A Machine Learning-Based Control Strategy for Improved Performance of HVAC Systems in Providing Large Capacity of Frequency Regulation Service

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Abstract: Heating, ventilation and air-conditioning systems (HVAC), at demand side, have been regarded increasingly as promising candidates to provide frequency regulation service to smart power grids. In many control systems, chilled water outlet temperature setpoint is reset to change the power use of HVAC systems after the regulation capacity is determined. However, the conflict between changed power use and unchanged cooling/heating demand could become a prominent problem when a large regulation capacity is provided. This problem can deteriorate the performance of frequency regulation service provided by HVAC systems. In this study, a machine learning-based control strategy is proposed to solve this problem for improved performance of HVAC systems in providing large capacity of frequency regulation service. It adjusts the power use of HVAC systems by simultaneously resetting chilled water outlet temperature setpoint and indoor temperature setpoint. The proposed control strategy is validated on a simulation platform. Results show that the strategy can significantly increase the performance of service when an HVAC system provides different regulation capacities. Moreover, the robustness of the strategy is studied. The results show that the strategy can still work effectively even the machine learning algorithms has a relatively low prediction performance in real application due to practical difficulties.

Keywords: HVAC system; building demand response; machine learning; ancillary services; grid-responsive building.

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Nomenclature

ACE	area control error
AGC	automatic generation control
C_{reg}	regulation capacity
CNN	convolutional neural networks
DNN	deep neural network
k	the length of the average window
LSTM	long short-term memory
MA	moving average
MAE	mean absolute error
ML	machine learning
P	power use (W)
PJM	Pennsylvania-New Jersey Maryland Interconnection, regional transmission organization
PUF	power use following
RB	regulation bidding
RF	random forest
RNN	recurrent neural networks
S	score
SVR	support vector regression
T	temperature (°C)

Subscripts

b	baseline
c	correlation
chw	chilled water
d	delay
i	indoor
out	outlet
p	precision
set	setpoint

1. Introduction

The balance of power grids is reflected in power grid frequency which should be maintained within a narrow range. Normally, it is guaranteed by frequency regulation service provided by power stations at supply side. However, the integration of renewable power generations is increasing rapidly, and because of their intermittent nature, more frequency regulation capacity will be needed to maintain the balance of the power grids [1].

In recent years, many policies have been passed to encourage the resources at demand side to provide frequency regulation service [1, 2]. The mechanism and process for the demand resources to provide frequency regulation service are elaborated as follows. First, the power grid authorities monitor the "area control error" (ACE) which is the amount of the power imbalance between the supply and demand sides. Then this "area control error" is normalized to automatic generation control (AGC) signal [3]. It means the range of each signal point is from -1 to 1. Normally, the time interval between two continuous signal points is from 2 to 4 seconds [4, 5]. This signal is then sent to demand resources that are willing to provide frequency regulation service. In specific, each demand resource should continuously adjust its power use to follow the AGC signal on the top of its power use baseline. It should be noticed that different demand resources can provide different regulation capacities (i.e., power use fluctuation range) according to their own flexibility. Although the regulation capacity provide by a small power consumer is limited, a larger number of them can collectively provide a great amount of regulation capacity which can effectively relieve the imbalance of power grids [6]. On the other hand, power grid authorities have a requirement of the quality of frequency regulation service, namely, how well can the demand side power use be adjusted to follow the AGC signal. For example, an electric power authority, PJM (Pennsylvania-New Jersey Maryland Interconnection, regional transmission organization) uses performance scores to quantify the quality of frequency regulation service provided by the demand side participants [1], including a delay score, a correlation score, and a precision score. A participant is only qualified when it can obtain a composite performance score (i.e., the average of these three scores) not less than 0.75 [7]. The calculation details of performance scores are shown in Appendix A. Among various types of demand resources, heating, ventilation and air-conditioning (HVAC) systems in buildings are one of the most promising sources to provide frequency regulation service [8]. The reasons are that they account for a large proportion of electric energy consumption [9, 10], and because of thermal inertia of buildings and HVAC systems, they have great power use flexibility [11].

Many studies have studied the possibilities of using HVAC systems for providing frequency regulation service. Chillers/heat pumps almost consume half of the energy consumption of the entire HVAC system [12]. They are therefore the most attractive components to be considered for providing this service.

In most previous studies, the power of HVAC systems is changed by resetting the chilled water outlet temperature setpoint. In an experimental study conducted by Su and Norford [4], a chiller serving a medium-sized commercial building was used to provide frequency regulation service by adjusting the chilled water outlet temperature setpoint. The composite performance scores achieved were above 0.86 which could meet the requirement of PJM (i.e., 0.75). In a simulation study of Kawachi et al. [13], the chilled water outlet temperature setpoint of a heat pump was also reset to provide the service. In the study of Cai and Braun [14, 15], a variable-speed packaged rooftop unit (RTU) and a split heat pump were utilized to provide frequency regulation service. The reported composite performance score could reach 0.88. In this test, the supply air temperature setpoint was used to change the power use. The fundamental principle is the same as that of using the chilled water outlet temperature setpoint. The reason is that in these systems, the heat-transfer medium is air rather than water. In an experimental study of Kim et al [16], a variable-speed heat pump was used to provide frequency regulation service by modulating the chilled water outlet temperature setpoint. The composite performance scores achieved were between 0.77 and 0.81 which could also meet the requirement of PJM.

In some studies, the power of HVAC systems is changed by resetting the indoor temperature setpoint. In the study of Zhao et al. [17], the whole HVAC system (including all components) was utilized to provide the service by resetting the indoor temperature setpoint. The composite performance scores were in the range of 0.7991 and 0.8957. In an experimental study of Beil et al. [18], an HVAC system serving a single 30,000 m^2 office building was used to provide frequency regulation service by modulating the indoor temperature setpoint. The composite performance scores were between 0.5 and 0.65 which failed to meet the requirement of PJM. The main reasons could be the time delays and control inaccuracies.

In other studies, the power of HVAC systems is changed by directly adjusting the compressor speed. In the study of Kim et al. [19], integrated with an isolated microgrid, the study proved that the variable-speed heat pump could be effectively utilized to provide frequency regulation service by directly changing its frequency. In the study of Bünning et al, a ground-source heat pump (with a water storage system) is used to provide frequency regulation service by adjusting the frequency of the compressor. The composite performance score achieved was above 0.8 [20].

In summary, there are mainly three methods to adjust the power use of HVAC systems (especially for chillers/heat pumps) to provide frequency regulation service, resetting (1) the indoor temperature setpoint, (2) the compressor frequency, and (3) the chilled water outlet temperature setpoint. The first method (i.e., resetting the indoor temperature setpoint) is very convenient and practical to be used in real applications. However, this method involves the most delays among these three methods, which normally results in the lowest performance score. By comparison, the second method (i.e., resetting the compressor frequency) can most rapidly change the power use. Therefore, it technically can obtain the highest performance score. However, this method is not applicable for most chillers/heat pumps as their compressor frequency cannot be changed directly. The third method (i.e., resetting the chilled water outlet temperature setpoint) can also change the power use rapidly although it is not as fast as the second method because it involves the internal control process of chillers/heat pumps. However, it is an applicable method in real applications. Therefore, this method is the most popular one in previous studies. Nevertheless, there is a problem that should be noticed. When the chilled water outlet temperature setpoint is reset to change the power use, the indoor temperature setpoint is not adjusted, which means the cooling/heating demand is not changed. The changed power use and unchanged cooling/heating demand are in fact conflicting with each other. This conflict may not be significant when the power use is not changed significantly because the thermal inertia of systems can temporarily reduce this conflict. However, a large change of power use can occur when a large regulation capacity is provided. This large change of power use can cause serious conflict with the unchanged cooling/heating demand, which finally exceeds the ability of the thermal inertia of systems. In this scenario, the power use cannot be changed properly and the performance of the service can be deteriorated significantly.

