The following publication X. Li, H. Li, J. Cao and S. Wang, "Robust Networked Control Adopting Prediction–Compensation Mechanism for IoT-Based Building Field-Level Control Concerning Network Uncertainties," in IEEE Internet of Things Journal, vol. 12, no. 11, pp. 15818-15827, 1 June 2025 is available at https://doi.org/10.1109/JIOT.2025.3531728.

IEEE Internet of Things Journal

Robust networked control adopting prediction-compensation mechanism for IoT-based building field-level control concerning network uncertainties

Xinyue Li, Hangxin Li, Jiannong Cao, *Fellow, IEEE* and Shengwei Wang

***Abstract*—Internet of Things (IoT) technologies offer great potential benefits to the development of smart buildings. However, the functionalities of IoT applications in buildings, especially those involving time-critical control tasks, are still limited due to the strict real-time and reliability requirements. These tasks could be easily affected by network uncertainties in the IoT environment. Current optimization methods aimed at mitigating network impacts have limitations in their applications and often overlook the impacts in real engineering cases. This study, therefore, proposes a robust networked control adopting the prediction-compensation mechanism to improve the robustness of building field-level controls implemented in the IoT-enabled building automation system. The control mainly consists of a predictor to estimate the controlled variable, and a compensator to evaluate the uncertainties. To assess the performance and the improvement on control robustness, a typical time-critical building field-level control task is implemented in a networked building field-level control simulation platform, considering network uncertainties. The proposed robust control is adopted for implementing the control task. The results show that the proposed robust networked control is a promising option due to its significant improvement in the control robustness when affected by network constraints, especially in critical conditions of the control process.**

***Index Terms*—Internet of Things (IoT); building automation; field-level; networked control; predictive control; compensation**

I. Introduction

As one of revolutionary technologies, Internet of Things (IoT) technologies bring benefits to nearly every field worldwide. The features of IoT, such as scalability and plug-and-play, show desirable advantages and potentials in various applications. With the trend of "connecting everything together", the number of IoT devices has a significant increase [1]. A report shows that there will be 75.4 billion IoT devices by 2025 [2]. The growth rate of IoT devices is around 10% every year, which is expected to be more than 10 times faster than the growth rate of Internet users [3]. With these advantages in various applications, IoT technologies are penetrating different industrial fields, including the building sector.

In the building sector, there are numerous successful practices of adopting IoT technologies in building automation (BA), mainly in the areas of security [4], indoor environment monitoring [5] and energy management [6]. However, there are only a few applications adopting IoT in building control. For example, Malkawi et al. proposed a IoT architecture for data-driven smart building operations [7]. In their architecture, the IoT sensors are utilized to collect indoor environment data for the multi-objective optimization involving indoor air quality, thermal comfort, and energy efficiency. Li et al. proposed an optimal control approach for IoT-enabled BA system. This approach is based on the fully distributed sensing agents to optimize the control of multi-zone fresh air systems [8]. Su et al. proposed a distributed control structure for heating, ventilation, and air-conditioning (HVAC) system [9]. In this structure, each field-device in the HVAC system is equipped an IoT controller for local optimization. From these studies, it can be seen that the functionality of IoT devices is limited. The typical usage is serving as an additional data source in a supplementary role for different purposes. Only a very few studies consider directly using IoT devices in decision-making of optimal control, which have less real-time and reliability requirements. However, as a fundamental function of BA system in buildings, the building time-critical control tasks, e.g., field-level process control tasks, are still implemented in the conventional direct digital control (DDC) architecture. This implementation adopts physical controllers and electrical cable to exchange digital/analog control signal. This manner can guarantee the real time and reliability for controls. No study on using IoT technologies for these time-critical control tasks is found. The capability and reliability of IoT technologies in real time applications are still an open question.

To achieve deeper penetration of IoT technologies in time-critical control tasks in building and industrial fields, the uncertainties from the impact of networks on control data transmission is a critical factor that cannot be ignored. In the

The research presented in this paper is financially supported by a General Research Fund (152223/23E) of the Hong Kong Research Grant Council (RGC). (Corresponding author: Shengwei Wang.)

X.Y. Li is with the Department of Building Environment and Energy Engineering and Research Institute for Sustainable Urban Development, The Hong Kong Polytechnic University, Kowloon, Hong Kong (e-mail: bse-xinyue.li@ connect.polyu.hk).

H.X. Li is with the Department of Building Environment and Energy Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong (e-mail: hangxin.li@polyu.edu.hk).

S.W. Wang is with the Department of Building Environment and Energy Engineering and Research Institute for Smart Energy, The Hong Kong Polytechnic University, Kowloon, Hong Kong and Shenzhen Research Institute, The Hong Kong Polytechnic University, Shenzhen, China (e-mail: beswwang@polyu.edu.hk).

J.N. Cao is with the Department of Computing, The Hong Kong Polytechnic University, Kowloon, Hong Kong (e-mail: jiannong.cao@ polyu.edu.hk).

conventional control architecture based on electrical cable connection, the control signals are in the analog form transmitted through the electrical cables. The transmission of electrical signals is real time with very high reliability. Thus, the signal transmission can be regarded as “perfect”, where delay and signal loss can be ignored [10]. However, when adopting IoT technologies, the control data, e.g., measurements from sensor(s) to controller(s), are transmitted through the network. Wireless networks, typically like Wi-Fi, are not designed for real-time communication with high reliability requirements [11]. For example, the delays of narrowband IoT (NB-IoT) are normally considered around 10s, making this network technologies much suitable for the delay-tolerant services rather than time-critical control tasks [12] [13]. As a result, the control could be affected by the uncertainties due to the unavoidable network constraints, which typically include network delay, packet loss, variable sampling/transmission interval, communication constraints, and quantization errors [14,15,16]. Among these constraints, network delay and packet loss are considered as two major constraints [17]. Su et al. analyzed the impacts of delay on the distributed optimal control in buildings [18]. The results show that the delay can result in lower convergence rate and bias in the optimization, leading to the degradation of energy performance. Li et al. investigated the impacts of network constraints in the HVAC process control [19]. The results show that the continuous packet loss can significantly degrade the control performance, causing large overshoot. From these studies, it can be concluded that these network constraints could significantly affect control performance, and packet loss is regarded as the most destabilizing reason for the networked control system due to the fact that a large number of packets may lost at simultaneously [20].

