution of reduction of CO_2 emission for all the buildings by DDPC.

all buildings in New York State used the DDPC, it is estimated that the GHG emission could be reduced by 11%. Therefore, the cities and the state will get significant dividend of GHG reduction for sustainability from data-driven smart control.

3.4. Analysis of the scalability of DDPC

In the present study, we developed the data-driven models based on actual collected data from 78 buildings in the RTEM database and used them for energy-efficient control. We found that the percentage of feasible DDPC working properly in over one thousand HVAC units was 84%. At most of the time, the robustness of DDPC was great. It provided reasonable operation to the HVAC systems. Therefore, the scalability of DDPC on control robustness was satisfactory. In addition, there were still some instances that the DDPC could not work properly. We analyzed and categorized these cases mainly in three stages.

A) Failure in model training.

Data outliers. We found zero value may occur at one time step for the data recording on air temperature as Fig. 10(a) and HVAC load as Fig. 10(b). These zero values may occur due to sensor drift, failure, malfunction, damage, or network connection issue. The actual value of air temperature should not be zero if in summer. As for HVAC load or air flow rate, it may be zero when the damper was fully closed. It was very difficult to distinguish whether it was the ground truth or the outlier. We also found that the air temperature and other measured data may be extremely high or low at one time step, as shown in Fig. 10(c). That may be due to the interference during the measurements. These outliers could negatively impact the training results. It may also cause the model to misjudge the performance during validation. To address these issues, we should process the data by filters in real time to identify and remove the outliers [51].

Constant load recording. We found the load of the HVAC system could remain unchanged for a long time, such as zero value as shown in Fig. 10(d). In these cases, the model was trained in only one load, thus it could not learn the building thermodynamics in varied complex conditions. So we should train the data-driven models in more conditions with varied loads. Another condition was that load was all zero on shoulder seasons when the HVAC system was not in use to condition the space. So we should especially avoid use the training data in shoulder seasons, because DDPC was not suitable to apply in shoulder seasons.

Discrete variables. We found that for some HVAC system, the recording of load or other parameters was constantly one value or discrete with several values, as an example of RTU heating output shown in Fig. 10(e). The constant or discrete parameter may be due to the system setting and design property itself. If the native system was constant load with on-off control or stage control, the control variable may not be able to change continuously. In this condition, data-driven DNN model cannot be used, because the training and optimization was based on gradient descent, which was not feasible for discrete parameters. As a result, it is recommended to use DDPC for continuous system.

Data abnormal variation and disturbance. We found that during a certain period of time, there were abnormal variation and disturbance in the training data with unknown reasons. The value may be still within the normal range. We did not know the exact cause. It may be due to occupant behavior, building envelope damage, or change of HVAC system parameters. At this time, the model training was not as effective because the relationship between inputs and output parameters was not clear.

B) Failure in model validation.