This study, therefore, proposes a control strategy to solve this conflict for improved performance of HVAC systems in providing large capacity of frequency regulation service. It should be noted that this strategy is not for determining the regulation capacity but for efficiently adjusting the power use. The proposed control strategy can simultaneously adjust the indoor temperature setpoint ($T_{i,set}$) and chilled water outlet temperature setpoint ($T_{chw,out,set}$). The chilled water outlet temperature setpoint is changed by a proportional integral derivative (PID) sub-controller and the indoor temperature setpoint is adjusted by a machine learning-based sub-controller and a moving average module. Tests are conducted on a TRNSYS-Python co-simulation platform to validate the proposed control strategy.

The paper is organized as follows. The conflict (changed power use and unchanged cooling/heating demand) is first elaborated in Section 2. Then the proposed control strategy is presented in Section 3. The test arrangement and test platform are introduced in Section 4. In Section 5, the results of the control strategy performance are presented and discussed. The conclusions are made in Section 6.

2. Explanation of the problem when resetting chilled water outlet temperature setpoint

In this section, the problem encountered (changed power use and unchanged cooling/heating demand) is elaborated. To facilitate the understanding of this problem, the conventional strategy (only resetting chilled water outlet temperature setpoint) is first introduced.

2.1. Strategy of resetting chilled water outlet temperature setpoint

The conventional strategy, resetting chilled water outlet temperature setpoint to provide frequency regulation service is illustrated in Fig.1. The system concerned is set up based on an HVAC system in the International Commerce Centre (ICC) in Hong Kong which is a typical HVAC system.

The core control scheme (shown in the blue blank) to provide frequency regulation service includes two controllers, a regulation bidding (RB) controller and a power use following (PUF) controller. The function of the regulation bidding controller is to determine the power use baseline (P_b) and regulation capacity (C_{reg}). The power use baseline refers to the power use of the system under normal control without providing frequency regulation service. It represents the power use needed to meet the space cooling/heating demand. The regulation capacity (C_{reg}), namely the capacity of frequency regulation service, is the power use modulation magnitude around the power use baseline (i.e., $P_b \pm C_{reg}$). The determination of power use baseline and regulation capacity can refer to our previous study[21] in which a model predictive control strategy is proposed. It can predict the influence of power use variation on the indoor temperature considering the uncertainty of AGC signals. The power use baseline and regulation capacity are finally decided after considering the tradeoff between financial reward (regulation capacity) and thermal comfort. In this paper, the proposed control strategy is dedicated to the power use following controller. The function of the power use following controller is to determine reference power use and to control the system power use to follow the reference power use. Here, the reference power use can be considered as the power use setpoint (P_{set}) which can be obtained by P_{set} calculator according to Eq. (1). Here, the AGC signal is given by power grids directly. The power use baseline (P_b) and regulation capacity (C_{reg}) are provided by the regulation bidding controller. After the power use setpoint (P_{set}) is calculated, a PID controller is used to reset the chilled water outlet temperature setpoint according to the current power use and reference power use. It should be noticed that some studies also consider the power use of fans because it is also affected when chillers/heat pumps are used to provide frequency regulation service [1].

$$P_{set} = P_b + AGC\ signal \times C_{reg} \tag{1}$$

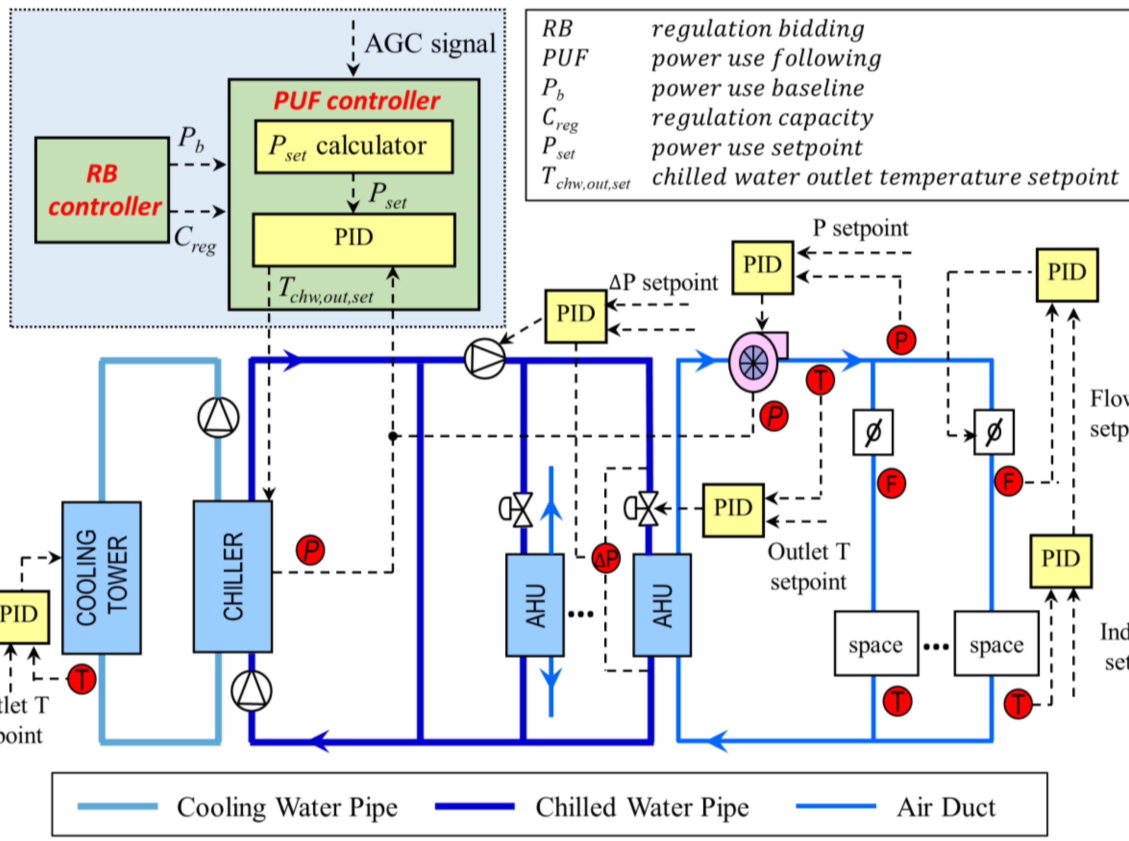

Fig. 1. Conventional control strategy for HVAC systems to provide frequency regulation service.

2.2. Problem explanation

To facilitate the understanding of the problem, a preliminary test under conventional control is conducted on a TRNSYS test platform. The test platform includes dynamic models of a building and an HVAC system which are developed according to the practical information of the International Commerce Centre (ICC) in Hong Kong. They are introduced in Appendix B. It should be noted that the frequency regulation service is in the time scale of a second. The dynamic HVAC models used are revised based on the original TRNSYS models after considering delays.