Currently, many studies use different optimization approaches to mitigate the impacts of network uncertainties caused by network constraints and enhance control performance. The common approaches include optimizing control design, adopting advanced network technologies, and using compensation methods. For the optimization by control design, many studies focus on optimizing the control structure or topology, or the parameters of control system. For example, Li et al. proposed a robust optimal control method for HVAC system in a networked IoT control environment, considering network failure [8]. This method shows good performance in cases of communication link failure, where the performance of the conventional approaches has significant degradation. Ploplys et al. proposed an adaptative sampling method for networked control of a rotating base pendulum [20]. This method can maintain the packet loss rate under 5% by reducing the sample rate to ensure the control performance when network congestions happened. Li et al. proposed an enhanced network control strategy and optimized its deployment in networked IoT environment [19]. In this strategy, the control loop is optimized, and each smart IoT device is responsible for part of control decision-making. This enhanced strategy can effectively reduce the overshoot and deviation caused by packet loss.

The optimization by adopting emerging network technologies is also considered by many studies. For example, the fifth-generation (5G) cellular network attracts many attentions due to its features of ultra-low latency and high reliability [21]. Many studies pointed out that the 5G networks can be expected to meet the strict requirements of control tasks [22] [23]. There are some emerging practices of applying the 5G network into control tasks. Wang et al. analyzed the performance of adopting the 5G network on grid interaction. It shows that the transmitted delay in the core network can be stabilized around 30 ms, which is significantly lower than the regulation signals of smart grids. It concluded the feasibility of adopting 5G networks for the smart grid regulation [24]. Li et al. employed the 5G network in the control of a gantry crane in a harbor with adopting end-to-end communication topology [25]. The results shows that the 5G network can provide a network environment with good reliability and low latency. Furthermore, some cellular networks can allocate dedicated network resources for specific tasks. Li et al. implemented networked control in a dedicated fourth-generation (4G) cellular network with industrial configurations to test performance using dedicated network resources [26]. The results show good performance with less interference from other network users. The 5G network provides the feature of network slicing, where dedicated network resources can be allocated by only software configuration. In this manner, the control environment can be more reliable with less interference.

For using compensation methods, the networked predictive control is commonly used to mitigate the impacts of network delay and packet loss. This method is highly applicable to different applications as it does not require on network infrastructure or modifications to control design. This control adopted prediction-compensation mechanism, which consists of two parts, i.e., control prediction generator and compensator, as shown in **Fig. 1** [14]. The design of this mechanism considers the nature of networks: data are transmitted in the form of “packet” in the network, which can contain multiple values or other data [27]. Base on this concept, the control prediction generator, serving the same function as controller, can generate a serial of future control predictions with timestamps and send them to the actuator in a signal packet. The compensator can select the proper prediction value by the corresponding timestamp. Thus, once packet loss happened, the actuator can still operate based on the prediction value, rather than only relying on the control decision made by out-of-date control signals.

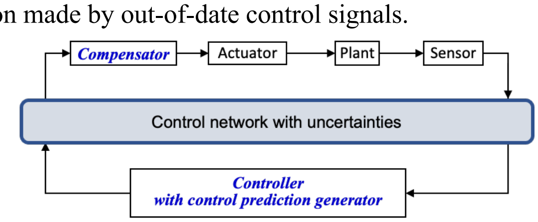


Fig. 1. Structure of networked predictive control

Many studies in the control field theoretically analyzed the feasibility of networked predictive control. For example, Xia et al. proposed a control prediction generator and a network delay compensator for a networked control system with random delay and packet loss. Its feasibility is validated by a theoretical analysis [27]. Liu et al. analyzed the stability of the networked predictive control with delays in the forward and feedback channels, and assessed the performance using a numerical model in real network environments [28]. It is theoretically proven that the necessity of using compensation methods in network environments. The results show that the negative effects of Internet delay on control can be compensated. Gao et al. optimized the prediction control by adopting a data-driven prediction method [29]. The simulation results from the tests adopting a ball-beam system model show the effectiveness of this method. However, from these studies, it can be seen that these compensation methods are based on theoretical analyses, or implemented using numerical or simple demo. In engineering cases, there is still a lack of investigation regarding the impacts of real-world control system on the mechanism performance, such as characteristics of control components in the system. The effectiveness in the real engineer cases, which can be influenced by multiple factors and different operation conditions, is worth to investigate.

In summary, it can be concluded from above studies that the uncertainties caused by network constraints significantly limit the applications of IoT technologies, especially in the time-critical tasks. In the building sector, the time-critical control tasks could be easily affected by the network uncertainties. To adopt the IoT technologies in more essential control functions beside the non or less time-critical tasks, an optimization method is necessary to ensure the control performance when affected by the network uncertainties. When considering different optimization methods to mitigate network constraints, adopting compensation methods has been proven effective with better applicability for different control tasks. However, to adopt this method in real engineer cases, the impacts of real engineering control system, the proper implementation ways, and the performance in real engineering projects still need further investigation, which is significant for more reliable networked control in a real-world engineering.

This study, therefore, proposes a robust networked control to improve the robustness of building field-level controls implemented in the IoT-enabled building automation system considering network uncertainties and impacts in the engineering control system. The control adopts the prediction-compensation mechanism, which includes a predictor to estimate the controlled variable, and a compensator to evaluate the uncertainties. To validate its performance, the proposed robust control is adopted to implement a typical building field-level control task, i.e., supply air temperature control task. The task is implemented in a networked building field-level control simulation platform considering network uncertainties. The improvement of control performance and robustness under impacts of network constraints are investigated.

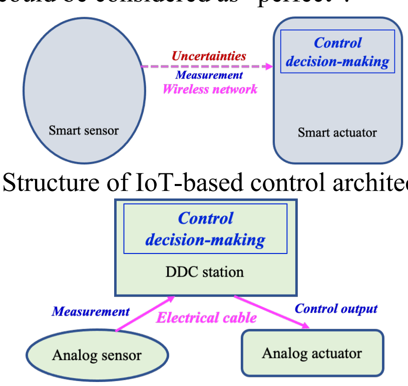
II. Proposed Robust Networked Control for Field-Level Control

The basic methodology of this study is to propose and adopt an optimization method to improve robustness and performance of building field-level control implemented in networked IoT environments. For this purpose, a robust networked control adopting prediction-compensation mechanism is proposed. The improvement of performance and robustness is validated by implementing the control in the simulation platform of the networked IoT environment in the next-generation of building automation system.

A. Overview of architecture for field-level control in networked IoT environment

When the control is implemented in the networked IoT environment, the control architecture could be significantly different. **Fig. 2.a** shows the IoT-based control architecture for field-level control deployed in the networked IoT environment, while **Fig. 2.b**, serving as a comparison, shows the conventional direct digital control (DDC) architecture for field-level control in current building automation systems.

