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Analysis of HVAC sensor characteristics for operation and maintenance to propose indoor environment: A case research on public building HVAC

Abstract: Sensors are a crucial component in heating, ventilation and air conditioning (HVAC) control systems and the quality of these plays an important role in control accuracy. In research of fault detection and control optimization, improving sensor data quality has the inspiring potential for application. It has largely been limited to the application of signal processing methods in research focus, which has not conducted a detailed analysis of the characteristics of signals from various sensors within the HVAC system. Therefore, it analyzes the time-frequency domain characteristics of control sensors within HVAC systems through integrating the structural design and control logic of HVAC systems. Additionally, the research examines the correlations between control sensors in HVAC systems. Based on statistical principles and the energy-mass dynamic laws of the equipment, defines first-class (I) correlated sensors and second-class (II) correlated sensors. To sum up, it is to conduct a fundamental study on the characteristics of control sensors within HVAC systems, providing theoretical reference for future research on HVAC system fault diagnosis and control optimization.

Keywords: HVAC control sensor, Time-domain, Frequency-domain, Sensor noise

Highlights:

1. This paper analyses the time-frequency domain characteristics of sensors in HVAC systems
2. This paper analyses the noise content of HVAC system sensors.
3. This paper analyses the inter-sensor correlation characteristics of the HVAC system.

1. Introduction

The International Energy Agency (IEA, 2022) has reported that global energy consumption is approximately 30% attributed to the building sector. The electricity consumption of heating, ventilation and air conditioning (HVAC) systems accounts for over 50% of the total electricity used in buildings. Effective control strategies can enable energy savings, emissions reduction and optimized management for HVAC systems (Li et al., 2021). The monitoring is a significant issue in HVAC control loop, where relevant variables need to be measured for either controlling, monitoring or fault detection (Guo et al., 2024). Therefore, numerous sensors are installed in HVAC system to monitor various physical quantities. Due to differences in distribution characteristics, coverage range, measurement principles and accuracy, sensors exhibit significant variability in the uncertainty of their measurements (Zhang et al., 2024). In summary, analyzing the characteristics of each sensor in HVAC systems is key to obtaining accurate sensor measurements, which may help control loops enhance the energy efficiency and improve thermal comfort in indoor environments.

In last decade, scholars have been studying the impact of sensor noise on the operation of HVAC systems. Yoon et al. (2022) demonstrated that sensor noise within an AHU can lead to cooling load errors of up to 14.8% on the air and refrigeration sides. Zhao et al. (2024) analyzed the impact of indoor temperature fluctuations caused by outdoor environmental conditions and indoor occupants on the uncertainty of HVAC sensor measurements. The findings indicated that when the

measured temperature range in 18.9°C - 20.6°C, the error in sensor measurements due to uncertainty typically falls within the range of 2.4°C - 2.9°C. Based on the differences between simulated and real data, Li et al. (2023) studied the uncertainty of mixed air temperature sensors, supply air flow sensors and supply air temperature sensors. O'Neill et al. (2017) demonstrated that uncertainty of 3.76% in input parameters could increase the annual energy consumption and peak energy consumption of standalone buildings HVAC systems by approximately 4%. Pang et al. (2025) explored the relationship between the degradation of sensor measurement accuracy and issues such as wasted building energy, reduced indoor thermal comfort, and delayed control response. The results showed that decreased accuracy of sensor data could lead to potential negative impacts. Akari et al. (2024) found that a 10% variation in sensor accuracy resulted in a 34% increase in HVAC energy consumption, a 9.5% deviation in supply air temperature from the setpoint and a longer time required for the system to reach the setpoint. Shadi et al. (2022) quantified the impact of temperature sensor uncertainty within the AHU on system performance under different control sequences. As the AHU research subject, Yan et al. (2017) conducted simulation experiments using EnergyPlus to study the effects of sensor uncertainty within the AHU on outdoor airflow control parameters and control responses.

Considering the frequent changes in indoor environmental demands and outdoor climate conditions, achieving satisfactory measurement accuracy for the heating and cooling loads in HVAC systems is challenging. Due to sensor aging, improper installation and performance degradation, HVAC sensor measurements can cause low-accuracy and even errors (Du et al., 2008; Du et al., 2014). Random errors resulting from external environmental disturbances and sensor measurement uncertainty (often defined as noise) can cause the operation of HVAC systems to deviate from expected performance. In addition, sensor noise can easily be confused with fault signals, leading to increased operation and maintenance costs for monitoring systems.

Table 1
Summary of previous research

Methods	Research object	Research direction
Kalman-based	Chiller sensors (Yan et al., 2015), Temperature and speed of supply air sensors in AHU (Sun et al., 2014; Azarbani et al., 2019; Shi, 2019), Building thermal model (O'Brien, 2019)	FDD (Yan et al., 2015; Sun et al., 2014), State estimation (Azarbani & Abbasi, 2019), Parameter estimation (Shi & O'Brien, 2019)
EEMD-based	Chiller sensors (Li et al., 2016; Zhang et al., 2023; Mao et al., 2018)	FDD (Li et al., 2019; Zhang et al., 2023; Mao et al., 2018)
SG-based	AHU sensors (Wen et al., 2023; Guo et al., 2017; Liang, 2014; Jin et al., 2016)	FDD (Wen et al., 2023; Guo et al., 2017), Control optimization (Liang, 2014; Jin & Duanmu, 2016)
Wavelet analysis	AHU sensors (Li et al., 2014; Fan et al., 2010), Building thermal model (Cheng et al., 2017; Khalilnejad et al., 2020; Vanus et al., 2023)	FDD (Li & Wen, 2014; Fan et al., 2010), Control optimization (Cheng et al., 2017), Energy consumption prediction (Khalilnejad et al., 2020; Vanus et al., 2023)

Numerous filtering methods have been applied to reduce the negative impacts caused by HVAC sensor measurement uncertainty. It can be categorized through theoretical foundation: Kalman-based (Yan et al., 2015; Sun et al., 2014; Azarbani & Abbasi, 2019; Shi & O'Brien, 2019), ensemble empirical mode decomposition (EEMD)-based (Li et al., 2016; Zhang et al., 2023), Savitzky-Golay

(SG)-based (Wen et al., 2023; Guo et al., 2017) and wavelet analysis-based (Li & Wen, 2014; Fan et al., 2010; Cheng et al., 2017; Khalilnejad et al., 2020; Vanus et al., 2023). For instance, Kalman filtering methods can strip noise from signals even when the sensor signal and noise statistical characteristics are not completely accurate. While the EEMD-based method is typically suited for nonlinear systems, which aligns with the nonlinear and non-stationary signal characteristics of HVAC systems. Given the advantages of SG in preserving waveform peak shapes and amplitudes, and the slow dynamic changes of AHU systems. Therefore, SG-based filtering studies have mostly focused on AHU systems. Wavelet analysis methods have significant advantages in filtering sensor signals with prominent frequency-domain features. As shown in Table 1, considering the diversity of application targets and problem-solving requirements, above methods have been extensively proposed in previous researches.

The Kalman filter has effectively enhanced the diagnostic efficiency of grey-box models in AHU faulty supply air temperature and air speed sensor fault diagnosis and detection (FDD) (Azarbani & Abbasi, 2019). Zhang (2023) leverages temporal characteristics for single-source and multi-source sensor faults in chiller system to propose an EEMD -based method. And, Hu (2018) proposed an EMD-based method with hard-threshold (EMD-TD) denoising to address bias faults in temperature sensors within chiller systems. Experiment has shown that filtering sensor fault data with EMD-TD can improve the diagnostic accuracy. SG-based methods primarily focus on sensors in AHU system. Wen (2023) used SG as a filter to enhance the fault diagnosis rate of clustering methods for AHU temperature sensors. While, Guo et al. (2017) employed SG to improve the fault diagnosis rate of principal component analysis (PCA) in AHU temperature sensors. Similarly, wavelet analysis has been effectively combined with PCA, neural networks and clustering methods, achieving improved FDD efficiency for HVAC sensors (Li & Wen, 2014; Fan et al., 2010). On the other hand, reducing the uncertainty of sensor data is also a current research focus in the research on control optimization for HVAC systems. For instance, Ke et al (2015) proposed the extended Kalman filter to filter sensor signals in chiller systems. In the design of feedback controllers for AHU humidity sensors, Azarbani (2019) proposed an unscented Kalman filter (UKF) based on scaled unscented transformation to improve the accuracy and speed of state estimation in AHU. In the research on prediction and control of building thermal models, a constrained dual extended Kalman filter-based method has been utilized for parameter prediction and state estimation (Shi and O'Brien, 2019). Because of advantages of the SG method in preserving the shape and height in waveform peaks and the slow dynamic changes in AHU, the SG method enhances the robustness of the AHU control system (Liang, 2014). In the research on the dynamic regulation of indoor thermal comfort, the SG filter has been used for smoothing the data of supply air temperature and air speed sensors in the AHU (Jin and Duanmu, 2016). Meanwhile, Wavelet analysis-based filtering methods have been applied to parameter identification of spatial thermal models (Cheng et al., 2017), prediction of energy demand (Khalilnejad et al., 2020), and assessment of operational loads (Vanus et al., 2023).

By reducing the uncertainty in sensor measurement and clarifying the distribution characteristics of sensor signals, it can significantly improve the FDD efficiency and control accuracy in HVAC. However, HVAC systems contain numerous sensors, which can be classified based on their specific tasks into control sensors and measurements sensors (Du et al., 2017). The measurement principles, ranges, accuracy requirements and operating environments of different sensors vary widely. Even sensors monitoring the same physical quantity from different systems

exhibit uncertainty characteristics that are challenging to standardize. For instance, the data characteristics of temperature sensor in AHU differ significantly from that in chiller. Even in the chiller, the data distribution characteristics of pressure sensors at different points vary widely (Zhang et al., 2024). The research of sensor signal characteristics should take into account the HVAC operating conditions. Unfortunately, current research lacks a comprehensive description of sensor characteristics across HVAC system. For instance, previous researches have not conducted a quantitative analysis of the noise levels in control sensors within HVAC systems to measure sensor uncertainty. Additionally, the correlations among sensors within HVAC systems are critical for FDD and control parameters optimization. However, it remains unexplored in existing research. Moreover, current research has primarily focused on developing novel sensor signal filtering methods to improve the efficiency in HVAC FDD and control optimization. Previously proposed signal filtering methods rely on the temporary-frequency characteristics of signals. Although these methods have improved the efficiency of FDD and control optimization, they lack research on the specific signal characteristics of control sensors within HVAC systems. Therefore, relevant researches lack solid interpretability and theoretical foundations. Additionally, the lack of a global understanding of HVAC sensor signals can lead to methods that are limited in scope, making proposed methods only to specific systems such as chillers or AHU systems. This significantly limits the practicality of the methods.