In this test, the HVAC system was controlled to follow a 40-min RegA (a type of AGC signal with a relatively low frequency) test signal with providing 10% of its current working rate as regulation capacity. This signal is provided by PJM which is dedicated to testing the performance of frequency regulation service [22]. The results are shown in Figs. 2(a-c). It should be noticed that before the case, the test platform has run four hours to achieve a stable condition.

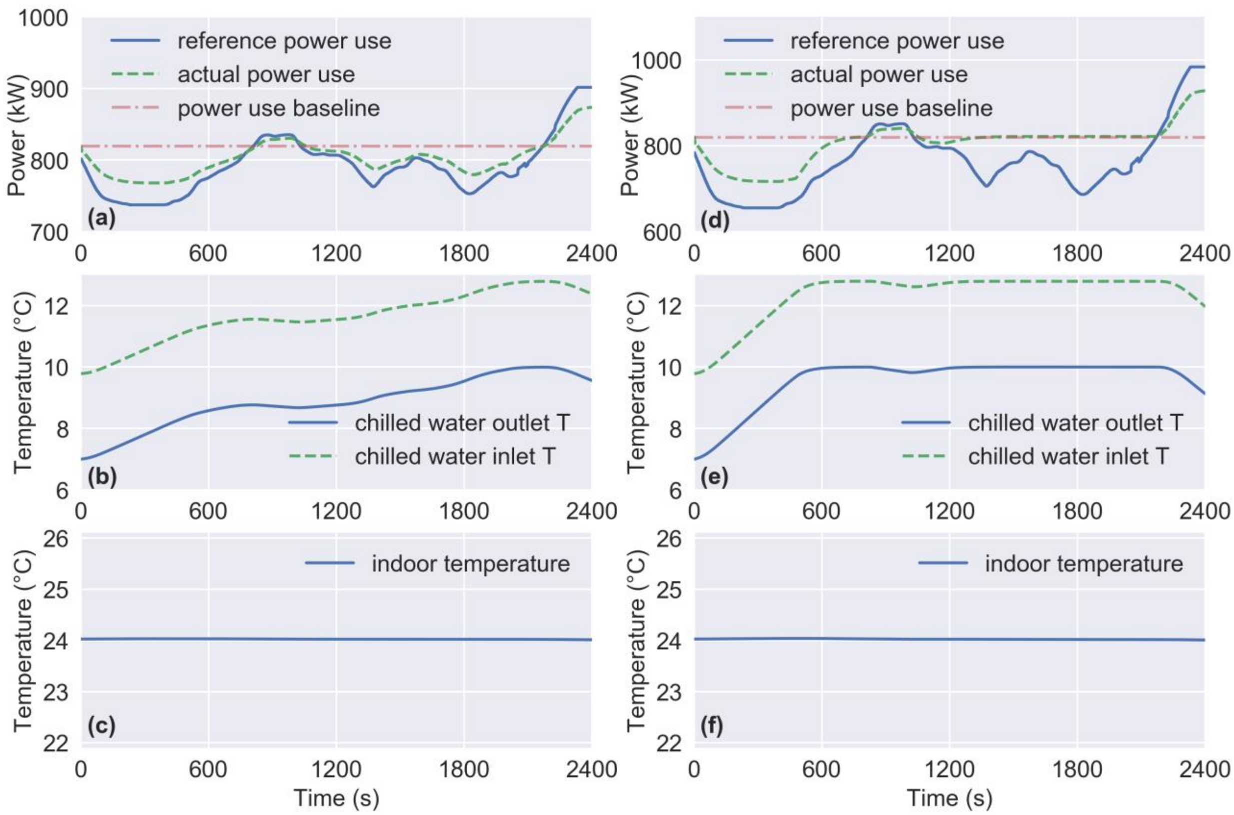

Fig. 2. Cases when an HVAC system is used to provide frequency regulation service by resetting chilled water outlet temperature setpoint with providing (a-c) 10% (d-f) 20% of its current working rate as regulation capacity.

In Fig. 2(a), it can be observed that the actual power use can follow the reference power use properly. The average performance score achieved was 0.846, which could meet the requirement of PJM (i.e., 0.75). It should be noticed that, at the beginning of the case (from 0 s to 600 s), the cooling supply of the system decreased because of the decrease of power use. By comparison, the cooling supply to the room remained stable since the indoor temperature was maintained at

24 ℃. Therefore, there was extra cooling to compensate for the imbalance between the cooling supply of the system and the cooling supply to the room. In fact, this extra cooling came from the cooling stored in the chilled water. As shown in Fig. 2(b), both the chilled water outlet and inlet temperature increased obviously which released extra cooling. Here, it should be noticed that the cooling stored in the internal mass of the building was not used in the process. It is because the indoor temperature was remaining at 24℃. Technically, the heat transfer between internal mass and indoor air didn't change after the system provided frequency regulation service.

Figs. 2(d-f) show the case when the regulation capacity increased to 20% of the current working rate. The indoor temperature can still be maintained properly at 24 ℃. However, the composite performance score achieved is as low as 0.598. The main reason can be found in Fig. 2(d), during the latter part of the process (from 1200 s to 2000 s), the actual power use didn't decrease to follow the reference power use. It is because the system cannot further increase the chilled water outlet temperature which has reached its upper limit of 10 ℃ (shown in Fig. 2(e)). It also means that the system has used up the cooling stored in the chilled water from 0 s to 600 s. Since the indoor temperate setpoint was remaining at 24 ℃ from 1200 s to 2000 s, the system needed to provide the corresponding cooling to maintain the indoor temperature. This cooling needed limits the variation of the power use of the system which failed to follow the reference power use during the latter part of the process.

The above two cases demonstrate that resetting chilled water outlet temperature method may not be able to work well when a relatively large regulation capacity is provided. The reason is that the cooling/heating stored in the chilled water is limited, which only can temperately reduce the conflict between the changed power use and unchanged cooling/heating demand. To provide a large regulation capacity, the indoor temperature setpoint should be adjusted simultaneously. There are two reasons for this implementation. First, the change of indoor temperature setpoint means the change of cooling/heating demand which can fundamentally solve its conflict with the changed power use. Second, the changed indoor temperature also enables the extra heat transfer between indoor air and internal mass. This means the cooling/heating stored in the internal mass can also be used to reduce the conflict.

3. Mechanism of the proposed control strategy

In this section, the mechanism of the proposed control strategy is introduced which is developed on top of the conventional control strategy, as shown in Fig. 3. It adjusts the power use of HVAC systems by simultaneously resetting chilled water outlet temperature setpoint (reset by a PID sub-controller as the conventional control strategy) and indoor temperature setpoint. The indoor temperature setpoint is reset by a machine learning (ML)-based controller and a moving average module (to smooth the change of indoor temperature setpoint). It should be noted that the machine learning-based model is a static model. This controller and module are then introduced in Section 3.1 and Section 3.2, respectively.