In the IoT-based control architecture, the control data (e.g., measurements) are transmitted through the network. These data could be affected by network constraints, e.g., delay and packet loss. The smart device makes the control decisions according to the received data with uncertainties from the network. The transmitted data might be loss, delay, or disorder. Thus, the control performance could be affected by the network constraints. In contract, in the conventional DDC control architecture, a DDC controller is responsible for aggregating measurements from analog sensor(s) via electrical cable and making control decisions. The transmission of control data could be considered as “perfect”.



a) Structure of IoT-based control architecture

b) Structure of conventional DDC control architecture

Fig. 2. Different architectures for control implementation

B. Development of prediction-compensation mechanism

As a key part of the proposed robust networked control, the prediction-compensation mechanism is implemented and adopted to compensate the impacts of network constraints (e.g., packet loss and delay) on networked building controls. The structure of the implementation of this mechanism is shown in **Fig. 3**. There are two main parts in the mechanism, namely “predictor” and “compensator”. The predictor is used to predict the optimized control variable, according to the received value and the estimated value. The compensator is used to evaluate the uncertainties of these two types of value for the predictor.

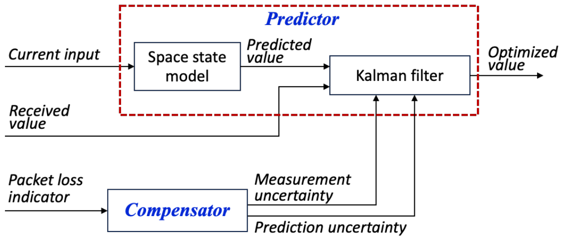


Fig. 3. Structure of prediction-compensation mechanism implementation

The predictor mainly consists of a space state model and a Kalman filter. The space state model employs the current system input (i.e., current valve opening, V) to generate a predicted control variable (i.e., supply air temperature, T_{sup}). In each sampling interval, the Kalman filter combines the predicted value and received value (i.e., from the network) to compute an optimized value according to the uncertainties. The parameters of Kalman filter are also updated at same time. The Equations of the Kalman filter is shown in (1)-(5) [30].

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1} \quad (1)$$

$$P_k^- = AP_{k-1}A^- + Q \quad (2)$$

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \quad (3)$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \quad (4)$$

$$P_k = (I - K_k H)P_k^- \quad (5)$$

Where, E.q. 1-2 are the prediction steps, and E.q. 3-5 are the update steps. In these equations, $\hat{x}_k^-$ is a priori state prediction of T_{sup} at step k; A is the state-transition model; $\hat{x}_k$ is a posteriori state prediction of T_{sup} at step k given measurement z_k; B is the control input model; u_{k-1} is the control input (i.e., V); P_k is the measure of the estimated accuracy of the state estimate; H is the observation model; z_k is the measurement of true state of x_k at step k; K_k is the Kalman gain; Q is the covariance of the process noise; R is the covariance of the measurement noise;

The compensator employs the indicator of packet loss as input, and records the numbers of continuous lost packets. It calculates the covariance matrices of the estimated value and the received value, which are treated as measurements of uncertainties. When an expected packet is successfully received, the uncertainty of received value is set to zero, which means that the Kalman filter completely relies on the received value. When the packet(s) is lost, the uncertainty of received value is increased with the number of lost packets. It leads the Kalman filter much more rely on the predicted value.

C. Simulation test platform and implementation of proposed control

i. Simulation platform and experimental validation

The networked building field-level control simulation platform is used to simulate the implementation of field-level control in IoT-enabled building automation system. The supply air temperature control of an air-handling unit (AHU), which is a typical HVAC field-level control task, is implemented in the platform. The control diagram is shown in **Fig. 4**. It can be seen that the valve opening directly tracks the deviation between supply air temperature (T_{sup}) and its setpoint ($T_{\text{sup,set}}$). Proportional and integral (PI) control is employed and implemented in the controller.

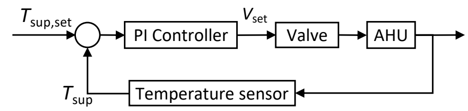


Fig. 4. Diagram of AHU supply air temperature control strategy

The schematic of the simulation platform used in this study is shown in **Fig. 5**. The simulation platform mainly includes two parts, i.e., the HVAC process model and the network operation model.

The HVAC process model includes the physical processes involved in the supply air temperature control considering the effects of unfavorable component characteristics. Three physical processes are considered, including the valve movement process, water flow rate regulation process, and air-handling process. The effects of component-level characteristics include valve dead band, valve movement speed, valve sensitivity, and maximum heating capacity of AHU.

The network operation model is used to simulate the details of data transmission through the network with the consideration of network constraints. Two main network constraints, i.e., packet loss and network delay, are taken into consideration. The packet loss is modelled by using a Markov chain, which consists of two states, i.e., packet received or lost. The transition between these two states depends on the current state and transition probability of each state. The network delay is modelled adopting the probability of normal distribution. Once the packet loss is not happened, the packet will be held for a random time, which is generated based on the defined probabilities distribution from the experimental test, before being send to the receiver.

For the integration of the network operation model, given that the controller is deployed in the smart actuator, only the data transmission from the smart sensor to the smart actuator needs to go through the wireless network and may be affected by network constraints. Thus, the network operation model is integrated into the link from the sensor to the controller (smart valve) in the control loop.

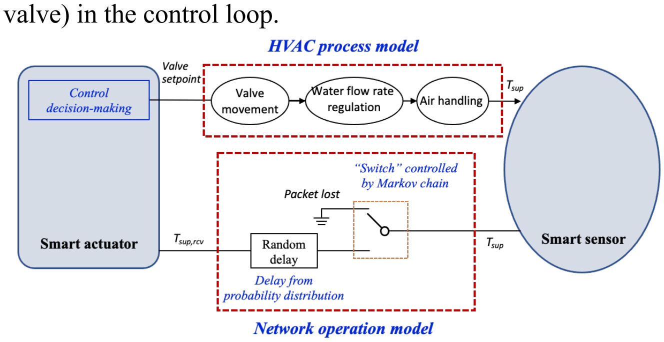
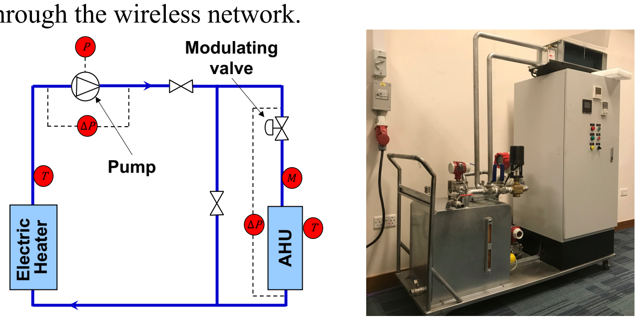


Fig. 5. Schematic of simulation platform

To experimentally validate the simulation platform and provide real-world network conditions, a compact HVAC test rig is constructed, as shown in **Fig. 6**. The prototypes of smart devices (e.g., smart valve) are also developed and integrated in the test rig, as shown in **Fig. 7**. The test rig implements the supply air temperature control, similar as the HVAC system in buildings. Typical settings in commercial HVAC systems are adopted in the validation for the platform. For the smart devices, the valve is integrated with an IoT controller, forming a "smart valve". The IoT controller includes a STM32 microcontroller and a Wi-Fi module. It enables the data exchanging from the Wi-Fi network and control decisions making. The sensor (i.e., supply air temperature sensor) is also "updated" to a smart sensor by aggregating the existing analog sensors into a computer via IO modules. It is also equipped with a Wi-Fi module to communicate with other smart devices through the wireless network.