To sum up, the research aims to analyze the data characteristics of HVAC sensors, providing theoretical references and foundations for subsequent methodological research. The contributions mainly include three parts:

(1) It analyzes the noise level of various control sensors in HVAC based on the signal-to-noise (SNR). And, it compares the filtering efficiency through four filtering methods, which have been predominantly refined based on the fundamental principles of the above techniques in previous research.

(2) Research conducts a quantitative analysis of the correlations among various control sensors in HVAC systems. It provides a theoretical foundation for parameter selection and sensitivity analysis in subsequent research on constructing FDD and control parameters optimization. Furthermore, it examines the factors influencing sensor correlations.

(3) The study analyzes the sensitivity of different control sensors in HVAC systems in both the time and frequency domains. This research provides a theoretical direction for future adaptive optimization of HVAC system sensors. Additionally, it explored the reasons behind the differences in time-frequency domain sensitivity characteristics among various sensors

2. Application

2.1 System description

As shown in Fig. 1, it takes the lager public building HVAC in Dalian University of Technology as the research subject. The research building has a floor area of 1184m² and a height of 20m. The relevant physics parameters of the equipment are shown in Table 2. The return air mixes return air and fresh air according to a specified ratio. The mixed air is then sent through filters, a humidifier, and a cooling coil before being delivered to the room via the fresh air duct (Yan et al., 2023). As summer operation condition for example, the mixed air passes through the cooling coil in the AHU, where it exchanges heat with chilled water, reducing the air temperature to ensure that the supply air temperature meets the set point. To ensure indoor environment comfortable and healthy, AHU

has installed sensors for relative humidity, CO₂ concentration and PM2.5 concentration in the supply air duct.

Table 2
The illustration of HVAC system in public building

Equipment	Chiller	Water pump	AHU
2 unit of chiller, COP: 2.77, 3 Variable frequency, chilled water pumps 3 Variable frequency cooling water pumps, 1 Water distributor and collector, 2 AHUs, 1 Cooling tower	Rated cooling input power 104.4 kW, Cooling capacity 626.4 kW	Rated power: 15 kW, Rated frequency: 50 Hz	Air supply volume: 25000m ³ /h, Cooling capacity: 137kW, Power: 15kW, Duct cross-sectional area: 1.20×0.80m

The chiller is composed of evaporator, condenser, compressor, etc. The transmission medium is refrigerant and water. In summer conditions, the refrigerant enters the compressor after completing heat exchange through the evaporator, which converts the refrigerant into a high-temperature and high-pressure vapor form. Then, refrigerant passes through the condenser to complete heat exchange in the cooling medium, which turns the refrigerant into a liquid state to complete the next cycle of cooling the surrounding environment (Xie et al., 2017). Key parameters of chiller include temperature, pressure, and flow rate. These parameters are comprehensively monitored through the water-side control loop, ensuring that the heat transfer on the water side meets the indoor thermal environment requirements.

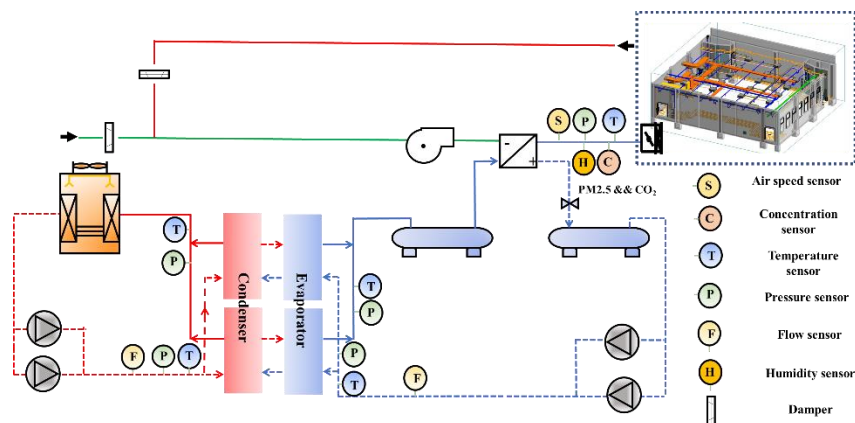


Fig 1. The description of HVAC system

2.2 Data collection

Table 3 shows the specific parameters of the sensors. Sensor measurement accuracy and principles vary because of differences in the physical quantities measured and the locations of sensors. Additionally, due to differing control logic and setpoints, even sensors monitoring the same physical quantity exhibit distinct signal distribution characteristics at different operational points, making it challenging to generalize these characteristics. The sensor data collection period spanned from 14:40 on June 15, 2023, to 20:25 on June 20, 2023. The collection interval is 5min. The

experiment collected a total of 1509 data sets. The data were gathered from the HVAC system under steady-state operating conditions. The data were collected from 0:00 to 24:00, which includes the characteristics of all-weather data under summer conditions. And, it can represent the operating data characteristics of HVAC systems in large public buildings in Dalian, China.

As illustrated in Fig 2, sensor parameters are collected through a programmable logic controller (PLC) (Li et al., 2023). Control loop controllers adjust the operating parameters of the HVAC system to reach the setpoints. The control logic of the control loop is based on proportional integral derivative control. The data collection and storage process can refer Ref (Zhao et al., 2023). The collected data is made available to operations and maintenance personnel via an online monitoring system and is uploaded to the cloud for storage.



Fig 2. System control cabinet (left) and monitoring (right)

Table 3

The basic parameters of various sensors in the experiment system

Description	Point	Unit	Range	Precision	Principle
Supply air temperature	T1	°C	-20-50	±0.1°C	Resistive
User-side supply water temperature	T2	°C	-30-130	±0.1°C	
User-side return water temperature	T3	°C	-30-130	±0.1°C	
Cooling tower-side supply water temperature	T4	°C	-30-130	±0.1°C	
Cooling tower-side return water temperature	T5	°C	-30-130	±0.1°C	
User-side water flow rate	F1	m ³ /h	0-10	±1.0%	Ultrasound
Cooling tower-side water flow rate	F2	m ³ /h	0-10	±1.0%	
Supply air static pressure	SP	Pa	0-250	±0.075%	Capacitance
User-side supply water pressure	P1	Bar	0-9	±0.05%	
Cooling tower-side supply water pressure	P2	Bar	0-9	±0.05%	
Cooling tower-side return water pressure	P3	Bar	0-9	±0.05%	
User-side return water pressure	P4	Bar	0-9	±0.05%	Mechanical
Supply air humidity	H	%	0-100	±1%	
Supply air speed	S	m/s	0-15	±0.2m/s	
Supply air CO ₂ concentration	C	ppm	0-2000	±3%	Infrared ray
Supply air PM2.5 concentration	PM	ppm	0-2000	±3%	

3. Time and frequency-domain analysis of characteristics

Chapter 3 analyzes characteristics of HVAC system sensors signal from both time-domain and frequency-domain, respectively. Section 3.1 starts with the fundamental parameters of the HVAC system and, based on its basic operating principles, analyzes the distribution range differences of each sensor signal. Section 3.2 investigates the time-domain characteristics of various control sensors in the HVAC system from the perspective of temporal correlation, providing a theoretical

foundation for time-domain-based signal filtering and feature extraction methods. Section 3.3, based on the operating principles of the HVAC system, examines the frequency-domain characteristics of each control sensor from a frequency-domain perspective.

3.1 The overall analysis of HVAC sensor's characteristics distribution

Table 4 presents the analysis of the mean, percentage standard deviation, variance, skewness and kurtosis. In the research of FDD and calibration of sensor data, analyzing the mean of the data serves as an important criterion for determining whether a sensor is faulty or if the data is inaccurate. The mean of control sensors measurement reflects the data distribution range of the physical quantities measured by each sensor within the HVAC system. Obviously, even for the same physical quantity, data distribution range can vary significantly depending on the monitoring location. The primary reason for the differences among the measured physical quantities lies in the HVAC structure. For instance, the difference between the supply water flow rate on the user side and the cooling tower water side is nearly fourfold in chiller. Ref (Salehi et al., 2024) indicates that the mean values of supply air temperature, supply air humidity and supply air PM2.5 concentration in the AHU are closely related to the meteorological environment of the HVAC system. Therefore, analyzing the data values of supply air temperature and humidity during the energy demand curve process for a building in a specific region is an important basis for this analysis.

Table 4
Characteristics parameters of sensors in HVAC

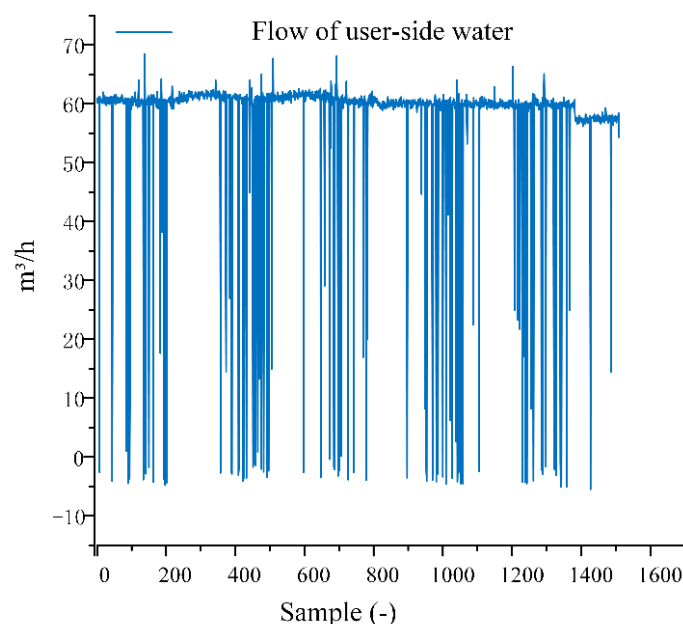
Sensor Point	Mean (-)	Percentage standard deviation (%)	Variance (-)	Skewness (-)	Kurtosis (-)
T1	18.42	0.29	0.23	0.31	2.13
C	509.72	3.17	773.24	1.52	5.59
H	86.65	0.78	5.01	-1.74	6.52
PM	5.91	2.09	3.91	0.28	2.55
SP	73.38	0.38	3.01	-0.01	2.73
S	4.50	0.55	0.04	-0.29	3.06
T2	10.38	0.52	0.44	0.52	2.54
T3	12.18	0.65	0.78	0.25	1.63
T4	11.92	0.20	0.08	0.31	3.44
T5	11.09	0.11	0.02	0.03	1.85
P1	2.67	0.18	0.01	0.22	1.90
P4	2.14	0.20	0.01	0.30	1.93
P2	1.50	0.26	0.02	0.30	2.03
P3	0.59	0.41	0.02	0.29	2.01
F1	56.49	4.92	207.23	-3.64	14.70
F2	201.58	0.06	0.11	0.22	2.94

The percentage standard deviation and variance reflect the stability of the HVAC system's operation and measurement accuracy of the sensor data. In the analysis of sensors on AHU side, the percentage standard deviation of the supply air CO₂ concentration sensors is the highest, reaching 3.17%. This indicates that the concentration of CO₂ within the building experiences significant fluctuations, which may be attributed to variations in personnel density in the enclosed environment of public buildings. Therefore, in studies of human behavior in indoor environments, changes in CO₂ concentration parameters can more accurately reflect air quality of the indoor environment (Huang et al., 2024). Meanwhile, considering the large variance in carbon dioxide concentration, the noise in this data may interfere with the reflection of the results. In the fresh air ratio control

system, the sensor measurements from the supply air CO₂ concentration sensor are typically used as the basis for feedback regulation in the control loop. The sensor data accuracy for temperature, humidity and static pressure of supply air is relatively high, which are key control elements in AHU. These sensors are involved in controlling the chilled water flow rate to the cooling coil, the humidification rate of the humidifier, and the speed of the supply air fan, respectively.