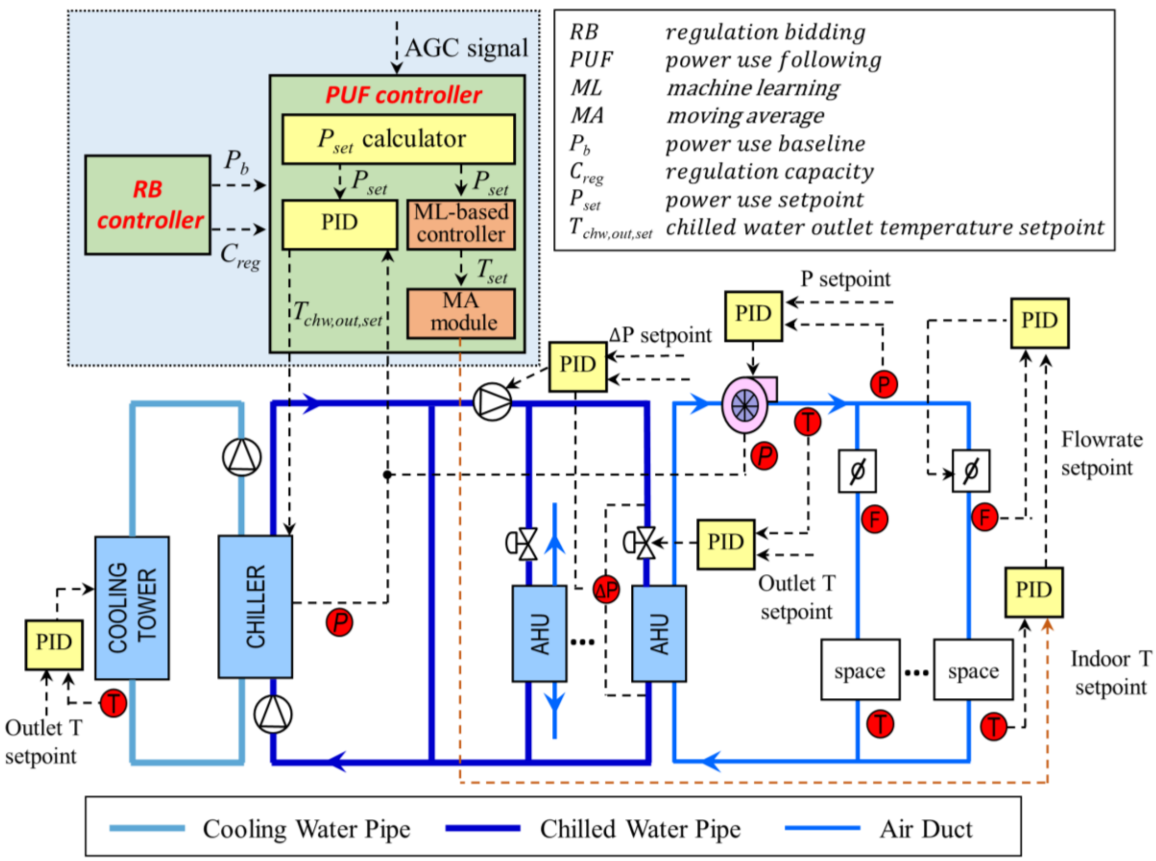

Fig. 3. Proposed control strategy for HVAC systems to provide frequency regulation service.

3.1. Machine learning-based controller

The machine learning-based controller is a prediction model which can directly predict the corresponding indoor temperature according to the reference power use (P_{set}). The fundamental of this controller is elaborated as follows. For a building with a certain HVAC system, there is a mapping relationship between indoor temperature and power use in steady states when other variables (e.g., weather condition, time) are certain. Inversely, according to the desired power use (reference power use) and other variables, the indoor temperature can be determined. There are four steps to train this prediction model, including feature selection, data collection, data cleaning, and prediction technique selection.

3.1.1 Feature selection

In our previous studies [23, 24], a rigorous analysis of feature selection has been conducted. Therefore, in this study, six features are directly selected as inputs, including the outdoor temperature, relative humidity, radiation, hour of the day, day type (working day or non-working day), and reference power use (P_{set}) to predict the corresponding indoor temperature (one output).

3.1.2 Data collection

To train the prediction model, a large amount of training data that can reflect the relationship between inputs and outputs is needed. In this study, these data are collected from the test platform (i.e., a building model and an HVAC system model which are introduced in Appendix B) in which various working conditions are simulated. In specific, the indoor temperature setpoint is randomly set in the range between 20 and 28 ℃ for each hour and the simulation runs for 5 years to cover different working conditions (such as different indoor temperature and weather conditions). The building model is set in free cooling mode in which an infinity cooling supply can be provided. In this mode, the system is automatically controlled to provide a certain cooling supply that can just meet the requirement for controlling the indoor temperature at its setpoint. After integrating with the corresponding steady-state model of the HVAC system, the power use under various working conditions can be obtained. It should be noticed that the weather data of Hong Kong is used which belongs to the hot summer and warm winter zone. Therefore, only cooling is needed throughout the year.

The simulation interval is set as 3 minutes. Therefore, for each hour, 20 sets of data are generated while only the set in the last point is collected. It is because the cooling demand at the beginning of each hour cannot reflect the real cooling demand in this hour because of the thermal inertia of the envelope and internal mass. Therefore, 43,800 (i.e., 8,760×5) sets of data in total are collected.

3.1.3 Data cleaning

Normally, in the procedure of data cleaning, the missing or abnormal data is detected and corrected (or removed). In this study, the main task in this process is to remove the data which is not useful in the real application of the machine learning-based controller. This implementation can significantly increase the prediction accuracy of the predictor. There are two types of data that need to be removed. First, only the datasets within working hours are remained (from 7 am to 8 pm) while the datasets within non-working hours are removed. The reason is that the machine learning-based controller is only used during working hours while for non-working hours, the HVAC system doesn't provide frequency regulation service. Second, the datasets whose power use is zero are removed. The reason is described as follows. In the process of data generation and collection, the indoor temperature setpoint is randomly set so the following cases may occur. The outdoor temperature is relatively low while the indoor temperature setpoint is relatively high. There is no need to start the HVAC system for cooling, so the power use is zero. Since the HVAC system doesn't even start, it obviously cannot provide frequency regulation service. Therefore, the datasets whose power use is zero are also removed.

3.1.4 Prediction technique selection

Three machine learning techniques are compared and the best one is selected for the machine learning-based controller. These techniques are support vector regression (SVR), random forest (RF), and deep neural network (DNN). These techniques are powerful machine learning methods that have been successfully used for building energy prediction in previous studies [25].

The parameters to be optimized for each technique are briefly introduced as below. The support vector regression with a Gaussian radial basis function kernel is used in this study. Optimization is performed considering the complexity parameter C and parameter gamma. In general, a larger C tends to make the model more prone to overfitting while a smaller C is more likely to cause under-fitting. The parameter gamma controls the shape of the decision boundary. A smaller gamma makes the decision boundary more flexible and smoother, while a larger gamma makes the decision boundary more complicated and sharper. In this study, the candidate values of parameter C take the form of 2^x, and x are integers ranging from 10 to 15. The candidate values of gamma take the form of 10^y in which y are integers ranging from -5 to 1.

Random forest is an ensemble learning method based on the decision tree. This means the prediction results of many decision trees are considered together to determine the final result. This can effectively avoid the overfitting problem. The main model parameters of the random forest include the number of trees in the forest, the depth of each tree, and the minimum number of samples at a leaf node.