a) Schematic of the experimental test rig b) Image of the experimental test rig

Fig. 6. Compact HVAC test rig

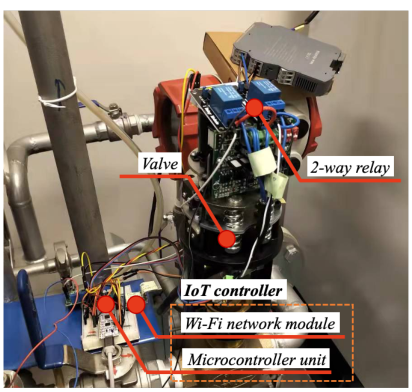


Fig. 7. Structure of smart valve

ii. Implementation of robust networked control

The implementation of the robust networked control in the simulation platform is shown in **Fig. 8**. The module of prediction-compensation mechanism is implemented in the smart valve. It means that the valve is responsible for the data receiving, compensation, local control decision-making, and actuator operation. The received packet is directly processed by the prediction-compensation module. If there is no packet loss, the received packet will be directly used in the control decision-making process. If the packet loss happens, a predicted value generated by the prediction-compensation module will be used, alternatively. In the real-world engineering case, given the low computation load of the Kalman filter in the mechanism module, the IoT controller of smart device has sufficient computational resource to execute the whole process.

The simulation platform and models are programmed using Simulink. A PC with 2.0 GHz quad-core CPU and 16 GB memory is used to executed the simulation.

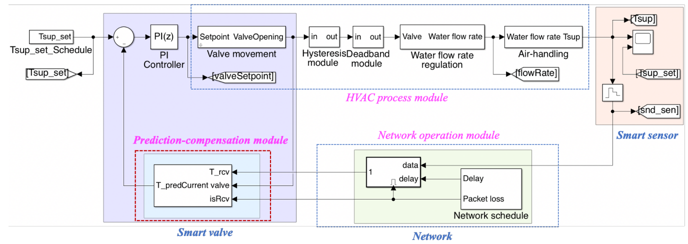


Fig. 8. Structure of implementation of robust control in simulation platform

iii. Simulation test arrangement

After implementing the proposed control into the simulation platform, the settings, similar as the practical settings in commercial HVAC systems, are adopted to assess the improvement on control performance and robustness under impacts of network constraints. In these settings, three different setpoints of supply air temperature ($T_{\mathrm{sup,set}}$) are adopted: 50 °C, 45 °C and 43 °C. These setpoints are adjusted step by step after the output is stable. According to the setting of modulating valve characteristics, setting the $T_{\mathrm{sup,set}}$ below 45 °C could high likely result in the instability of control output (T_{sup}). It is due to the fact that the corresponding water flow rate is lower than the controllability range of the valve. When the water flow rate is lower than the minimum controllable range, the valve may cut down the water flow rate due to the fact that the valve opening reaches its dead band. The cut off water flow rate could significantly reduce the supply air temperature, causing the control instability.

The parameters of network conditions are obtained from a typical research and teaching building. The network deployment is shown in **Fig. 9**. This network deployment is similar to the deployment of IoT-enabled BA system where the network coverage of smart field-level devices is poor, resulting in a marginal network condition for time-critical tasks. The obtained network parameters include mean network delay, standard deviation of delay, and packet loss rate in different states.

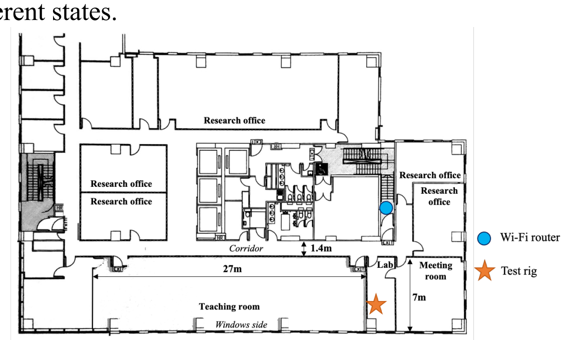
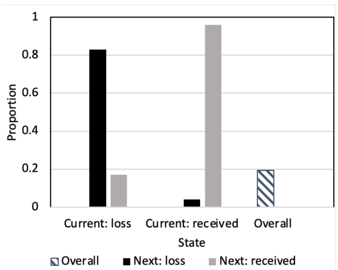
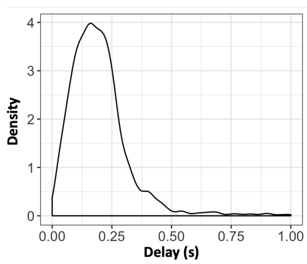


Fig. 9. Deployment location for network condition assessment

The delay distribution and packet loss rates are shown in **Fig. 10.a** and **Fig. 10.b**, respectively. The overall packet loss rate is 19.2%. Among the packet loss rate in different state, the possibility of continuous packet loss (i.e., packet loss happened when the previous packet is lost) is significantly high, which figure is 83.1%. It means that once the packet loss happened, a large number of packets may be lost continuously. For the distribution of network delay, the mean value is 292 ms, while the standard deviation is 148 ms. It can be seen that most of the delay is lower than 500 ms. Only a few packets with delay high than 1 s, which proportion is 3.1%. Based on these parameters from experimental tests, a schedule of network delay and packet loss is generated. Each simulation test utilizes this same schedule to assess the performance enhancement of the proposed robust control. This approach can avoid the difficulty from random network constraints in field tests for comparison, while reflect on-site network conditions.



a) Statistics of packet loss rate



b) Distribution of network delay

Fig. 10. Characteristics of tested network condition

In this study, dynamic and steady-state performance of the control is assessed. The dynamic performance includes overshoot, peak value, peak time, and rise time. The steady-state performance, considering for the setpoint of 50°C, includes the steady value, standard deviation, and steady-state error. The oscillation range of the control output, i.e., supply air temperature, is recorded, which can be used to assess the network impact on the control performance in the critical condition of the actuator. These indicators are compared in different simulation tests to assess performance and improvement of the proposed robust control.

III. Simulation Results and Analysis

In this study, the control task implemented in the conventional DDC control architecture is first simulated, serving as a baseline for comparison. In this simulation, the data exchange is regarded as "ideal", which means that there is no network constraints effect. Then, the control task implemented in the IoT-based control architecture without adopting proposed robust control is simulated. The performance of this case is compared to the baseline, revealing the impacts of network uncertainties on the control task. Next, the control task implemented in the IoT-based control architecture with adopting the implementation of proposed robust control is simulated. The improvement of compensating the network constraints on networked control performance is assessed.