In some AHU control strategy designs, monitoring the supply air velocity is also used to control the supply air fan speed. However, considering that the accuracy of airflow velocity measurements is lower than that of supply air static pressure, research recommends using the supply air static pressure as the monitored value in airflow-related control loops. In the relatively research on the water side, sensors can be categorized by the type of physical quantity monitored, specifically into temperature sensors, pressure sensors and flow sensors.

Overall, lower variance in water-side sensors may indicate that their measurements accuracy is indeed superior to that air-side sensors. As shown in Fig. 3(a), the user-side water flow has the highest percentage error. The flow sensor is an electromagnetic flow meter in this research, whose measurement accuracy is unaffected by changes in fluid density, viscosity, temperature, pressure and conductivity. The induced voltage signal maintains a linear relationship with the average flow velocity (Wang et al., 2006). However, when the speed of the user-side circulating water pump is adjusted via the frequency converter, the variation in flow significantly interferes with the flow sensor's measurement accuracy. As shown in Fig. 3(b), since the soil-side circulation pump operates at a fixed frequency, no frequency converter is installed to adjust the soil-side circulation water flow. Consequently, the sensor's standard error percentage is only 0.06%. In summary, it recommends prioritizing the monitoring of supply-return water pressure values when designing control strategies related to the number and frequency of user-side pump activations and deactivations.



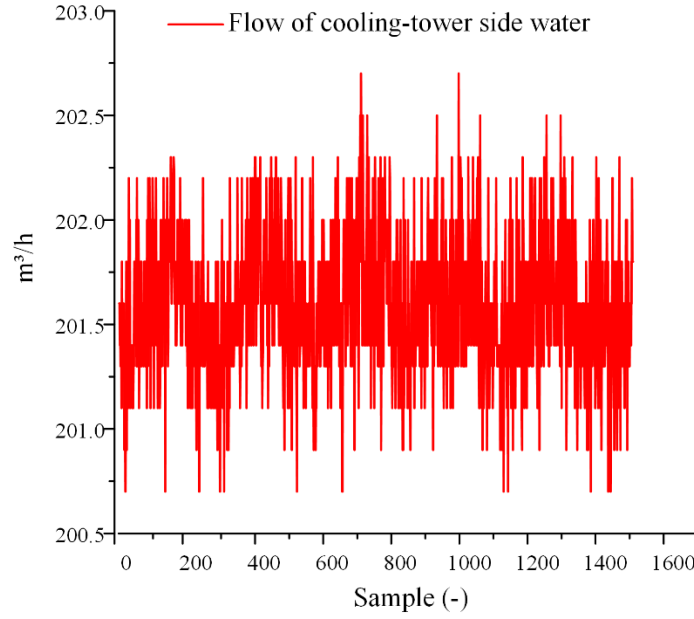


Fig 3. The flow of user-side and cooling-tower side water

Research on HVAC sensor signal feature extraction methods has been widely applied in sensor signal fault diagnosis and optimization of control strategies (Cotrufo and Zmeureanu, 2016). Skewness analyzes the distribution state of sensor signals in the HVAC system to clarify the characteristics of the signals, while kurtosis examined the sharpness of the data distribution. In previous Ref (Cotrufo and Zmeureanu, 2016; Li et al, 2016), they have often been assumed that the distribution characteristics of sensor data within the HVAC system are symmetric and conform to Gaussian distribution properties. As shown in Table 4, the skewness and kurtosis indicate that the sensor signals related to fans and pumps exhibit better symmetry in distribution, with data clustered around the mean. It is related to the control loop setting of the HVAC. Under steady-state conditions, the control logic of fans and pumps in the HVAC system is trapezoidal control (Li et al., 2023). Therefore, the skewness of the sensors related to the pumps and fans is lower, and their kurtosis is also closer to 3 (when the kurtosis value is 3, it indicates that the sensor data distribution is closer to a Gaussian distribution with lower extreme values). Although the skewness and kurtosis of the user-side water flow sensor data indicate poor signal distribution symmetry. This is primarily caused by measurement errors in the sensor signals. Meanwhile, the supply and return water pressure sensor signals on the evaporator(user-side) and condenser (cooling tower-side) sides indicate poor symmetry. The calculation of the pressure difference shows that its value still conforms to the trapezoidal control data characteristics. In contrast, for sensors that are greatly affected by the environment, such as the CO₂ concentration sensor, data exhibit poor symmetry. To sum up, the measurement accuracy of sensors can influence the analysis of the distribution characteristics of certain sensor signals. Distribution characteristics of that are still related to the control logic within the HVAC system. Therefore, it is essential to perform outlier filtering and noise reduction when extracting the distribution of sensor signal characteristics.

3.2 Time-domain analysis for HVAC sensors

The research analyzes the temporal relationship between each signal and its lagged sequence

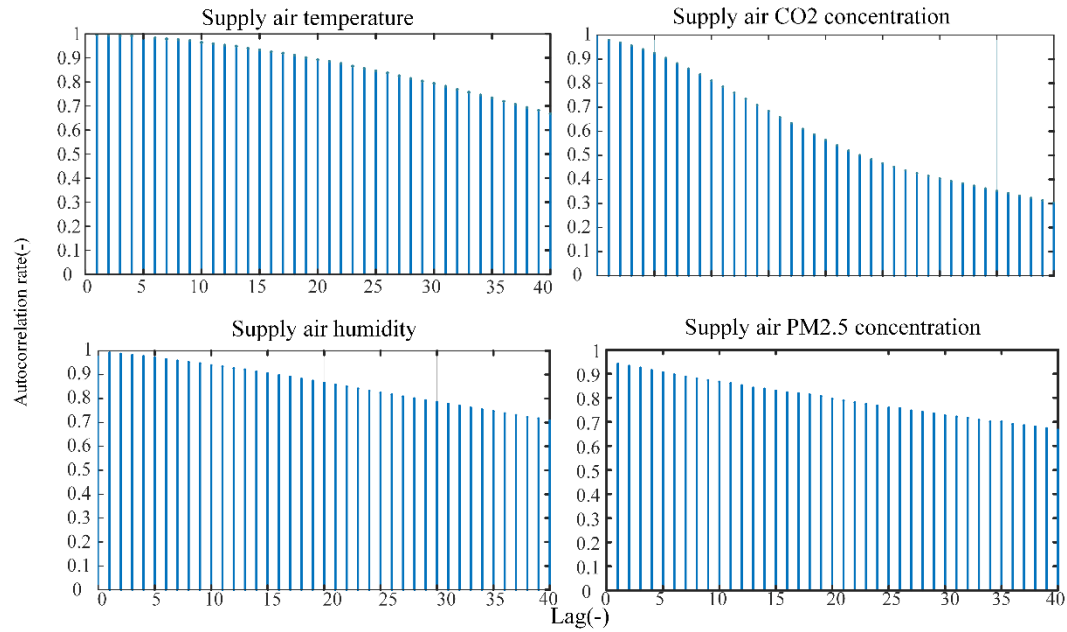
of 40 times intervals, with a time lag of 200 min in the signal collection. As shown in Fig. 4, based on the temporal characteristics of sensor signals, it can be categorized into three types of temporal features: time-decay, non-temporal and unstable periodic type. As shown in Fig. 4(a-1) and Fig. 4(a-2), the autocorrelation of the signals exhibits a strong correlation within a short lag time for sensor signals with temporal decay characteristics. However, as the lag time increases, the autocorrelation of the sensor signals gradually diminishes. In contrast, as illustrated in Fig. 4(b), non-temporal sensors demonstrate lower autocorrelation. Some sensor signals even exhibit alternating patterns of negative correlation and weak positive correlation. As depicted in Fig. 4(c), the research highlights the autocorrelation characteristics of unstable periodic sensors. These sensor signals show a high level of autocorrelation with lagged signals (typically, a correlation coefficient above 0.6 is defined as strong correlation (Zhao et al., 2023)). However, unlike sensors with temporal decay characteristics, it does not exhibit a distinct temporal decay trend, indicating that such sensor signals possess strong periodic characteristics.

The supply air temperature, supply air CO₂ concentration, supply air humidity, supply air PM2.5 concentration, user-side return water temperature, cooling tower-side return water temperature, user-side supply and return water pressure sensors all exhibit a clear time-decay characteristic according to the lag time. Among them, the autocorrelation plots of sensors such as supply air temperature, supply air humidity and cooling tower return water temperature indicate that these sensors exhibit slow-changing data characteristics. The temporal relationship between signals demonstrates long-term correlation. In contrast, signals temporal characteristics from the supply air CO₂ concentration and the user-side supply and return water pressure sensors decay quickly. This indicates that the temporal dependency between signals is short-term; as the lag time increases, the signal correlation weakens. Overall, the above sensors exhibit strong temporal autocorrelation, making them suitable for applying time-domain-based data filtering and feature extraction methods in data modeling, fault diagnosis and control optimization.