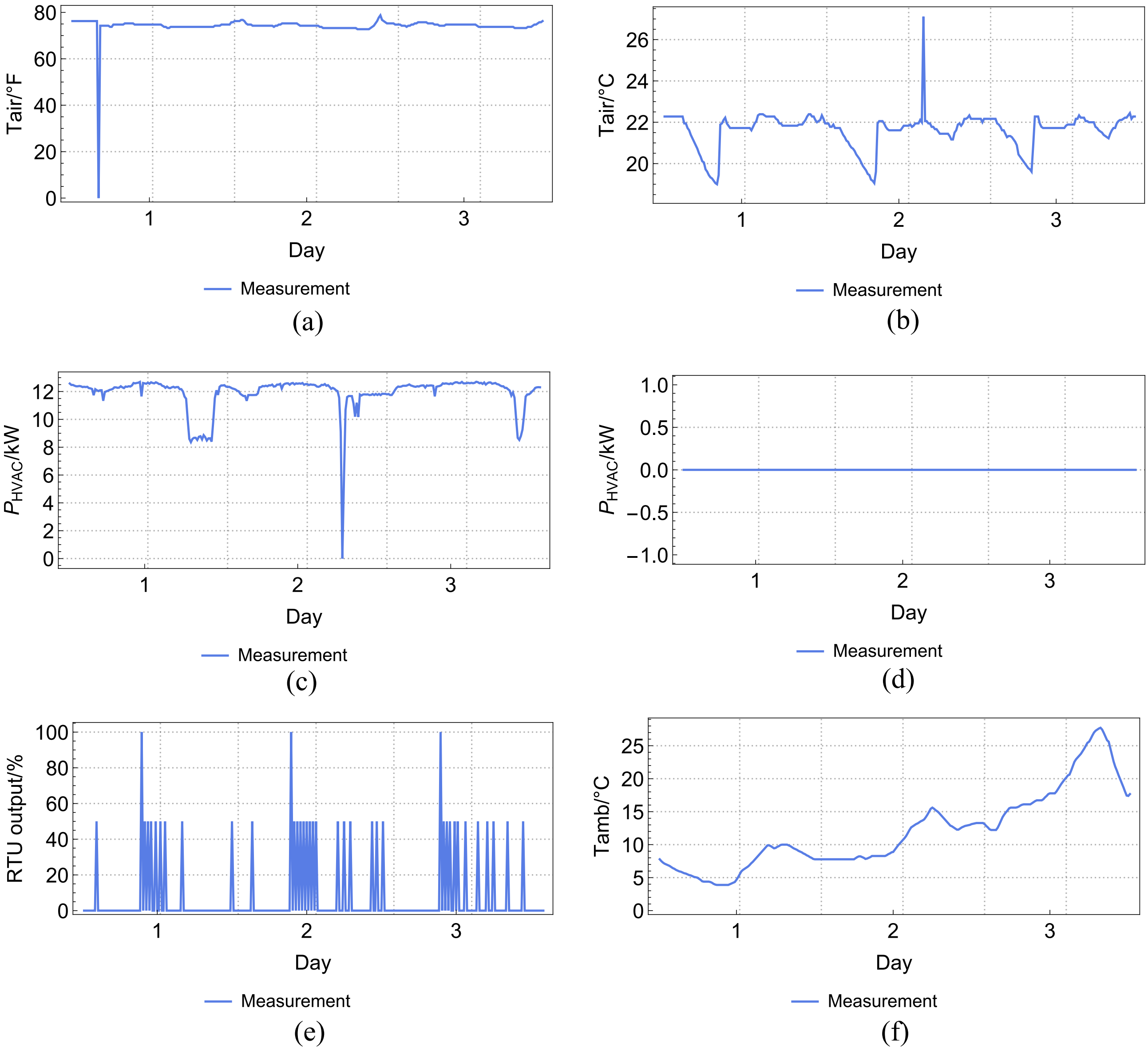

Fig. 10. Typical challenges of scalable DDPC deployment: (a) Measured temperature outlier: zero value; (b) Measured temperature outlier: extreme value; (c) Measured HVAC load outlier: zero value; (d) Measured HVAC load constant value; (e) Measured discrete RTU heating output; (f) Outdoor air temperature conditions beyond training.

Underfitting. The inaccurate validation results may be because of the data-driven model with insufficient training. The possible reason could be the use of inappropriate training parameters. To improve the results, it is important to set the hyperparameters of the DNN model carefully and obtain accurate model results. We could also train the model multiple times with different parameters to find the best model.

Overfitting. Overfitting may also lead to inaccurate validation results. To prevent this, we could use regularization or set up early stopping and dropout.

C) Failure in control.

Cannot find optimal solution. Sometimes the data-driven predictive control could not find the optimal solution for the optimization problem. This could be due to a variety of factors such as inappropriate environmental parameters, or inaccurate model predictions. If the constraints are too restrictive and prevent finding the optimal solution, either. A feasible solution could be relaxing the constraints appropriately.

Conditions beyond training set. In the database when we tested the DDPC, there were conditions that not be trained before but occurred in the control process. For example, the ambient air temperature in winter exceeded 20 °C as Fig. 10(f) shows. This was very rare occurrence and happened once every a few years. The data-driven model could not work effectively, as it was not trained to make predictions for these conditions.

Too large cumulative error. The prediction model was used at each time step iteratively. So the inaccurate prediction result at one step will lead to larger subsequent errors. In this condition, we should calibrate the model with actual data corrected every day or every few days as possible solution.

4. Discussions and lessons learned

In this study, we used the data from 78 buildings in the RTEM database to analyze the scalability of data-predictive control. The model only required the time-series data on zone air temperature, outdoor air temperature, room occupancy, and load of HVAC system. And the results of this study showed great scalability of DDPC among various HVAC systems and buildings. The proposed method can be easily implemented in more buildings in New York State to reduce the energy and GHG emissions. The proposed method could also be easily implemented for many types of buildings, such as both commercial buildings and residential buildings. The proposed approaches would not need a complex retrofit, but only implement the smart control algorithm for the BMS. Thus, it would be easy for the building owners to adopt. Hence, the cities and the state will reap the dividend of energy and GHG reduction for sustainability.

The well-organized data structure of the RTEM database was already very easy to work with, and it was convenient for the researchers to develop and validate different models. However, we still encountered some obstacles during the development of data-driven models and the control algorithm.