A. Performance of control implemented in conventional DDC control architecture

As a baseline for the comparison, **Fig. 11** shows the test results of the simulation when the control strategy is implemented in the conventional DDC control architecture. The profile includes supply air temperature (T_{sup}) and its setpoints ($T_{sup,set}$). **TABLE I** shows the major control performance indicators in this test. Given that there is no network constraints impact, and all control signal transmission can be regarded as "ideal". At $T_{sup,set}$ of 50 °C, the control output (i.e., T_{sup}) can be effectively controlled due to the fact that the corresponding water flow rate is in the controllable range of the valve. Only 0.39 K of steady-state error can be seen at this setpoint. When the setpoint is lower (i.e., at the setpoint of 45 °C and 43 °C), the T_{sup} becomes oscillated and the control process becomes more dynamic. The oscillation ranges for these two setpoints are 7.6 K and 8.2 K, respectively.

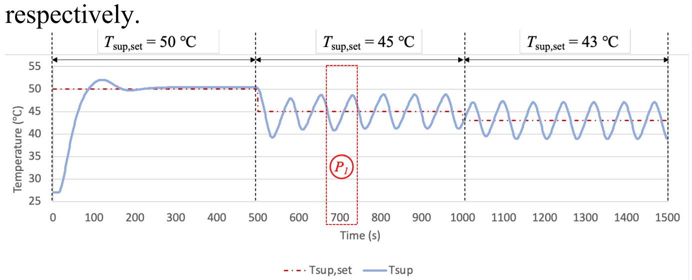


Fig. 11. Major control and system variables when control employing the conventional DDC control architecture

TABLE I
CONTROL PERFORMANCE EMPLOYED THE CONVENTIONAL DDC ARCHITECTURE

	$T_{sup,set}$=50°C	$T_{sup,set}$=45°C	$T_{sup,set}$=43°C
Overshoot	4.1%	-	-
Peak value (°C)	52.0	-	-
Peak time(s)	121	-	-
Settling time (±5%, s)	71	-	-
Steady value (°C)	50.4	-	-
Standard deviation (Last 60s, K)	0.02	2.64	2.74
Steady-state error (K)	0.39	-	-
Oscillation range (K)	-	7.6	8.2
Oscillation interval(s)	-	76	74

A typical period of oscillation is indicated as P_1 in **Fig. 11**. The system variables involved in the control process, including water flow rate (Q), actual detected valve opening (V), and valve opening setpoint (V_{set}), are shown in **Fig. 12**. At t_1, the decrease of the valve reaches its dead band for water flow rate regulation. The water flow rate is cut off immediately. However, due to the longer response time of the air-handling process, the supply air temperature (T_{sup}) continues to increase, while the valve opening continually decreases within the dead band due to the decisions of the PI control. After T_{sup} finally starts to decrease, the valve needs time to move out of the dead band until t_2, after which the water flow rate can be regulated. At this time, the T_{sup} is lower than the setpoint, while the valve remains increasing the open ratio, which will cause T_{sup} to increase after a while. As a result, the oscillation happens at these lower setpoints.

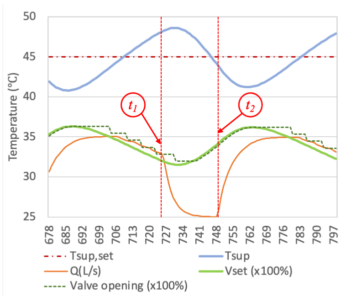


Fig. 12. Effect of dead band on the control in the oscillation period

B. Performance of control implemented in IoT-based control architecture without adopting robust networked control

Fig. 13 shows the test results of the simulation when the control strategy is implemented in the IoT-based control architecture without adopting the robust networked control. **TABLE II** shows the same major indicators of control performance. It can be seen that the control output (i.e., T_{sup}) is much more fluctuated compared to that in the case using the conventional DDC control architecture. Even at the setpoint of 50 °C, which is in the controllable range for the valve, the T_{sup} has a large decrease due to the network impacts. For the setpoints of 45 °C and 43 °C, the oscillation range is considerably enlarged. The maximum oscillation range is 20.1 K at the setpoint of 43 °C. The overall performance is noticeably degraded.

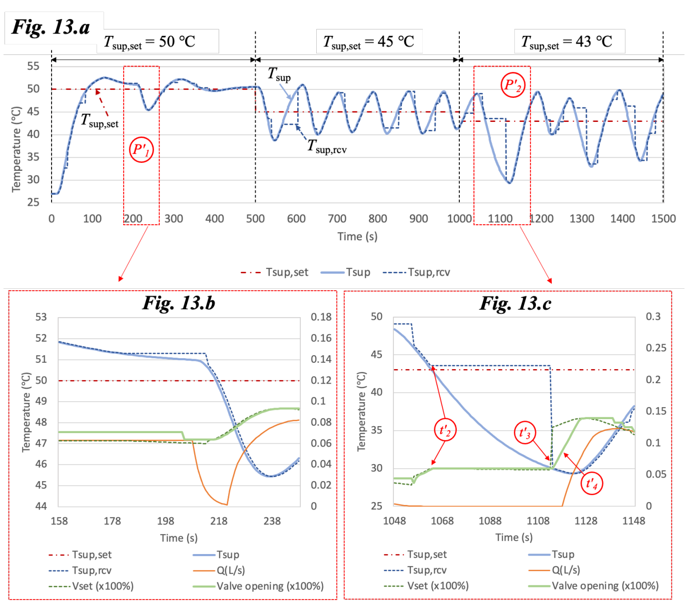


Fig. 13. Major control and system variables when control employing the IoT-based control architecture without robust control
(Fig. 13.a: Overall profiles; Fig. 13.b: Network constraints impacts in controllable range; Fig. 13.c: largest packet loss impacts)

For the detailed impacts of network constraints on the control process, there are two worth noting periods of packet loss, indicating as P_1 and P_2. The system variables involved in the control process of these two periods are shown in **Fig. 13.b** and **Fig. 13.c**, respectively. P_1 is in the controllable range of the valve, while P_2 is the largest continuous packet loss in this test. During P_1, as shown in **Fig. 13.b**, the valve operates within the controllable range at 50 °C of setpoint ($T_{sup,set}$). Due to the continuous losses of 31 packets, the received measurement is not updated to the actual supply air temperature. The controller accumulates the bias and continuously reduces the output (i.e., V_{set}) according to the mechanism of PI control. At t'_1, the difference between the valve opening setpoint and current valve opening exceeds the threshold of valve movement. Then, the valve starts to move and reaches its dead band, cutting off the water flow rate. It causes -4.6 K (down to 45.4 °C) decrease of T_{sup}.