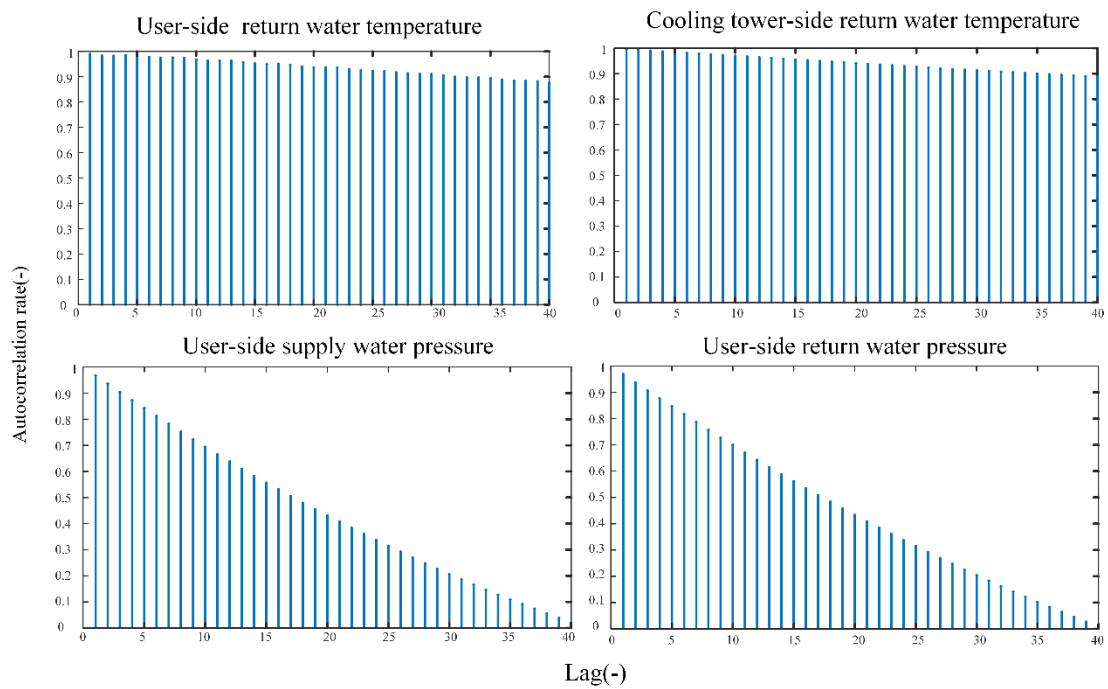
On the other hand, the autocorrelation of the user-side supply water temperature signal exhibits a distinct periodic variation with respect to lag time. The primary reason for this phenomenon is that the user-side supply water temperature is an important control parameter, which influences the number of chillers operating and the refrigerant flow rate in the chiller. Therefore, the user-side supply water temperature will be adjusted in real-time based on the changes in cooling demand. Meanwhile, considering that the chiller unit is the most economically valuable and energy-consuming equipment in the HVAC system. Ensuring the stable operation of the chiller unit can effectively extend the lifespan of the equipment. The variation in supply water temperature is typically quite steady. To sum up, above reasons result in the user-side supply water temperature exhibiting a distinct periodic variation, with strong temporal correlation but a slow decay rate. However, the noise in the sensor signals is also one of the reasons for this phenomenon from the perspective of signal autocorrelation. It is demonstrated that the random error in its measurements is relatively low through calibrating the measurement data from the user-side supply temperature sensor. Additionally, the strong autocorrelation of the data (with correlation values between 0.7 and 0.8) indicates that this phenomenon is not likely caused by sensor noise.

Finally, for sensors such as the supply static pressure sensor, supply air velocity sensor, cooling tower supply, return water pressure sensors, user-side supply flow rate and cooling tower side flow rate sensors, these sensors exhibit no significant temporal correlation. Therefore, it is not recommended to use time-domain based data filtering and feature extraction methods for these

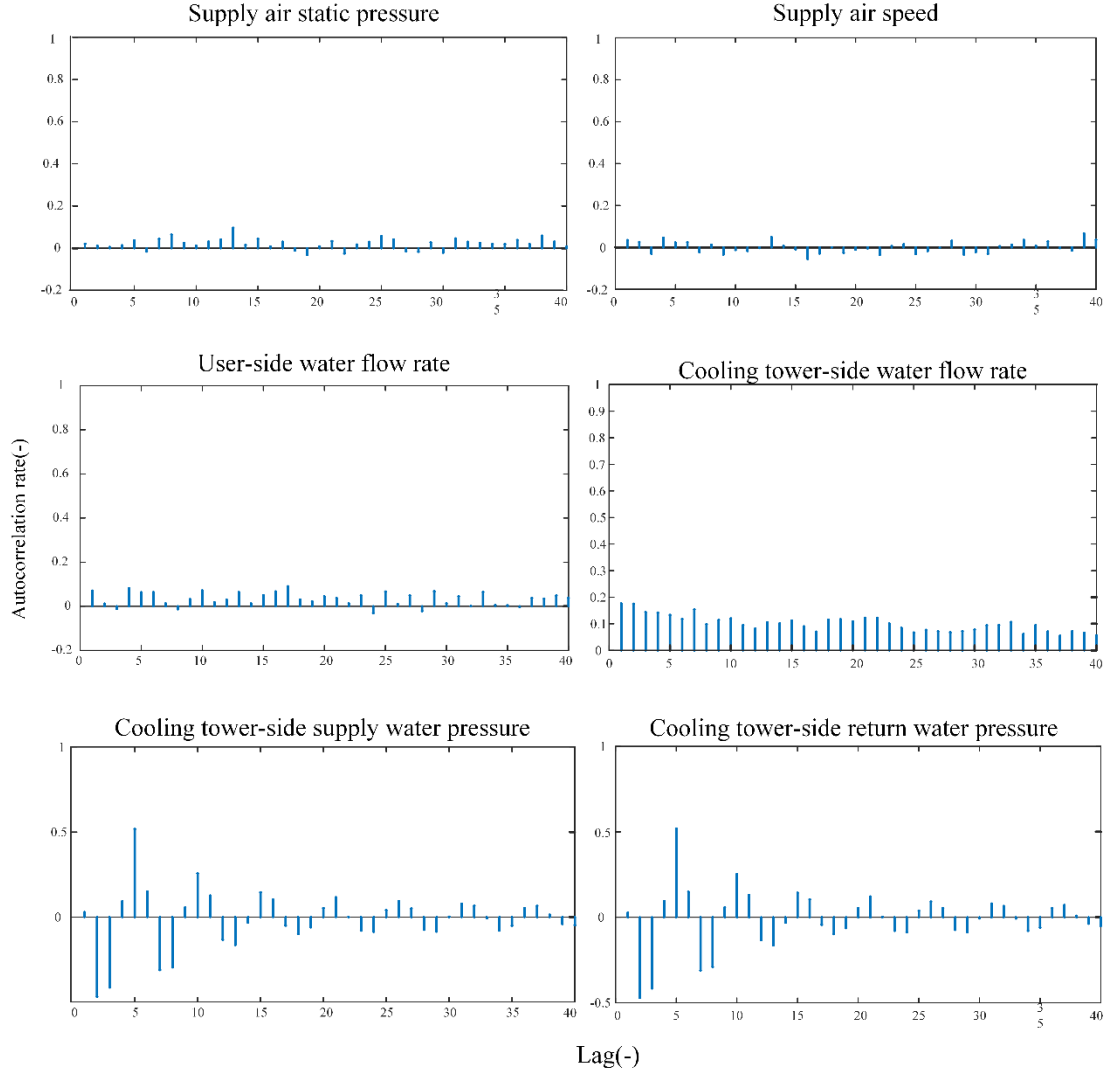
sensors. The parameters of the above sensors are all regulated by the actions of pumps and fans, as the control strategy for both pumps and fans are trapezoidal control. For instance, during a period of steady-state operation, the fan speed is typically constant. The supply air static pressure and supply air velocity do not change correspondingly over time with a delay. Therefore, the measurement values of the above sensors are not suitable for data filtering and feature extraction methods based on time-domain characteristics.



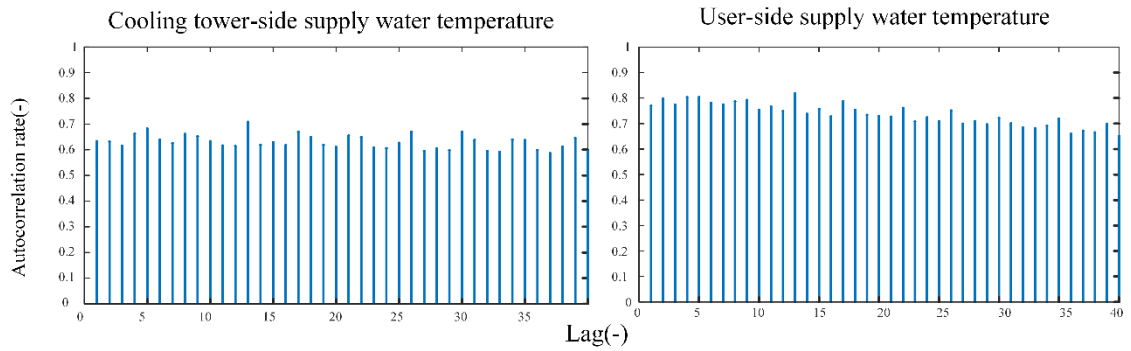
(a-1) Time-decay type sensors



(a-2) Time-decay type sensors



(b) Non-temporal type sensors



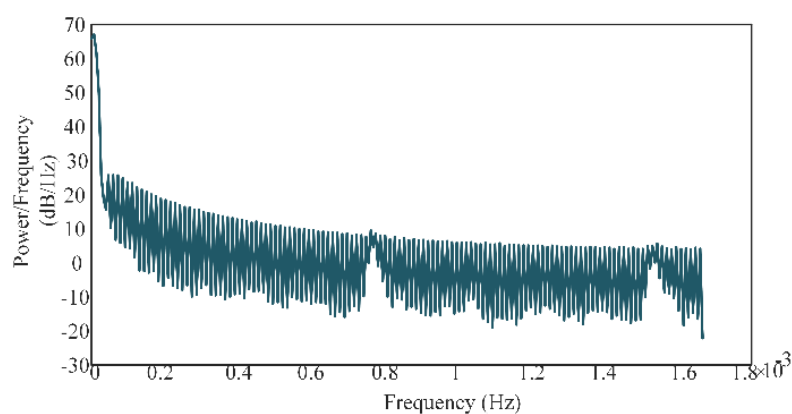
(c) Unable periodic type sensors

Fig 4. Autocorrelation analysis of HVAC sensors

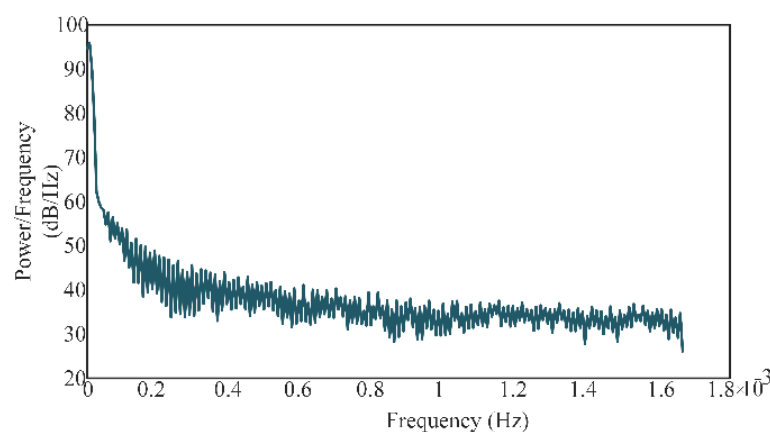
3.3 Frequency-domain analysis for HVAC sensors