Deep neural network is a technique that allows computational models with multiple processing layers to learn representations of data with multiple levels of abstractions. A typical neural network usually has three layers, i.e., one input layer, one hidden layer, and one output layer. By contrast, deep learning models could have several hidden layers and each layer may have different functions, e.g., performing nonlinear transformations or convolution operations. Accordingly, there are many types of deep learning techniques, such as fully connected neural networks, convolutional neural networks (CNN), recurrent neural networks (RNN), long short-term memory (LSTM) [26]. In this study, a fully connected neural network is used and the main parameters to be optimized are the number of hidden layers and the number of neurons in the hidden layers. In this study, the numbers of neurons in different hidden layers are set as the same.

The model parameters of each machine learning technique are optimized through cross-validation and parameter grid search. In the process of parameter optimization, the computation load should also be considered besides prediction accuracy. The reason is that in some cases, the prediction accuracy and computation load could both increase with the increase of some parameters (e.g., the number of trees in the random forest, the number of hidden layers in deep learning). In these cases, the tradeoff between prediction performance and computation load is considered. For example, if the prediction accuracy cannot further significantly change with the change of a parameter, the value of the parameter corresponding to a lighter computational load is considered as an optimal value.

3.2 Moving average module

In the above section, the mechanism of the machine learning-based controller is introduced. Instead of directly using its real-time output to adjust the indoor temperature setpoint, a moving average module is first used to smooth the change of the indoor temperature setpoint. The reason is described as follows. The machine learning-based controller only can reflect the mapping relationship (between indoor temperature and system power use) in a steady state. However, in real applications, the system is in a dynamic state. The direct change of indoor temperature setpoint can result in a sudden change of power use. This phenomenon has been observed in conventional demand response events when the indoor temperature setpoint is changed to reduce the peak power use [27]. For example, during peak hours, the indoor temperature setpoint is reset from 24℃ to 26℃, and it is recovered after peak hours (i.e., from 26℃ to 24℃). At that time point, the indoor temperature (e.g., 26℃) is higher than the indoor temperature setpoint (24℃). According to the characteristic of the PID algorithm, the system would temporarily while significantly increase the power use for increasing the cooling supply to decrease the indoor temperature. This phenomenon is called power rebound [28]. In this study, this phenomenon can deteriorate the control performance significantly. Therefore, a moving average module is used to smooth the change of indoor temperature setpoint, as described in Eq. (2).

$$y_t = \frac{1}{k} \cdot \sum_{i=1}^{k} y_{t-k+1} \tag{2}$$

where k is the length of the average window. Normally, different HVAC systems have different response speeds. k should be set case by case. In this study, k is set as 600 (corresponding to 10 minutes).

4. Test arrangement and test platform

4.1 Test arrangement

To comprehensively analyze the performance of the proposed control strategy, a series of simulation tests are conducted to accomplish the following three subtasks.

Subtask One – Study the performance of the proposed control strategy when the HVAC system follows the 40-min RegA test signal with providing 20% of its current working rate as regulation capacity. This specific test is used to compare with the convention control strategy under the same working condition (described in Section 2.2). The result of this subtask is presented in Section 5.2.

Subtask Two – Study the performance of the proposed control strategy in various working conditions. For this purpose, tests are conducted when the HVAC system follows historical hourly RegA signals in the whole year of 2018 with providing different regulation capacities (10%

to 50% of the current working rate with an increment of 10% of the current working rate). This means that as many as 43,800 (i.e.,8,760×5) tests are expected. The results are presented in Section 5.3.

Subtask Three – Study the robustness of the proposed control strategy. In real applications, the amount of building operation data is limited. The machine learning-based controller may have a relatively poor prediction performance. Therefore, it is valuable to study the robustness of the proposed control strategy, namely, to study the impact of prediction performance of machine learning-based controller on the performance of the proposed control strategy. For this purpose, artificial errors are introduced in the machine learning-based controller. To be specific, unbiased and zero-mean random errors (4 levels) are introduced to change the variance of prediction results. Constant errors (4 levels) are introduced to change the bias of prediction results. These cases are conducted based on the subtask two (8,760 hourly RegA signals and 5 different regulation capacities). Therefore, it means that as many as 350,400 (i.e., 43,800×8) tests are expected. The results are presented in Section 5.4.

4.2 Test platform

As a large number of repetitive tests are required, a computer-based dynamic simulation test platform is constructed to set test settings and perform the tests automatically, as shown in Fig. 4. Simulation tests are also considered as an effective and reliable approach for repetitive comparison tests, which can remove the interference of uncertainties in repetitive tests. In this study, the building model and the HVAC system model are built in TRNSYS 18 (64-bit) [29], which are introduced in Appendix B. The PID controller that reset the chilled water outlet temperature setpoint and the moving average module are also built in TRNSYS. The machine learning-based controller is built in Python 3.6 (64-bit), and Python is also used to manage the repetitive tests automatically.

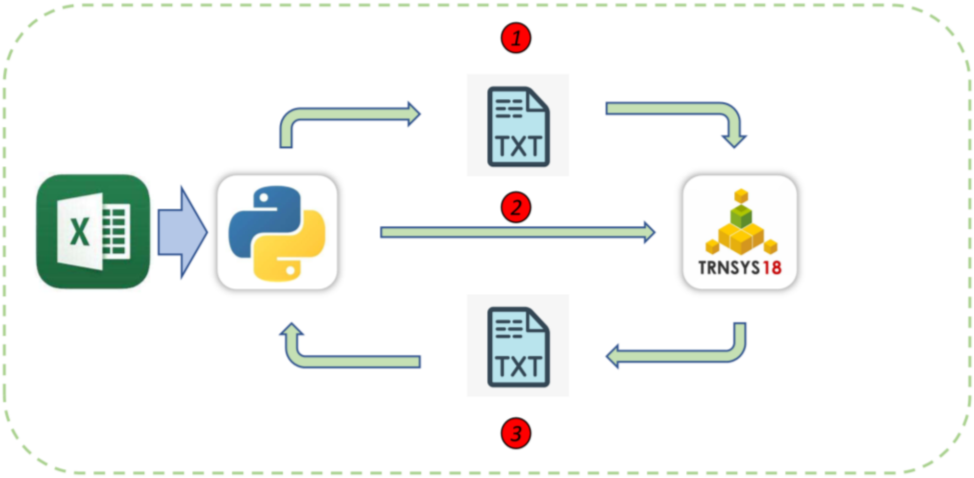

Fig. 4. TRNSYS-Python co-simulation test platform.

Before the simulation tests, the data of the historical AGC signal in 2018 (together with the 40-min RegA test signal) are all saved to an Excel file. When the simulation tests start, the Python program first read all the data and restored these data in the memory space. Then the following steps are repeated. In the first step, the Python program calculates the indoor temperature setpoint by the integrated machine learning-based controller under different working conditions (i.e., following certain signal, providing certain regulation capacity, or introducing certain artificial errors in the result of the controller) and writes the results to an input file (in text form) of TRNSYS. In the second step, the Python program runs the TRNSYS (a .dec file). In the last step, the Python program extracts the required variables from the output file (in text form) of TRNSYS.

5. Result and discussion

Before presenting the results of the three subtasks mentioned in Section 4.1, the selection of prediction technique for machine learning-based controller is first presented in Section 5.1.