TABLE II
CONTROL PERFORMANCE EMPLOYED THE IOT-BASED CONTROL ARCHITECTURE WITHOUT ROBUST CONTROL

	$T_{sup,set}$=50°C	$T_{sup,set}$=45°C	$T_{sup,set}$=43°C
Overshoot	5.1%	-	-
Peak value (°C)	52.5	-	-
Peak time(s)	131	-	-
Settling time (±5%, s)	71	-	-
Steady value (°C)	50.2	-	-
Standard deviation (Last 60s, K)	0.29	3.16	4.77
Steady-state error (K)	0.18	-	-
Oscillation range (K)	-	12.3 (max)	20.1 (max)
Oscillation interval(s)	-	89.4	106.7

The largest continuous packet loss is shown in **Fig. 13.c**, where a total of 50 packets are lost continuously. The period of packet loss starts at t'_2. At this time, the latest updated measurement of T_{sup} is 43.6 °C, which is very close to the setpoint of 43 °C. Thus, the valve remains unchanged at the low opening position. However, due to the different response speeds of the air-handling process and valve movement, the T_{sup} continually decreases at such a low valve opening. At t'_3, the measurement packet is updated finally, and the controller provides new valve opening setpoint immediately. The valve needs time to move the spindle out of the dead band (i.e., from t'_3 to t'_4) to reach the higher setpoint, while the bias of control output (i.e., T_{sup}) continues to increase. As a result, the packet loss causes 13.7 K (down to 29.3°C) decrease of T_{sup}.

C. Performance of control implemented in IoT-based control architecture with adopting robust networked control

Fig. 14 shows the test results of the simulation when the control strategy is implemented in the IoT-based control architecture with adopting the robust networked control. **TABLE III** shows the same major indicators of control performance in this case. It can be seen from **Fig. 14** that the control output (T_{sup}) is significantly stable compared to the case without adopting the proposed robust control, even when the control task is subjected to the same effects of network delay and packet loss. At the setpoint of 50 °C, the control output (i.e., T_{sup}) is not significantly interfered by the network constraints. The oscillation ranges at the setpoints of 45 °C and 43 °C are 8.84 K and 8.91 K, respectively. These values are significantly lower than the maximum oscillation ranges of 12.3 K and 20.1 K observed in the case without adopting the proposed robust control. It can be concluded that the introduction of the proposed robust networked control can significantly improve the control performance and reduces the impacts of network uncertainties on the networked control process.

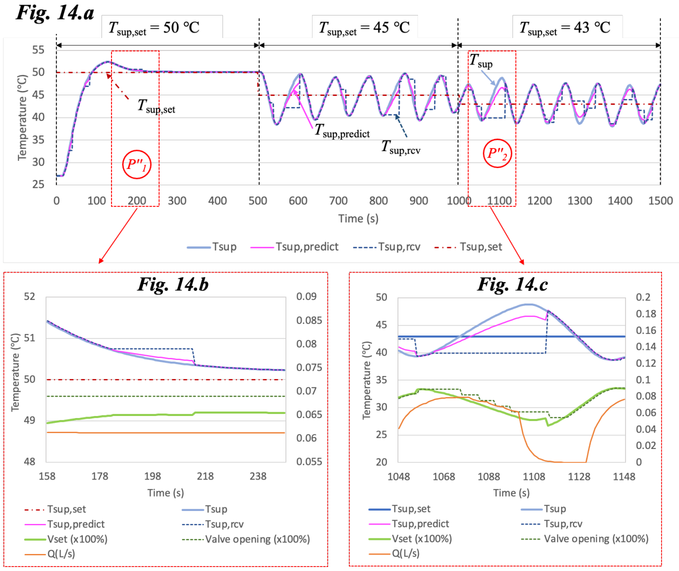


Fig. 14. Major control and system variables when control employing the IoT-based control architecture with robust control

(Fig. 14.a: Overall profiles; Fig. 14.b: Network constraints impacts in controllable range; Fig. 14.c: largest packet loss impacts)

TABLE III

CONTROL PERFORMANCE EMPLOYED THE IOT-BASED CONTROL ARCHITECTURE WITH ROBUST CONTROL

	$T_{sup,set}$=50°C	$T_{sup,set}$=45°C	$T_{sup,set}$=43°C
Overshoot	2.4K (4.8%)		
Peak value (°C)	52.4		
Peak time(s)	128		
Settling time (±5%, s)	72		
Steady value (°C)	50.0		
Standard deviation (Last 60s, K)	0.50	3.18	2.86
Steady-state error (K)	0.05		
Oscillation range (K)	-	8.84	8.91
Oscillation interval(s)	-	89	81

For the details of the improvement by the proposed control, the same periods of network effect are indicated as P''_1 and P''_2. In **Fig. 14.b**, when packet loss happened, indicated by t''_1, the predicted values are used for control decision-making. These predicted values can follow the trend of the supply air temperature, even with slight bias. The valve opening setpoints then slightly increase according to the control decisions. Thus, the valve does not reach its dead band range, where the water flow rate will be cut off, similar to the case shown in **Fig. 13.b**. During the largest packet loss in P''_2, as shown in **Fig. 14.c**, the predictor continuously provides the predicted values for control decision-making. Even though there are some bias in the predicted values, the controller can still make more proper decisions compared to directly using the out-of-date measurements. It can be seen the control output, i.e., supply air temperature, is not significantly affected by the losses of measurement packets. The highest deviation during this period is 5.8 K, which reduce 57.7% compared to the deviation of 13.7 K observed in the case without adopting the robust control, as shown in **Fig. 13.c**.

Fig. 15 shows the performance of the prediction-compensation mechanism during packet loss. The model shows acceptable performance with 0.962 of R^2. However, it can be seen from **Fig. 14.c** that the bias could slightly increase with an increasing number of lost packets. The predicted values tend to be slightly lower than the actual supply air temperature. This phenomenon is due to the fact that the weight of predicted value becomes higher with the increase of lost packets. It is means that the predictor relies more heavily on the state-space model. However, it is difficult to capture the nonlinear factors of the control process accurately, such as dead band and saturation. It could cause the deviation between the final optimized values and actual values. Nevertheless, when continuous packet loss happens, using the predicted values, even with some bias, is significantly better than directly using the out-of-date measurement data for the control decision-making.

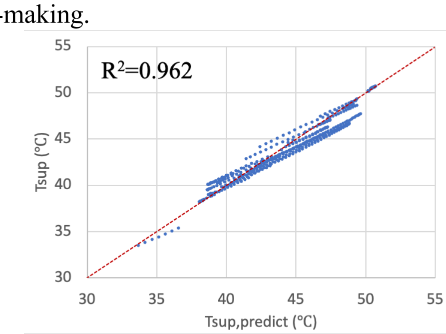


Fig. 15. Performance of prediction

IV. DISCUSSION

From the results of this study, it can be seen that adopting IoT technologies in the field level of BA systems still exists many fundamental issues to be addressed. Directly adopting wireless networks may hard to meet the requirements of timing and reliability for control tasks. The control performance may have significant degradation due to network constraints. Therefore, it is necessary to implement optimization methods to improve control robustness for the networked controls in IoT-enabled BA systems.