Considering that some sensors in HVAC systems exhibit weak temporal characteristics, it analyzes the frequency domain characteristics of control sensors within HVAC systems. The frequency domain features of different control sensor signals were discussed using Power Spectral

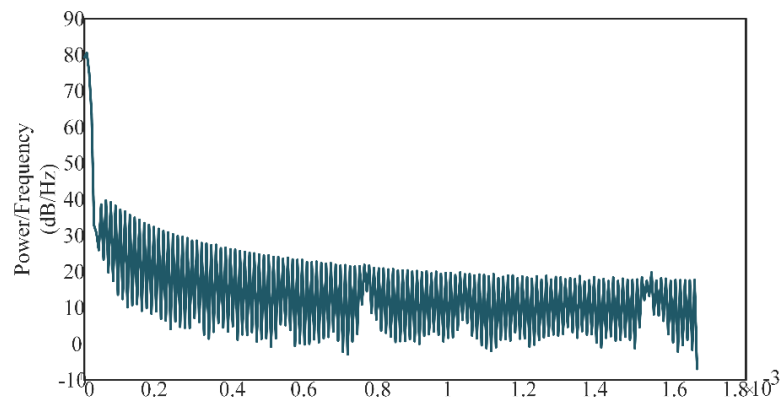
Density (PSD) analysis. The PSD plot reflects how the energy or power density of a signal varies with frequency in the frequency domain. The useful information in sensor signals is primarily concentrated in the low-frequency range, while noise is mainly distributed in the high-frequency range (Zhang et al., 2023). The PSD of AHU control sensors is shown in Fig. 5. The supply air temperature sensor exhibits a distinct energy distribution in the low-frequency range, indicating that the temperature sensor's measurement data has long-period fluctuation characteristics. In the high-frequency region, the energy distribution in the PSD significantly decreases and displays noticeable oscillatory characteristics, which may result from sensor noise or environmental disturbances. And, it further confirms that the noise content is relatively low by examining its energy distribution in the low-frequency range. Although the PSD of supply air humidity and supply air CO₂ concentration shows some graphical similarity to that of supply air temperature. However, PSD in the high-frequency range for the supply air humidity and CO₂ concentration sensors is higher than that of the supply air temperature sensor. This indicates that the noise content in the measurements from the supply air humidity and CO₂ concentration sensors is greater than that in the temperature sensor measurements. In terms of waveform, the measurements from the supply air humidity and CO₂ concentration sensors also display long-period fluctuation characteristics. In the PSD analysis of supply air static pressure and air speed, the transition band shows a higher power density compared to other sensor signals, and the high-frequency signal energy decays rapidly. This suggests that the noise content in the static pressure and air velocity measurements is relatively high, with fewer rapid fluctuations in system airflow. This aligns well with the trapezoidal control strategy used for the fan.



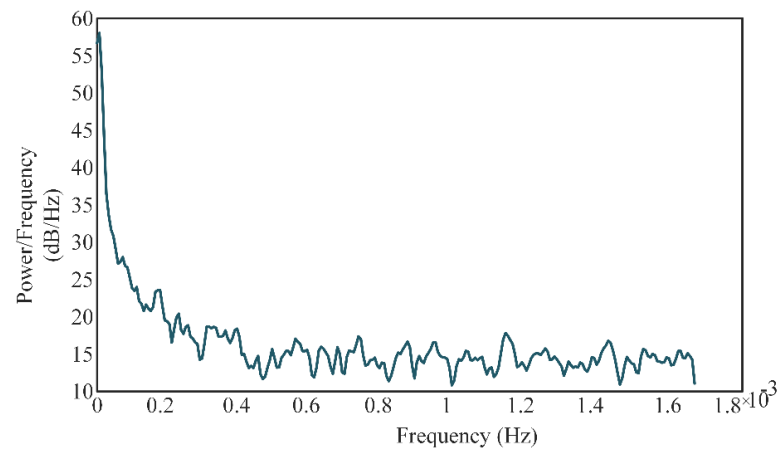
(a) Supply air temperature



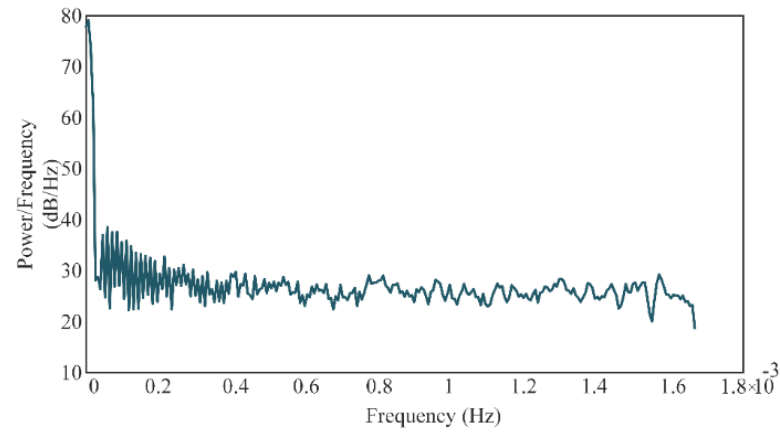
(b) Supply air CO₂ concentration



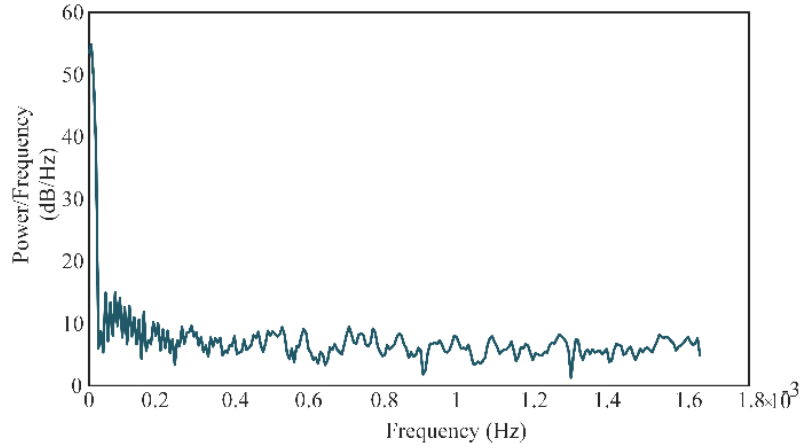
(c) Supply air humidity



(d) Supply air PM 2.5 concentration



(e) Supply air static pressure



(f) Supply air speed

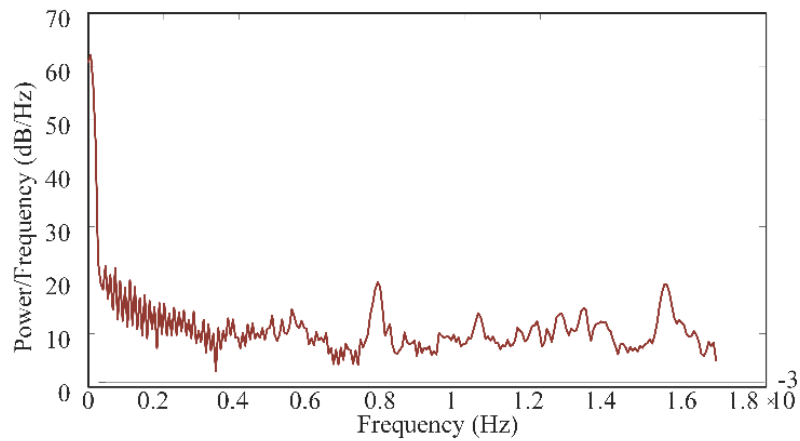
Fig 5. Power spectral density of sensor signals in HVAC: air-side sensors

The PSD of the water-side control sensors is shown in Fig. 6. From the PSD of the user-side supply and return water temperature, it can be seen that the power is higher in the low-frequency range. This indicates that the PSD energy power of the user-side supply and return water temperature are primarily concentrated in the low-frequency region, and the temperature changes in the system are relatively stable under steady-state conditions. In the mid-frequency range, both supply and return water temperatures exhibit slight oscillations, which are related to the adjustment of the chiller's cooling operating conditions. The low power level and rapid decay rate in the high-frequency range indicate that the noise content of the measurement values, which is from the supply and return water temperature sensors signal on the user-side, is relatively low.

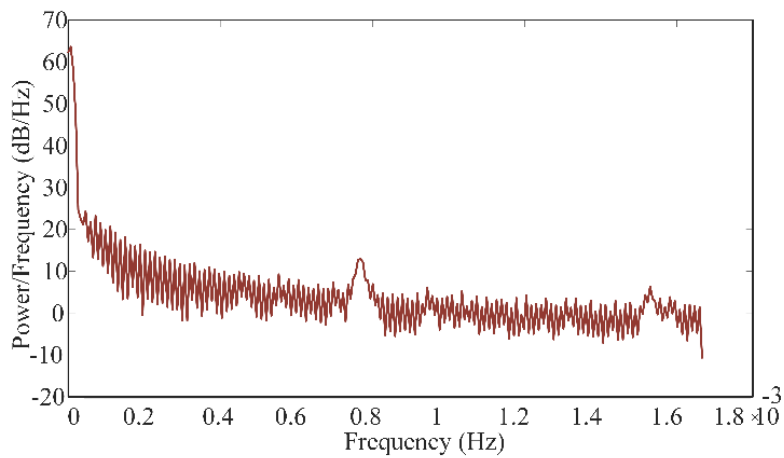
Compared to the supply and return water temperature sensor signal in the user-side, the power level of that in the cooling-tower side is higher in the low-frequency range. This indicates that the adjustment rate of the supply and return water temperatures in the cooling tower side is slower. Additionally, the faster decay rate in the high-frequency range suggests that the cooling tower's supply and return water temperature measurements are less affected by high-frequency noise disturbances. Moreover, the power decay of the return water temperature on the cooling tower side in the high-frequency range is better than that of the supply temperature. The presence of oscillations in the mid-frequency range indicates that this sensor may be influenced by the periodic effects of the mechanical equipment on the cooling tower side. Therefore, in the related control loops for the supply and return water temperatures on the cooling tower side, the measurement accuracy of the return water temperature is superior to that of the supply water temperature.