5.1. Selection of prediction technique for machine learning-based controller

In this section, the prediction performances of three prediction techniques, support vector regression (SVR), random forest (RF), and deep neural network (DNN), are presented and compared. Here, two metrics are used to quantify the prediction performance, i.e., R-square and mean absolute error (MAE). The results are shown in Table 1.

Table 1 Optimal parameters and prediction performance of different prediction techniques

Prediction technique	Parameters	Value	R-square	MAE
Support Vector Regression (SVR)	C	16384	0.899	1.286
	gamma	1		
Random Forest (RF)	number of trees	180	0.928	0.490
	depth of each tree	22		
	minimum number of samples at a leaf	1		
Deep Neural Network (DNN)	number of hidden layers	3	0.932	0.465
	number of neurons in hidden layers	170		

It can be observed in Table 1 that the DNN technique achieves the best performance, with the highest R-square and lowest MAE. Therefore, DNN is finally selected for the machine learning-based controller.

5.2. Case when providing 20% current working rate as regulation capacity

Figs. 5(d-f) shows the cases when the HVAC system is controlled by the proposed control strategy with providing 20% of its current working rate as regulation capacity. For comparison with the convention control strategy, the previous case (described in Section 2.2) under the same working condition is shown in Figs. 5(a-c).

From 0 s to 600 s, the reference power use is remaining below the power use baseline. For the conventional control strategy, to reduce the conflict between the decrease of power use and unchanged cooling demand, the chilled water outlet temperature was increased significantly and achieved its up limit. Therefore, from 1200 s to 2000 s when the reference power use is below the power use baseline once again. The chilled water outlet temperature cannot be further increased. By comparison, for the proposed control strategy, from 0 s to 600 s and 1200 s to 2000 s, besides the increase of chilled water outlet temperature, the indoor temperature was also increased, which can directly decrease the cooling demand. In this way, the matching between power use and cooling demand was better achieved. Accordingly, the performance score can be guaranteed when a large regulation capacity is provided. As shown in Table 2, the composite performance score obtained under the conventional control strategy is 0.598. By comparison, the composite performance score obtained under the proposed control strategy is 0.862 which is significantly increased and meets the requirement (i.e., 0.75) of the electric power organization (i.e., PJM).

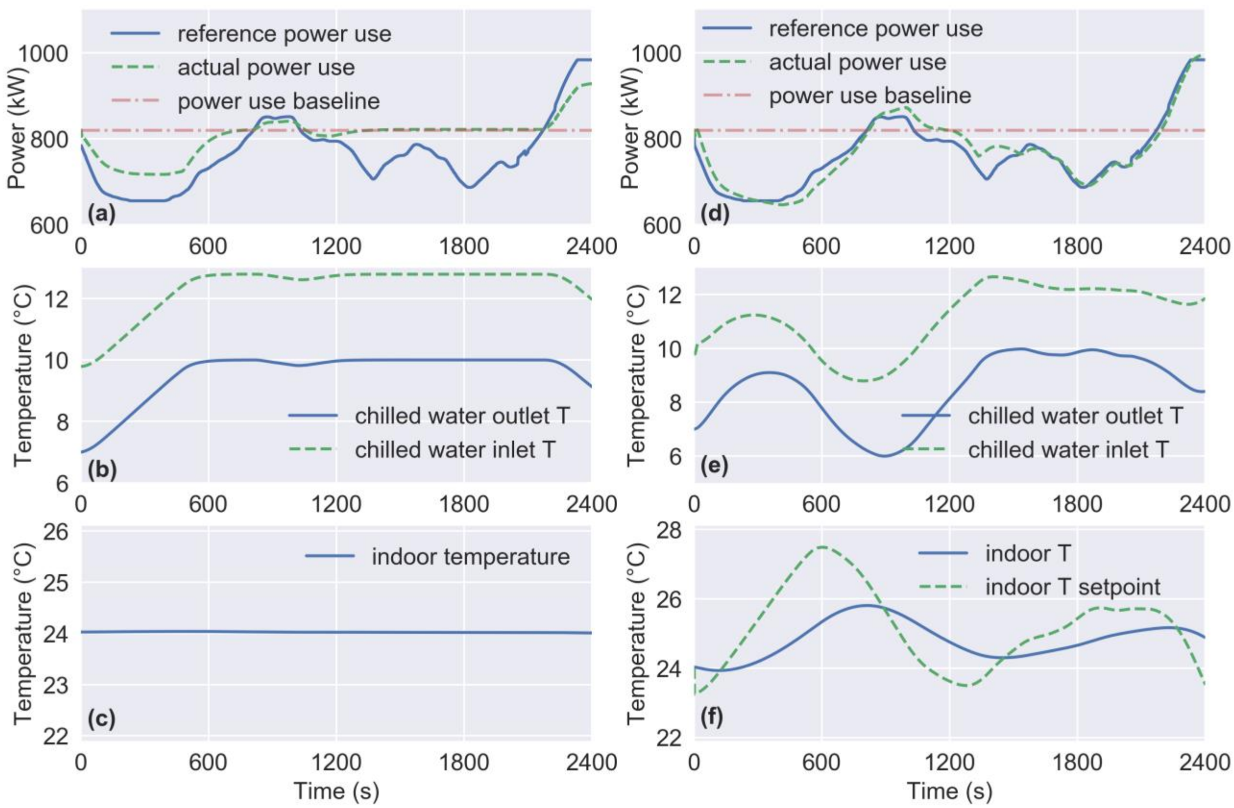

Fig. 5. Cases when an HVAC system provides frequency regulation service by (a-c) conventional control strategy (d-f) the proposed control strategy with providing 20% of its current working rate as regulation capacity.

In Fig. 5(e) and Fig. 5(f), it can be observed that because of the moving average module, the indoor temperature setpoint has some delay compared with the chilled water outlet temperature. This character in fact reflects the purpose of the proposed control strategy. The chilled water outlet temperature setpoint is rapidly changed mainly for adjusting the actual power use to follow the reference power use, while the indoor temperature setpoint is smoothly changed mainly for adjusting the cooling/heating demand.

In Fig. 5(f), it can be observed that compared with the indoor temperature setpoint, the indoor temperature has a lower amplitude of variation and more delay. It is quite reasonable because of the thermal inertia of the envelope and internal mass. In Fig. 5(f), it can also be observed that although there is some variation in the indoor temperature, it is remaining within an acceptable range. When a larger regulation capacity is provided, the indoor temperature may exceed the comfort zone, while determining a proper regulation capacity is the function of regulation bidding controller (shown in Fig. 3) which has been detailed introduced in our previous study [21]. The proposed control strategy in this study is dedicated to power use following controller. According to the results, it can work properly to improve the performance of the frequency regulation service when a large regulation capacity is provided.

Table 2 Performance scores of an HVAC system control by conventional and proposed control strategies to provide frequency regulation service

	Correlation Score	Delay Score	Precision Score	Composite Score
Conventional strategy	0.713	0.730	0.351	0.598
Proposed strategy	0.967	0.899	0.821	0.862

5.3. Control performance in various working conditions

This section shows the result of studying the performance of the proposed control strategy in various working conditions. As mentioned in Section 4.1, tests are conducted when the HVAC system follows historical hourly RegA signals in the whole year of 2018 with providing different regulation capacities (10% to 50% of the current working rate with an increment of 10% of the current working rate). This means that as many as 43,800 (i.e.,8,760×5) tests are expected.