To optimize the networked controls, using compensation methods, such as the proposed robust networked control, could be a good option compared to current methods. Currently, many studies have proven that optimizing control strategies [19] and using advanced communication technologies (e.g., 4th generation/ 5th generation network technology) [26,31] can improve the control robustness and performance under the impacts of network constraints, while these two methods have their limitations. For control design optimization, distributed control decision-making can improve the robustness. However, this manner requires changing the control strategy, or installing additional devices (e.g., sensors). In some specific scenarios, the control strategy may be fixed, or additional devices cannot be installed. For adoption of advanced network technologies, 5G network can provide ultra-low latency communication, and 4G/5G network can allocate dedicated network resources for specific tasks. However, in specific control scenarios, the location of the control system may not be within the coverage of the advanced network, or the cost of extending coverage may be too high, and the network infrastructure may not be available to support such network. Compared to these methods, using the proposed robust control with prediction-compensation methods has more flexibility for the real implementations of building control using IoT technologies. This method does not require additional devices or updated network communication infrastructure. Moreover, the smart field-level IoT devices possess computation capacity to execute such algorithm. Thus, this manner could have great potential to be applied for various control tasks in networked building controls.

In the deployment aspect, the prediction-compensation mechanism is implemented on the actuator side. The smart actuator is responsible for many functions, including data receiving, data processing, prediction-compensation, control decision-making, and actuation. The computational load needs to be seriously considered. In the previous studies of the authors [19,26], the proposed IoT devices show sufficient capacity for implementing networked control. Given the low computation requirements of Kalman filter adopted in the mechanism, it can be expected that the proposed robust control can be easily deployed in current commonly-used IoT controllers. Meanwhile, many network protocols can be used in real-world implementations, such as delivery-guarantee network protocols. These protocols can be implemented in the smart IoT devices to achieve higher reliability in the network transmission aspect.

For system engineering, the characteristics of control system need to be seriously considered. As a critical part of the proposed robust control, the performance of the model in the predictor has direct impacts on the compensation performance. The model should fit the system characteristics well in different operation conditions. When the system characteristics changed, the model should be easily to be updated. Based on the results of this study, it can be seen that even the performance of the state-space model is acceptable, there is still challenge when dealing with more difficult scenarios. As the increased number of packet losses, the bias of prediction is slightly increased correspondingly. Meanwhile, considering the long-term system operation, the characteristics of field-level devices may change, and their performance also may degrade. Thus, it could be beneficial to adopt an advanced method that accurately models the control process and adapts to the changes of field-level devices. The online update model or light-weight machine learning model could be the potential options.

V. Conclusion

This study proposes a robust networked control to improve the robustness and performance of networked building field-level controls affected by network uncertainties in IoT-enabled building automation systems. The proposed control adopts the prediction-compensation mechanism, which includes a predictor to estimate the controlled variable, and a compensator to evaluate the uncertainties. To test and assess the performance and improvement, the proposed robust control is adopted to a typical building field-level control task, i.e., supply air temperature control. The control is implemented in a networked building field-level control simulation platform, with experimental validation. The performance and robustness improvement by the proposed robust control under impacts of network constraints are investigated.

Based on the test results and analysis, the proposed robust networked control can significantly improve control performance under network impacts. Concerning performance of the prediction-compensation mechanism, the predictor can provide a satisfactory estimated value for control decisions with an R^2 value of 0.962, while the compensator can effectively evaluate the uncertainties of the received values and estimated values based on the network condition. Concerning the control performance, the proposed robust control can significantly reduce the control output deviation from 13.7K to 5.8K (57.7%) under the same period of continuous packet loss. Moreover, the computation load of the robust control is low enough to be easily implemented in todays' smart IoT controllers. Having the optimization methods to ensure the control performance in the networked IoT environments, IoT technologies could play more crucial roles building automation.

References

[1] D. Giusto, A. Iera, G. Morabito, L. Atzori (Eds.), The Internet of Things, Springer, 2010. ISBN: 978-1-4419-1673-0.

[2] Rana, A., Taneja, A., & Saluja, N. (2021). Accelerating IoT applications new wave with 5G: A review. *Materials Today Proceedings, 38*

[3] Huawei. (2021). *Intelligent World 2030* [White paper]. Huawei Technologies Corporation. https://www-file.huawei.com/-/media/corp2020/pdf/giv/intelligent_world_2030_en.pdf

[4] Thang, T. C., Pham, A. T., Cheng, Z., and Ngoc, N. P. (2011). Towards a full-duplex emergency alert system based on IPTV platform. *2011 3rd International Conference on Awareness Science and Technology (ICAST)*, 536–539.

[5] Quan P., Rachim, V., and Chung, W. (2019). EMI-Free Bidirectional Real-Time Indoor Environment Monitoring System. *IEEE Access*, 7, 5714–5722. https://doi.org/10.1109/ACCESS.2018.2889793

[6] Liang, X., Chen, K., Chen, S., Zhu, X., Jin, X., & Du, Z. (2023). IoT-based intelligent energy management system for optimal planning of HVAC devices in net-zero emissions PV-battery building considering demand compliance. *Energy Conversion and Management*, *292*, 117369.

[7] Malkawi, A., Ervin, S., Han, X., Chen, E. X., Lim, S., Ampanavos, S., & Howard, P. (2023). Design and Applications of an IoT Architecture for Data-Driven Smart Building Operations and Experimentation. *Energy and Buildings*, 113291.