In PSD of the supply and return water pressures on the user side, it can be demonstrated that the low-frequency power is relatively high, indicating that the water pressure regulation is smooth. In the mid-frequency range, the presence of high-frequency signal oscillations indicates that the supply and return water pressures undergo periodic adjustments, which aligns with the operational patterns of the pumps. The fluctuations in the mid-frequency power of the cooling tower side supply and return water pressure may be a contributing factor to the suboptimal performance of the sensor signals in the time-domain (shown in Fig. 4). However, considering that the cooling-tower side pump operates at a constant frequency without any control actions, its signal performance may be unrelated to control actions. In future research, the reason of this phenomenon will be researched

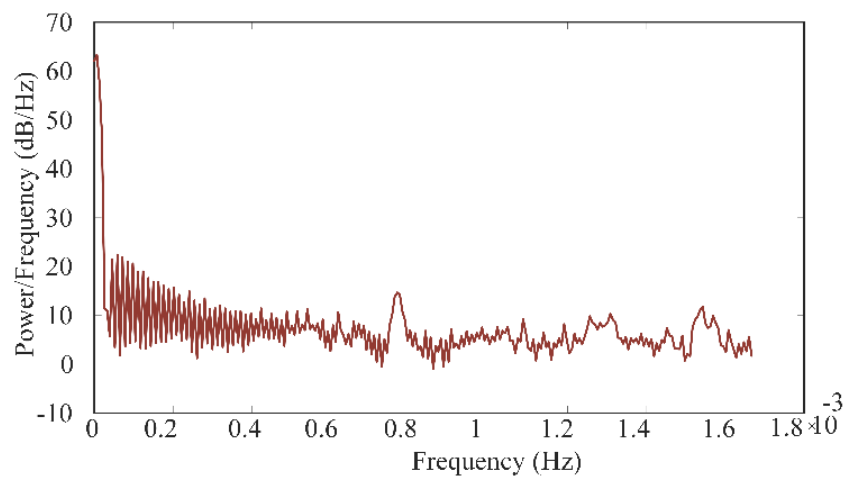
through aspects such as the principles of sensor measurement and the operational patterns of cooling tower water flow. In the PSD of the user-side water flow signal, it can be observed that the power density in the high-frequency range is significantly higher than that of other sensors on the water system side, indicating that the user-side water flow is affected by high-frequency disturbances and contains high-frequency noise. Similarly, the cooling tower side water flow sensor also contains high-frequency noise, but its energy density is lower than that of the user-side water flow, indicating that its noise content is less than that of the user-side water flow sensor.



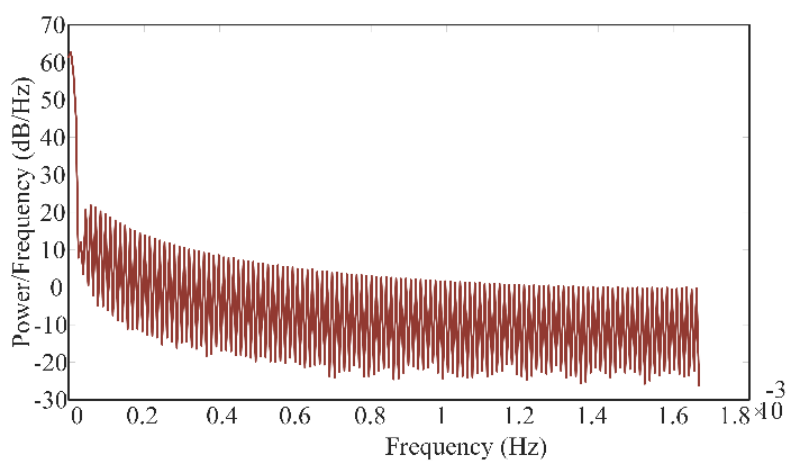
(a) User-side supply water temperature



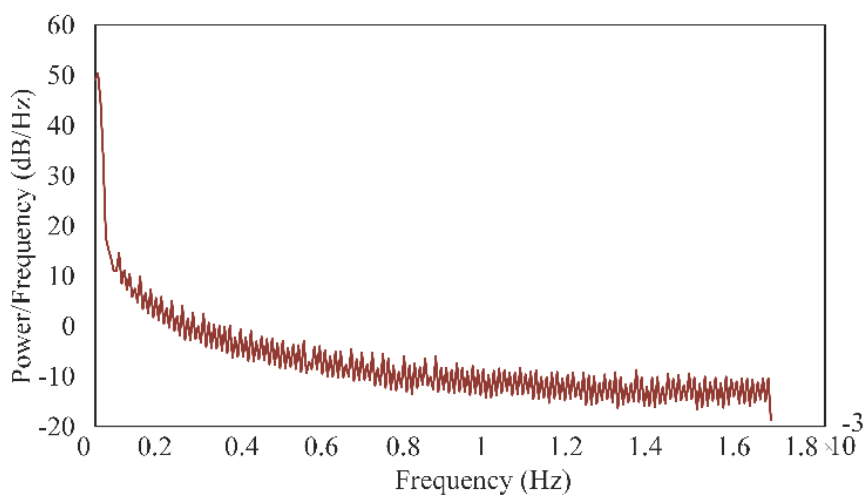
(b) User-side return water temperature



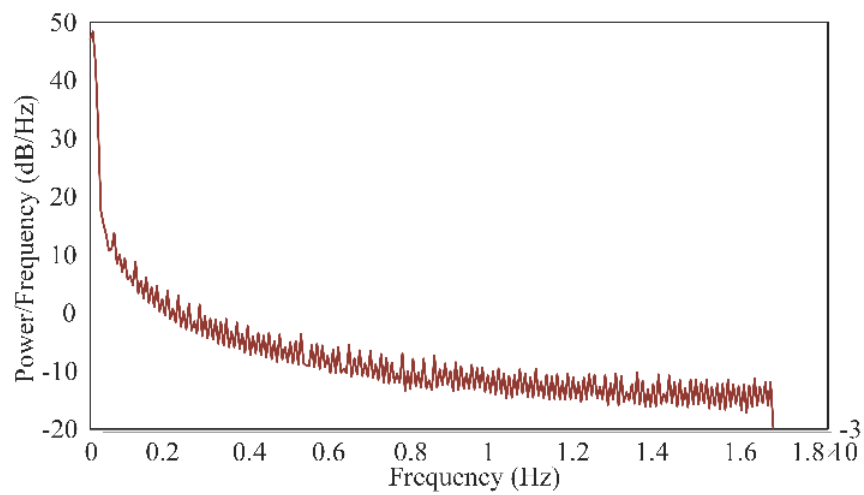
(c) Cooling tower-side water supply temperature



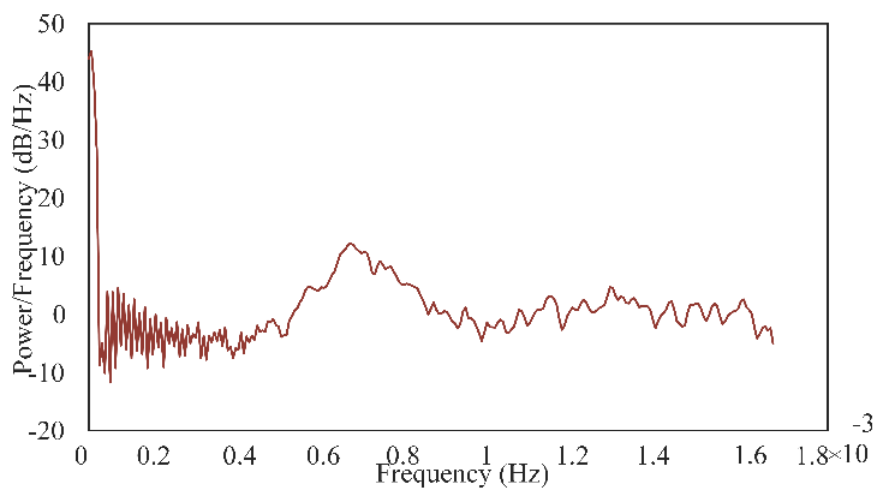
(d) Cooling tower-side return water temperature



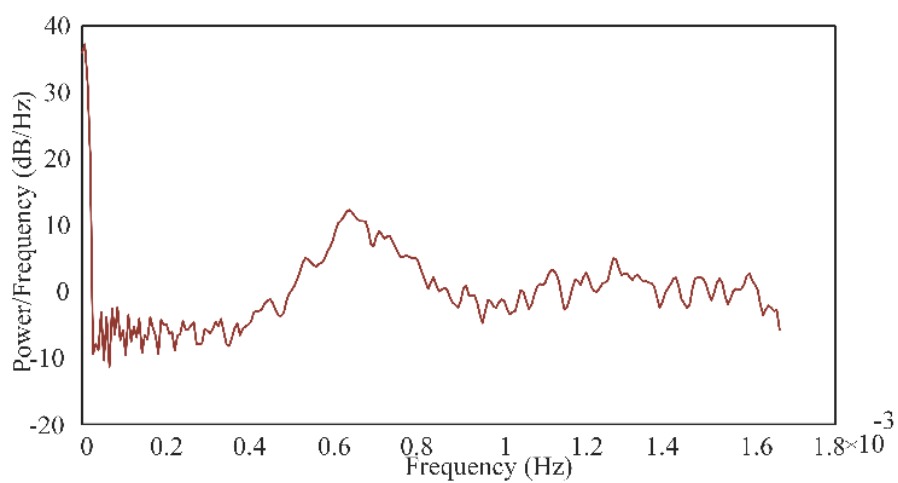
(e) User-side supply water pressure



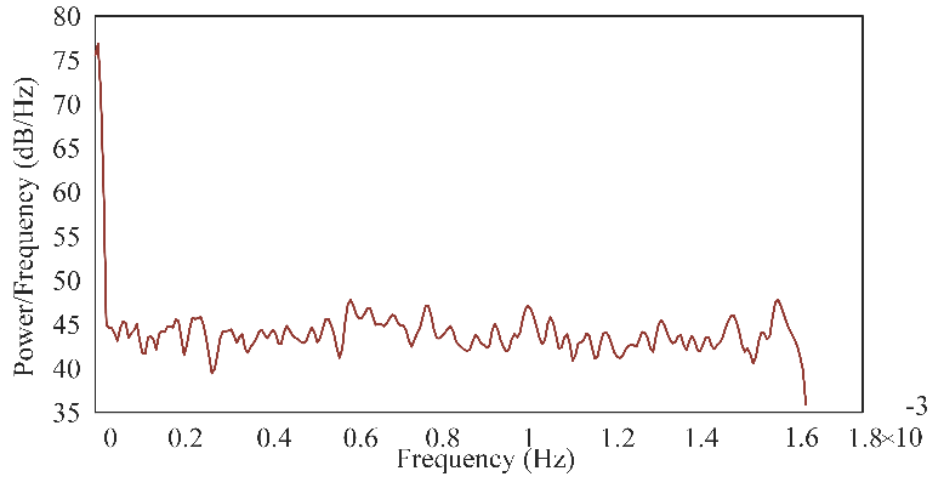
(f) User-side return water pressure



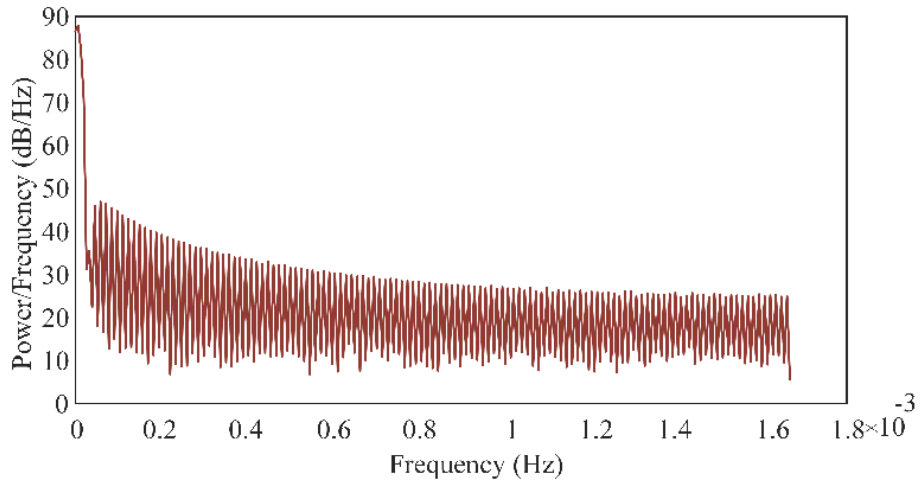
(g) Cooling tower-side supply water pressure