5.3.1 Simplification of process

To reduce the computation time, it is expected that fewer cases/hours in 2018, rather than 8,760 cases, are used while the composite performance score obtained from these fewer cases is closed enough to that obtained from 8,760 cases. Fig 6 shows the relative error of the average composite performance score of a certain number of cases (randomly selected) compared with that of full (8,760) cases. It can be observed that the relative error between the average composite performance score of 100 cases and the average composite performance score of full (8760) cases is small enough (less than 1%). Therefore, for each regulation capacity, 100 hourly RegA signals are finally used instead of 8,760 hourly RegA signals.

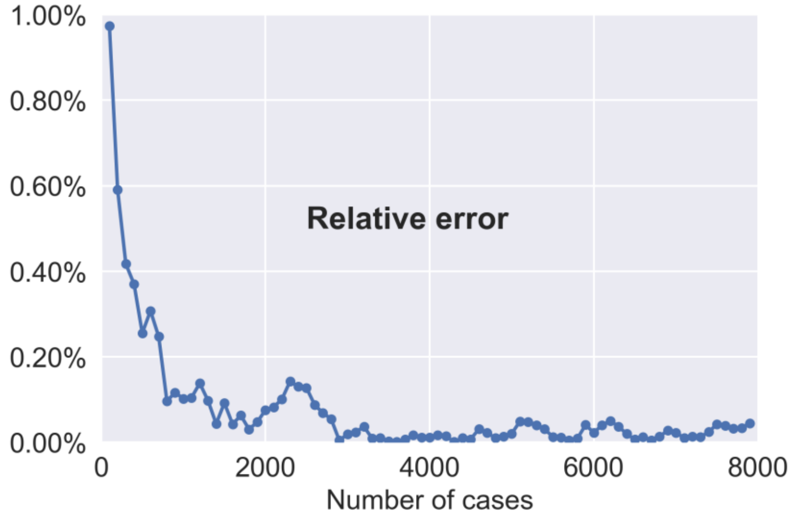

Fig. 6. Relative error of the average composite performance score of a certain number of cases compared with that of full (8,760) cases.

5.3.2 Performance when providing different regulation capacities

The results are shown in Fig. 7. It can be observed that, under the conventional control strategy, the composite performance score decreases significantly with the increase of the regulation capacity. The reason is that the cooling stored in the chilled water is limited. A larger regulation capacity can result in a larger deviation between reference power use and actual power use, which can decrease the composite performance score.

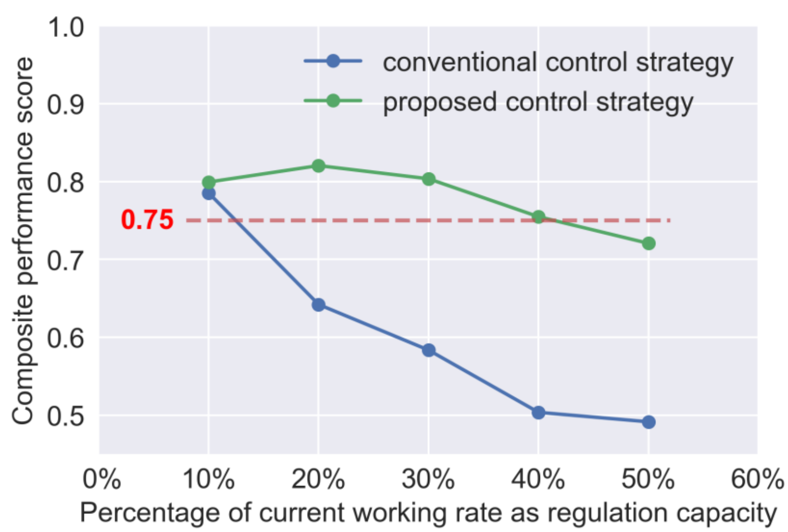

Fig. 7. Composite performance scores when an HVAC system is controlled by conventional and proposed control strategies with providing different regulation capacities.

Compared with the conventional control strategy, on one hand, the proposed control strategy can significantly increase the composite performance score under different regulation capacities. On the other hand, it, in general, shows the same trend that the composite performance score also decreases with the increase of the regulation capacity. The reason is twofold. First, even with the same prediction accuracy, a larger variation of reference power use may result in a larger absolute prediction error of indoor temperature. This can cause a larger deviation between reference power use and actual power use and decrease the composite performance score. Second, when the regulation capacity is small, the cooling stored in the chilled water can reduce the effect of prediction error to some extent. However, when the regulation capacity is larger, this compensation became less important.

5.4. The robustness of the proposed control strategy

The machine learning-based model can predict results efficiently while it needs a large amount of data for training. In practice, it is hard to obtain such massive data. There are two solutions to this problem. First, a physical model (e.g., EnergyPlus model) can be built up based on the building information. After the evaluation of the model, massive data can be generated. Second, instead of massive data, a relatively small amount of data can be obtained in practice. Both methods can decrease the prediction accuracy of the model. Therefore in this section, the robustness of the proposed control strategy is evaluated for the real application of the proposed control strategy. As mentioned in Section 4.1, to study the impact of prediction performance of the machine learning-based controller on the performance of the proposed control strategy, two different kinds of artificial errors are introduced. As shown in Table 3, for scenes 1-4, unbiased and zero-mean random errors with four different amplitudes are introduced. The original R-square of the predictor is 0.932 (shown in Table 2). After the errors are introduced, the R-square decreases to 0.8, 0.7, 0.6, and 0.5, respectively. The mean absolute error (MAE) is also increased accordingly. For scenes 5-8, four different values of constant errors (as bias) are introduced. Same as that in scenes 1-4, the R-square is also adjusted to 0.8, 0.7, 0.6, and 0.5, respectively. The mean absolute error is also increased accordingly.

Table 3 Scenes with different prediction performances of the machine learning-based controller

Scene	R-square	MAE	Scene	R-square	MAE

1	0.800	0.827	5	0.800	0.853
2	0.700	1.036	6	0.700	1.102
3	0.600	1.213	7	0.600	1.315
4	0.500	1.361	8	0.500	1.499

Fig. 8 shows the composite performance scores when the HVAC system is controlled by the proposed control strategy in different scenes. For scenes 1-4, it can be observed from Fig. 8(a) that the unbiased and zero-mean random errors have a neglectable impact on the composite performance score, even in scene 4 when the R-square has decreased to 0.500. The reason is that the moving average module can work effectively to eliminate the effect of unbiased and zero-mean random errors. For scenes 5-6, it can be observed from Fig. 8(b) that compared with unbiased and zero-mean random errors, the constant errors (as bias) have a much larger impact on the composite performance score. This impact is more significant when the regulation capacity is small. It is because a certain amount of temperature deviation, corresponding to a certain amount of power use deviation, is more likely to decrease the performance score when the regulation capacity is small. In practice, the error of the prediction model is unbiased and zero-mean random errors rather than constant errors (as bias). According to this information, the lower limit of the amount of data needed to train a prediction model with acceptable accuracy is then studied. It is found that for each month, only one week is needed to generate the training data for a prediction model with R-square larger than 0.5. It also needed to be noticed that the data collection work is only needed in the first year. This is very favorable for the real application of the proposed control strategy even when the machine learning-based controller may have a relatively poor prediction performance due to practical difficulties.