[8] Li, W., Tang, R., & Wang, S. (2023). A fully distributed robust optimal control approach for air-conditioning systems considering

uncertainties of communication link in IoT-enabled building automation systems. *Energy and Built Environment*.
[9] Su, B., Li, X., Wang, S., & Cao, J. (2021). Distributed Optimal Control for HVAC systems Adopting Edge Computing-Strategy, Implementation and Experimental Validation. *IEEE Internet of Things Journal*, 1-1. doi:10.1109/jiot.2021.3132033
[10] Ge, X., Yang, F., & Han, Q. L. (2017). Distributed networked control systems: A brief overview. *Information Sciences*, *380*, 117-131.
[11] Hamdan, M. M., & Mahmoud, M. M. (2022). Analysis and challenges in wireless networked control system: A survey. *International Journal of Robotics and Control Systems*, *2*(3), 492-522.
[12] Schlienz, J., & Raddino, D. (2016). Narrowband internet of things whitepaper. *White Paper, Rohde&Schwarz*, 1-42.
[13] 3GPP. (2016). *3GPP TR 45.820: Cellular system support for ultra-low complexity and low throughput Internet of Things (CIoT)* (Release 13).
[14] Mahmoud, M. S., & Hamdan, M. M. (2018). Fundamental issues in networked control systems. *IEEE/CAA Journal of Automatica Sinica*, *5*(5), 902-922.
[15] Wang, Y. L., & Han, Q. L. (2014). Modelling and controller design for discrete-time networked control systems with limited channels and data drift. *Information Sciences*, *269*, 332-348.
[16] Mahmoud, M. S. (2016). Networked control systems analysis and design: An overview. *Arabian journal for science and engineering*, *41*, 711-758.
[17] Li, Q., Yao, F. , Zhong, X. , & Xu, G. . (2015). Output feedback guaranteed cost control for networked control systems with random packet dropouts and time delays in forward and feedback communication links. *IEEE Transactions on Automation Science & Engineering*, 13(1), 284-295
[18] Su, B., & Wang, S. (2021). A delay-tolerant distributed optimal control method concerning uncertain information delays in IoT-enabled field control networks of building automation systems. *Applied Energy*, *301*, 117516.
[19] Li, X., Wang, S., & Cao, J. (2023). An IoT-Enabled Control Paradigm for Building Process Control: An Experimental Study. *IEEE Internet of Things Journal*, pp. 1-1. https://doi.org/10.1109/JIOT.2023.3348125
[20] Ploplys, N. J., Kawka, P. A., & Alleyne, A. G. (2004). Closed-loop control over wireless networks. *IEEE Control Systems Magazine*, *24*(3), 58-71.
[21] 3GPP. (2020). *3GPP TS 22.261: Technical Specification Group Services and System Aspects; Service requirements for the 5G System* (Release 17).
[22] Lin, X. (2022). An overview of 5G advanced evolution in 3GPP release 18. *IEEE Communications Standards Magazine*, *6*(3), 77-83.
[23] Khan, B. S., Jangsher, S., Ahmed, A., & Al-Dweik, A. (2022). URLLC and eMBB in 5G industrial IoT: A survey. *IEEE Open Journal of the Communications Society*, *3*, 1134-1163.
[24] Wang, Y., Han, J., Liu, Z., Wang, Y., & Feng, X. (2022, April). Impact of 5G base station participating in grid interaction. In *2022 7th Asia Conference on Power and Electrical Engineering (ACPEE)* (pp. 586-590). IEEE.
[25] Li, Y., Wang, D., Sun, T., Duan, X., & Lu, L. (2020, October). Solutions for variant manufacturing factory scenarios based on 5G edge features. In *2020 IEEE International Conference on Edge Computing (EDGE)* (pp. 54-58). IEEE.
[26] Li, X., Wang, S., & Cao, J. (2024). Cellular network-based IIoT architecture for time-critical control tasks of building automation. *Automation in Construction*. https://doi.org/10.1016/j.autcon.2024.105387
[27] Xia, Y., Liu, G. P., & Rees, D. (2006). Predictive control of networked systems with random delay and data dropout. *2006 IEEE International Conference on Networking, Sensing and Control.* doi:10.1109/icnsc.2006.1673221
[28] Liu, G. P., Xia, Y., Chen, J., Rees, D., & Hu, W. (2007). Networked predictive control of systems with random network delays in both forward and feedback channels. *IEEE Transactions on Industrial Electronics*, *54*(3), 1282-1297.
[29] Gao, R., Xia, Y., & Ma, L. (2017). A new approach of cloud control systems: CCSs based on data-driven predictive control. In *2017 Chinese Automation Congress (CAC)* (pp. 3419-3422). IEEE.
[30] Bishop, G., & Welch, G. (2001). An introduction to the kalman filter. *Proc of SIGGRAPH, Course*, *8*(41), (27599-23175).
[31] Li, X., Li, H., Cao, J., & Wang, S. (2024). Applicability of different wireless networks adopted for time-critical control tasks in buildings: a comprehensive comparison study. *Journal of Building Engineering*, 111394.

Xinyue Li received the B.S. degree in Building Environment and Energy Engineering, and Information security from Hunan University, Changsha, China, in 2017, and M.Sc. degree in Heating, Ventilation and Air-conditioning from Zhejiang University, Hangzhou, China, in 2020. He is currently pursuing the Ph.D. degree at the Department of Building Environment and Energy Engineering in The Hong Kong Polytechnic University, Hong Kong.

His research interests include advance control technologies, Internet of things, big data, and next-generation smart buildings.

Hangxin Li obtained her Bachelor' degree and Master's degree in Heating, Ventilation and Air-conditioning from Hunan University in 2012 and 2015 respectively. Her PhD degree was obtained in 2020 from the Department of Building Services Engineering at the Hong Kong Polytechnic University.

She is currently a research assistant professor in the Department of Building Environment and Energy Engineering, The Hong Kong Polytechnic University, Hong Kong. Her research expertise is mainly in the fields of zero/low energy buildings, optimal control of energy systems, and building demand response.

Jiannong Cao (M'93–SM'05–F'15) received the B.Sc. degree in computer science from Nanjing University, Nanjing, China, in 1982, and the M.Sc. and Ph.D. degrees in computer science from Washington State University, USA, in 1986 and 1990, respectively.

He is currently the Chair Professor of Distributed and Mobile Computing and the Otto Poon Charitable Foundation Professor in Data Science with the Department of Computing, The Hong Kong Polytechnic University, Hong Kong. He is also the director for Research Institute for Artificial Intelligence of Things (RIAIoT) and the director of the Internet and Mobile Computing Lab (IMCL). His research interests include parallel and distributed computing, big data and machine learning, and cloud/edge computing. He has coauthored 5 books, coedited 9 books, and published over 500 papers in major international journals and conference proceedings.

Shengwei Wang received the B.Sc. degree in Aerodynamic Mechanical Engineering in 1983 and M.Sc. degree in Refrigeration and Air-Conditioning in 1986 from Huazhong University of Science and Technology, Wuhan, China, and the Ph.D. degree in Building Energy Management and Control Systems from University of Liege, Liege, Belgium in 1993.

He is currently the Chair Professor of Building Energy and Automation and the Otto Poon Charitable Foundation Professor in Smart Buildings with the Department of Building Environment and Energy Engineering, The Hong Kong Polytechnic University, Hong Kong. He is also the Director of Research Institute for Smart Energy.

His interests cover energy systems and building automation systems, particularly optimal design, control and diagnosis of building energy systems; grid-interactive buildings; smart and distributed energy systems. He was one of the top 150 highly cited scholars worldwide in “Energy Science and Engineering” based on the Clarivate Analytics in 2016 and was ranked no. 20/22 in “Building and Construction” worldwide according to Stanford analysis in 2021/2020.