(h) Cooling tower-side return water pressure



(i) User-side water flow rate



(j) Cooling tower-side water flow rate

Fig 6. Power spectral density of sensor signals in HVAC: air-side sensors: Water-side sensors

4. Discussion

4.1 Inter-sensor correlation analysis

Table 5

The analysis of correlation degree

Range of Correlation	Degree of Correlation
0.8-1	Extremely strong correlation
0.6-0.8	Strong correlation
0.4-0.6	Correlation
0.2-0.4	Weak correlation
0-0.2	Extremely weak correlation

As shown in Table 5, when the correlation coefficient exceeds 0.4, it indicates a correlation between sensors; when it exceeds 0.6, a strong relationship between sensors can be determined. Considering that the HVAC is a typical nonlinear system, it analyzes the correlations among various control sensors within the system using both linear correlation (Pearson method) and nonlinear correlation (Spearman method). As shown in Fig 7, the results indicate that the correlations among

water-side sensors are stronger than those among air-side sensors. Overall, the non-linear correlations among sensors in the HVAC system are stronger than the linear correlations. Therefore, it adopts non-linear correlation as the primary reference and uses linear correlation coefficients for comparison to define the categories of sensor correlations.

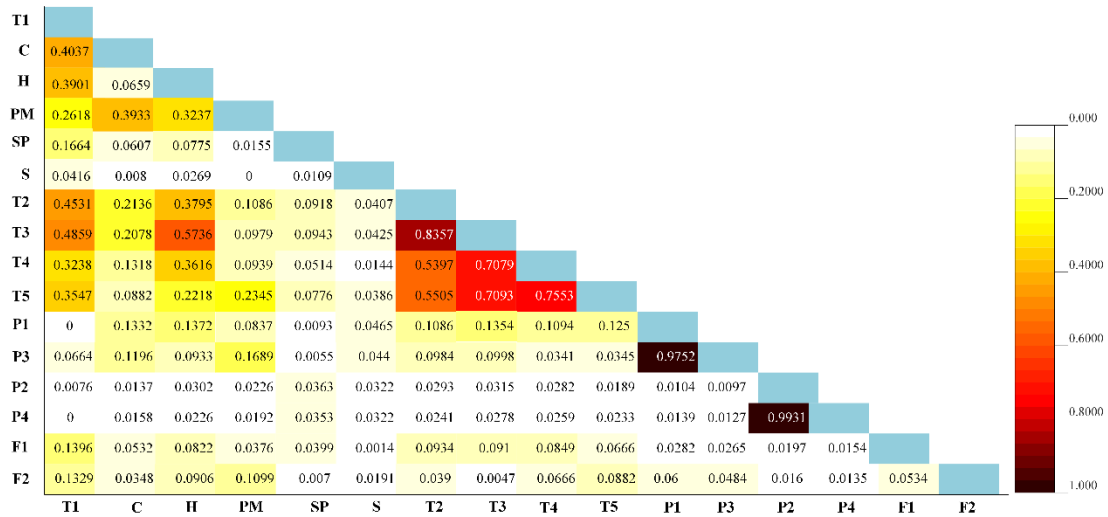
The internal correlations between HVAC sensors serve as an important theoretical basis for optimizing control strategies, establishing simulation models and diagnosing faults (Wang and Zhao, 2022). The experiment aims to analyze the correlations among sensors in HVAC to provide a theoretical foundation for parameter selection in the construction of simulation models and FDD models. As shown in Table 6, sensors that exhibit direct correlation effects and higher correlation coefficients are defined as first-class (I) correlated sensors. Sensors with indirect relationships and correlation coefficients approximately in the range of 0.3 to 0.4 are defined as second-class (II) correlated sensors.

The interrelationships between sensors reflect the correlation and common trends among HVAC mass and energy flows. As shown in Fig. 7, the data indicate that the correlation coefficients between the user-side supply and return water temperature sensors and the AHU supply air temperature are 0.3445 and 0.5002, respectively. This is because the heat on the supply air side is transferred through chilled water within the coil. Therefore, there is a correlation between the user-side supply and return water temperatures and the supply air temperature. This is because the heat on the supply air side is transferred through chilled water in the coil. Therefore, there is a correlation between the user-side supply and return water temperatures and the supply air temperature. The experimental results reveal that the linear correlation between the supply air temperature and the user-side supply water temperature is marginally stronger than the nonlinear correlation, indicating a predominant linear relationship between these variables. Compared to the direct correlation between user-side supply, return water temperatures and supply air temperature, supply air CO₂ concentration is a critical parameter in controlling the opening of the fresh air valve in the control loop. The fresh air valve opening is used to regulate the fresh air ration in the AHU supply air. When the CO₂ concentration rises, the fresh air valve opening increases, while the return air valve opening decreases. It will raise the demand for heat transfer on the supply air side under summer operating conditions. Since the impact of CO₂ concentration on supply air temperature is indirect, the correlation coefficient between above sensors is relatively low, at only 0.4213. Similarly, the correlation between the cooling tower side's supply and return water temperature sensors and the supply air temperature sensor is also low, at 0.3238 and 0.3547, respectively.

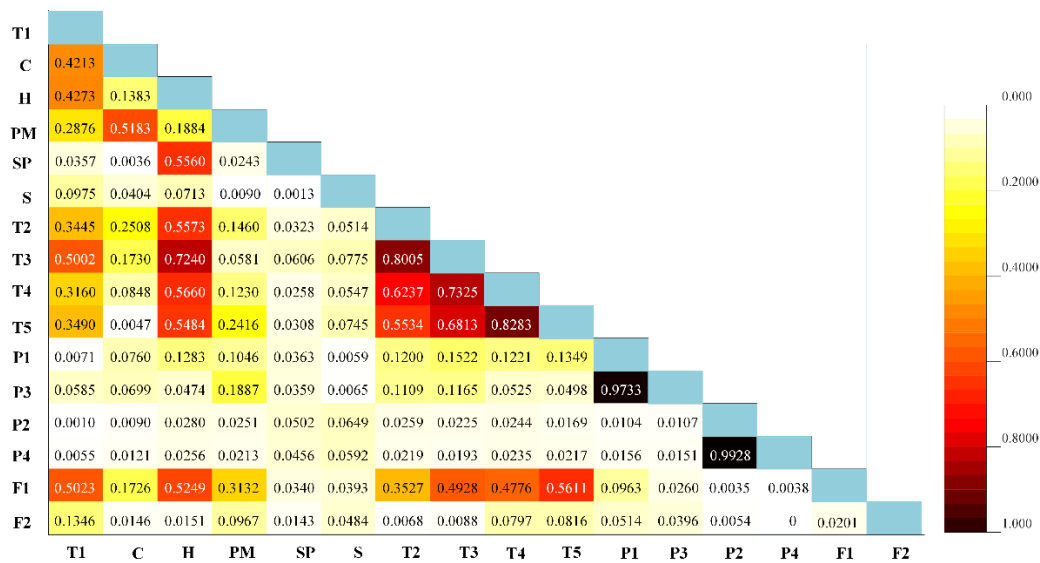
Environmental factors are a significant contributor to the correlation between sensors. For example, the rate of evaporation and diffusion of humidity increases in high-temperature environments, which can affect indoor humidity levels. This correlation is indirect. The correlation between supply air temperature and humidity is relatively low, at 0.4273. Similarly, both supply air CO₂ concentration and PM_{2.5} concentration are influenced by variations in fresh air supply, resulting in an indirect relationship with a correlation coefficient of 0.5183. In summary, internal sensor correlations are closely linked to the design structure of the HVAC system and the dynamics of energy and mass movement, with minimal influence from control strategies.

Overall, according to the design structure of the HVAC system, the correlation quality among water-side sensors is high, but the number of correlated sensors is relatively low. This is due to the high uncertainty of measurements from the air system sensors, where random errors in the measurements can affect the strength of the correlation between the sensors. Meanwhile, the

measurement points for AHU control sensors are more concentrated compared to those in the water system (primarily distributed on the supply air side), while the measurement points for sensors in the water system are more dispersed. This results in a smaller number of sensors that exhibit correlation. It is worth noting that there is a high correlation between supply air humidity and user-side return water temperature. A deeper research based on the mechanism of the HVAC system equipment will be conducted in subsequent studies to explore.