A) Unified naming, labeling, and unit of data

The way data was labeled and named greatly affected the automation of the model training and development. For some parameters, we needed to recognize different names to process the corresponding data by programming. For example, space air temperature could be named as temperature, temperature with room number, space temperature, zone temperature, zone air temperature, and relief temperature for various buildings in the database. It was also typically assumed the same as return air temperature/RA/RAT. Another example was that for various HVAC systems, supply air temperature, SA/SAT, discharge air temperature, DA/DAT, and auxiliary temperature/AUX typically represented the same variable. To ensure successful future automatic and large-scale implementation of data-driven predictive control, agreement and standardization of proposed names was critical. Sometimes, the units of data were not consistent. For example, air temperature and energy consumption could be in SI units or imperial units for various HVAC systems and buildings. Direct deployment without examination would result in a tenfold or hundredfold deviation.

B) Synchronization of time and control step

As for time, in addition to synchronization, the frequency of data recording and control step was also important. In the RTEM database, most buildings used 15 min for data recording. In large-scale deployment, same recording frequency for various sensors would make the data-driven predictive control easy to deploy in various buildings.

C) Automatic input feature selection

Finally, we manually selected space air temperature, ambient temperature, occupancy status, and load of the HVAC system as inputs, which was recorded in most BMS. But there were no information available for the number of occupants, internal heat gain, and wall temperature. So we did not analyze input feature selections in this study. In the near future, with the increasing use of more sensors and IoT (Internet of Things) devices in buildings [52], there will be greater amount of data and information available for developing data-driven models. To further leverage information and sensors in various buildings, we need to develop the automatic input feature selection to build better models and controls.

5. Conclusion

In this study, we explored the scalability of deploying data-driven predictive control on a large scale for over one thousand HVAC units in 78 buildings. This investigation led to the following conclusions.

1. We trained DNN models by using the data recording in over one thousand HVAC systems in 78 buildings in New York State. Then we automatically deployed DDPC on large scale to evaluate the performance. The results showed that it could save more than 60% of heating and cooling load on average. Meanwhile, DDPC could also reduce the peak load by 15%.
2. For the reduction of GHG emission, we found that DDPC could reduce the emission of CO_2 by 15.18 kg per m^2 per year in buildings. If assuming all buildings in New York State used the DDPC, the GHG emission could be reduced by 11%.
3. Deploying DDPC on large scale showed satisfactory scalability. The energy saving performance was similar for various kinds of HVAC systems. The percentage of feasible DDPC working properly in over one thousand HVAC units was 84%. Conditions that the DDPC could not work properly mainly due to data outlier, abnormal variation and disturbance, and beyond training. Obstacles for development of DDPC were unified naming and labeling of data, synchronization of time and control step, automatic input feature selection, and automatic diagnosis of failure and restoration of normal operation.

As for the limitation of this study and the future works, it is currently impractical to conduct field tests and validate the DDPC for different HVAC systems in a large number of buildings in different cities. It would take the cooperation of different universities and organizations to make it possible, which was one of the future work. In this study, we only focused on the air system and building heating/cooling load. It is necessary to develop and validate DDPC for more complex building energy systems, especially water systems (boiler, chiller, pump) and renewable energy system (PV panel and wind turbine). It could be a future direction to explore the data-driven predictive control for sustainable building and city. In this study, we focused on minimizing heating/cooling load with the DDPC strategy. In an actual HVAC system, the directly controlled parameters are the position of air duct dampers and heating coil valves. We will further develop the control strategy to adjust the position of the dampers and valves for practical implementation in buildings. What is more, for the energy consumption for dehumidification, it was related to indoor and outdoor humidity level. However, we found that most BMSs did not record data on relative humidity. Additionally, some HVAC systems, such as RTU and FCU, did not have dehumidification functions. Therefore, in this study, we focused on DDPC which optimized energy consumption for air temperature control. In future research, we can collect more data and consider the energy consumption of all HVAC components, including humidification/dehumidification, fan power, and reheating in addition to heating/cooling load.

Furthermore, though black-box data-driven models were more suitable for energy-efficient control of large-scale buildings, it was still challenging for complex buildings with multi-zone [13]. Data-driven coordinated control for complicated building energy system is also a future research topic. Additionally, DDPC could be easier than physics-based MPC to implemented in large number of buildings automatically. But the maintenance of data-driven model and control required attentions. In this study, we found many conditions when the DDPC could not work properly. The possible reason could because of the building envelope damage, equipment failure, and some unknown but extreme weather conditions. How to automatically detect these possible conditions, how to make the DDPC work better under these emergency conditions, and how to diagnose the failures and restore to normal operation of DDPC need to continue to be studied.

Author contributions

Zhipeng Deng was involved in conceptualization, investigation, resources, methodology, validation, visualization, and writing-original draft. Xuezheng Wang was involved in methodology, writing-original draft, and editing. Zixin Jiang was involved in methodology, writing-original draft, and editing. Nianxin Zhou was involved in data collection, software and validation. Haiwang Ge was involved in data collection, software and validation. Bing Dong was involved in project administration, conceptualization, methodology, supervision, writing-review, and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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