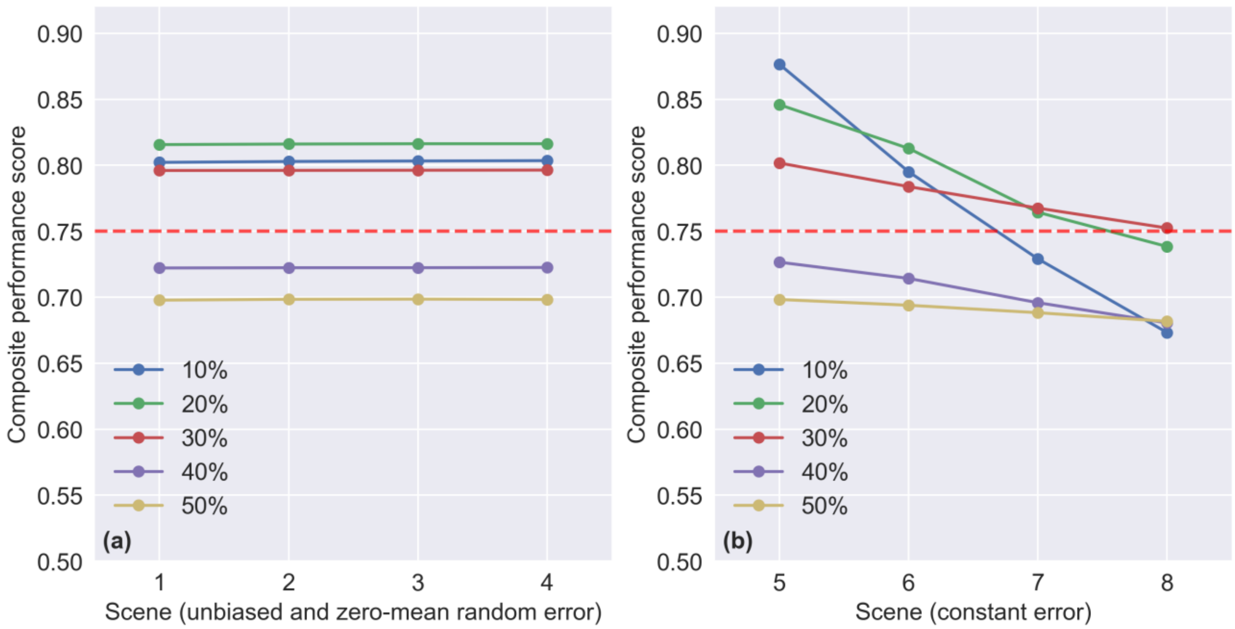

Fig. 8. Composite performance scores of an HVAC system controlled by the proposed control strategy with different prediction performances.

6. Conclusion

In this study, a machine learning-based control strategy for HVAC systems is proposed to provide frequency regulation service to power grids. It adjusts the power use of HVAC systems by simultaneously controlling the chilled water outlet temperature setpoint (reset by a PID sub-controller) and indoor temperature setpoint. The indoor temperature setpoint is adjusted by a machine learning-based controller and a moving average module (to smooth the change of indoor temperature setpoint). Tests are conducted on a TRNSYS-Python co-simulation platform to validate the proposed control strategy. The main conclusions are as follows.

- The proposed control strategy can effectively solve the conflict between the changed power use and the unchanged cooling/heating demand encountered by the conventional control strategy. It can significantly increase the composite performance score achieved by HVAC systems with providing different regulation capacities.
- In general, the control performance (reflected in the composite performance score) of the proposed control strategy decreases with the increase of the regulation capacity. However, it still has a good performance when a large regulation capacity is provided.

In the study, the composite performance score is still above 0.75 when the HVAC system provided 40% of its current working rate as regulation capacity.

- The proposed control strategy can effectively overcome the unbiased and zero-mean random errors in prediction. By comparison, it is relatively vulnerable to the constant error (bias) in prediction especially when a small regulation capacity is provided. In general, the proposed control strategy has good robustness.

There are also some limitations of this work. First, although the proposed has good robustness, an experimental study is also required to verify its performance in a real application. Second, the proposed control strategy is appropriate for signal-zone systems or for muti-zone systems which have a uniform indoor temperature setpoint. However, for multi-zone systems in which each zone has its own indoor air temperature setpoint, the proposed control strategy should be modified and further studied.

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Appendix A. Performance scores

- Delay score, S_d, shown as Eq. (A.1)
- Correlation score, S_c, shown as Eq. (A.2)
- Precision score, S_p, shown as Eq. (A.3)

The correlation and delay scores are determined together. The term δ is defined as the time shift with which the response has the highest correlation coefficient with the signal, and this highest correlation coefficient value is the correlation score, S_c. The average of these three scores forms a composite score.

$$S_d = \left|\frac{\delta - 5\ Min}{5\ Min}\right| \tag{A.1}$$

$$S_c = r_{Signal,Response\ (\delta, \delta+5Min)} \tag{A.2}$$

$$S_p = 1 - \frac{1}{n}\sum\left|\frac{Response - Regulation\ Signal}{Hourly\ Average\ Regulation\ Signal}\right| \tag{A.3}$$

Appendix B. Building model and HVAC system model

Building model: The building model is set up based on the International Commerce Centre in Hong Kong. This building is about 490 m high with a total floor area of approximately 321,000 m^2 served by a typical HVAC system including six identical chillers. The rated power consumption and cooling capacity of each chiller are 1,270 kW and 7,230 kW respectively [30]. Each chiller is associated with a chilled water pump and a cooling water pump. Both two types of pumps are constant speed and their on/off are interlocked with the on/off status of chillers. The air loop is a variable air volume (VAV) system. In this system, a PID controller maintains the indoor temperature at its setpoint by resetting the flowrate setpoint of each VAV box. Another PID controller modulates the valve opening to maintain the flowrate at its setpoint. To ensure the pressure in the air duct, the frequency of the fan is controlled by the third PID controller. In the test platform, only one chiller, corresponding to the hypothetical one-sixth area, is used. In this study, the model Type 56 in TRNSYS is used which is a detailed physical building model. Detailed settings in the building model (e.g., envelope, internal mass, internal heat gain, fresh air, and infiltration) are introduced in our previous study [31].

HVAC system model: Instead of steady state models, dynamic models of components in an HVAC system are used. This can more realistically describe the process of providing frequency regulation service. According to the experimental studies of He [32] and Su [4], it can be found that the measured power of a chiller can reach a steady state in 5 minutes after a step change of chilled water supply temperature setpoint. Therefore, the time constant of the chiller is set as 1 minute. The time constant of the Air handling unit (AHU) is set as 12 seconds according to previous experimental studies [33-35]. According to our previous experimental study [36], it can be found that the water flow only takes 2 seconds to reach a new steady-state condition after a step change of the frequency of the pump. Thus, a moving average method is used to represent the dynamic behaviors of water flow and air flow. The travel time of the water in the water loop and the travel time of air in the air loop are also considered as they could also have impacts on the response time of chiller power use. These times are estimated based on the practical information of the ICC building. The detailed settings of the chiller, Air handling unit (AHU), and water and air pipeline are introduced in our previous study [31]. The detailed setting of the fan is introduced in our another study [21].

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