(a) Linear correlation analysis



(b) Non-Linear correlation analysis

Fig 7. The diagram of inter-sensor correlation analysis

Table 6

Sensor relevance definition

Classification	Sensor1	Sensor2	Non-linear correlation	Linear correlation
II	Supply air CO ₂ concentration	Supply air temperature	0.4213	0.4037

II	Supply air CO ₂ concentration	Supply air temperature	0.4273	0.3901
II	Temperature of user-side water return	Supply air temperature	0.5002	0.4859
II	Flow rate of user-side water	Supply air temperature	0.5023	0.1396
II	Supply air PM2.5 concentration	Supply air CO ₂ concentration	0.5183	0.3933
II	Supply air static pressure	Supply air humidity	0.5560	0.0775
II	Temperature of user-side water supply	Supply air humidity	0.5573	0.3795
I	Temperature of user-side water return	Supply air humidity	0.7240	0.5736
II	Temperature of cooling tower-side water supply	Supply air humidity	0.5660	0.3616
II	Temperature of cooling tower-side water return	Supply air humidity	0.5484	0.2218
II	Flow rate of user-side water	Supply air humidity	0.5249	0.0822
I	Temperature of user-side water return	Temperature of user-side water supply	0.8005	0.8357
I	Temperature of cooling tower-side water supply	Temperature of user-side water supply	0.6237	0.5397
II	Temperature of cooling tower-side water return	Temperature of user-side water supply	0.5534	0.5505
I	Temperature of cooling tower-side water supply	Temperature of user-side water return	0.7325	0.7079
I	Temperature of cooling tower-side water return	Temperature of user-side water return	0.6813	0.7093
II	Flow rate of user-side water	Temperature of user-side water return	0.4928	0.0934
I	Temperature of cooling tower-side water return	Temperature of cooling tower-side water supply	0.8283	0.7553
II	Flow rate of user-side water	Temperature of cooling tower-side water supply	0.4776	0.0849
I	Pressure of user-side water return	Pressure of user-side water supply	0.9733	0.9733
I	Pressure of cooling tower-side water return	Pressure of cooling tower-side water supply	0.9928	0.9931
II	Temperature of user-side water supply	Temperature of supply air	0.3445	0.4531

4.2 Noise content analysis for HVAC sensors

Considering that noise in HVAC system sensor signals is mostly random noise, it is not possible to accurately predict the noise waveform. Therefore, the experiment first plotted the frequency domain spectrum of the sensor signals using PSD. Then, the experiment determined the cutoff frequency of the signals based on the empirical formulas from previous research. The cutoff frequency of the low-pass filter used to eliminate noise from the sensors is set to 1/3 to 1/5 of the sensor's sampling frequency (Choi and Jiang., 2006). A cutoff frequency of 1×10^{-3} Hz is selected for the sensor noise. Lastly, As shown in Table 7, the signal-to-noise ratios (SNR) of different control sensors in steady-state conditions within the HVAC system are analyzed.

Table 7
SNR analysis of HVAC control sensors

District	Point	SNR
Air-side	T1	47.97
	C	44.44
	H	46.06
	PM	31.93
	SP	39.65
	S	22.17
Water-side of user	T2	33.79
	T3	45.86
	P1	45.10
	P4	44.32
	F1	16.18
Water-side of cooling tower	T4	40.16
	T5	48.24
	P2	27.47
	P3	19.53
	F2	48.00

The SNR of the supply air temperature and supply air humidity sensors is relatively high. This indicates that the signals from these sensors are clear and contain low-levels of noise. In the design of fresh air ratio control strategies, it is preferable to use the CO₂ concentration sensor (SNR: 44.44) as the monitoring sensor for the control loop from the perspective of sensor measurement accuracy, rather than the PM_{2.5} concentration sensor (SNR: 31.93). Similarly, the measurement accuracy of the supply air static pressure sensor is significantly higher than that of the supply air velocity sensor. It suggests that the supply air static pressure sensor should be prioritized as the monitoring sensor in the control loop for regulating the AHU system's air supply.

In the water-side, SNR of the user-side supply water temperature sensor is lower than that of other temperature sensors, standing at only 33.79. During steady-state operation, the supply water temperature is influenced by the number of compressors starting and stopping (as the compressors operate at a fixed frequency and cannot implement variable frequency control), resulting in significant adjustment amplitudes. This leads to fluctuations in the measured supply water temperature during equipment operation, causing the signal spectrum to contain a higher level of high-frequency signals.

In contrast, SNR of the user-side supply and return water pressure sensors is relatively high, indicating good sensor signal quality with minimal noise impact on the signals. The user-side supply water flow sensor exhibits a higher noise content due to the presence of a large number of outliers

in its measured signals. Therefore, it is recommended to use the pressure differential of the chilled water supply and return as the monitoring value for the control strategy in the user-side supply water flow control loop. Conversely, in the control loop for the cooling tower side water flow, the quality of the water flow sensor signal is superior to that of the cooling water supply and return pressure sensor.

4.3 Impact analysis of de-noising method in sensors

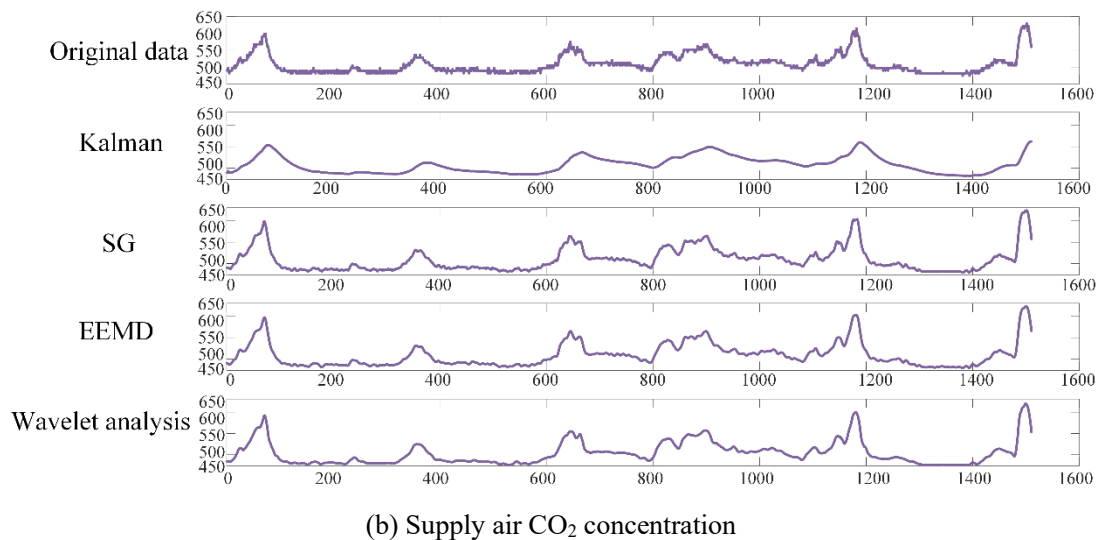
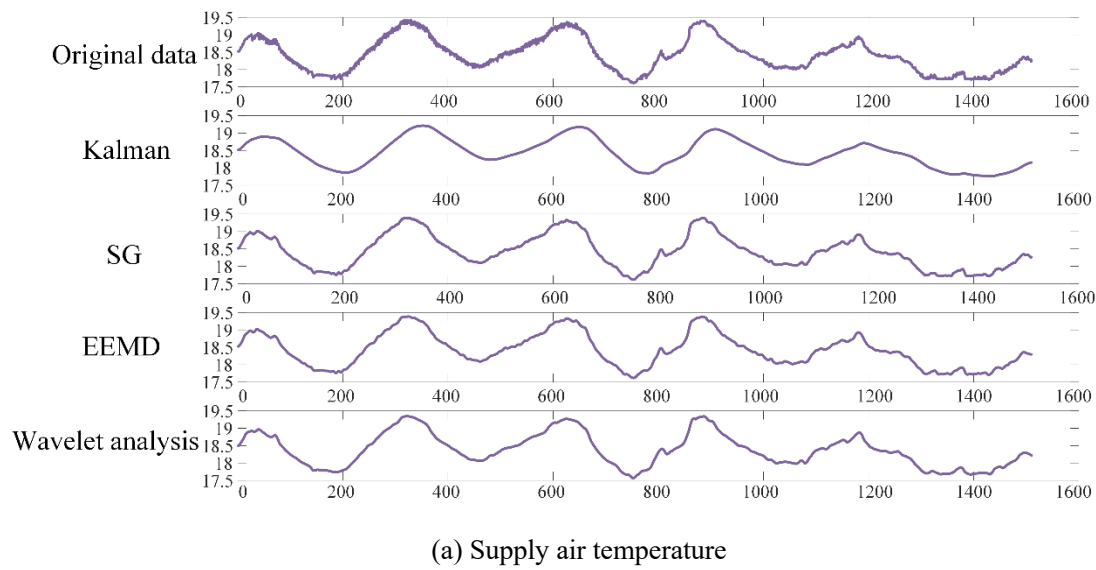
Table 8
The useful signal analysis of the de-noising methods

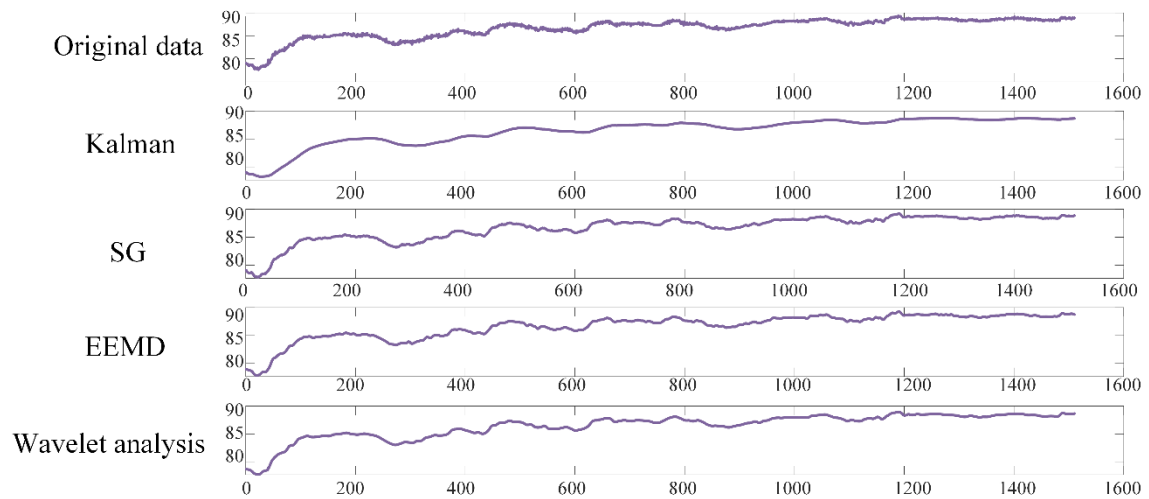
Sensors point	Kalman (%)	SG (%)	EEMD (%)	Wavelet analyze (%)
T1	100	99.99	99.97	99.51
C	100	99.99	100	97.72
H	98.51	99.98	99.97	98.42
PM	96.60	99.85	99.91	88.64
SP	99.99	99.99	99.92	95.49
S	99.16	99.41	98.66	65.26
T2	99.97	99.97	99.68	92.26
T3	100	99.99	99.96	98.00
T4	100	99.99	100	96.40
T5	100	100	100	99.84
P1	99.80	99.94	100	99.16
P4	99.71	99.99	100	99.38
P2	99.49	99.54	100	77.68
P3	96.49	97.11	100	48.40
F1	96.22	97.32	96.15	89.46
F2	99.99	99.99	100	99.53

Table 9
The noise component analysis of the de-noising methods

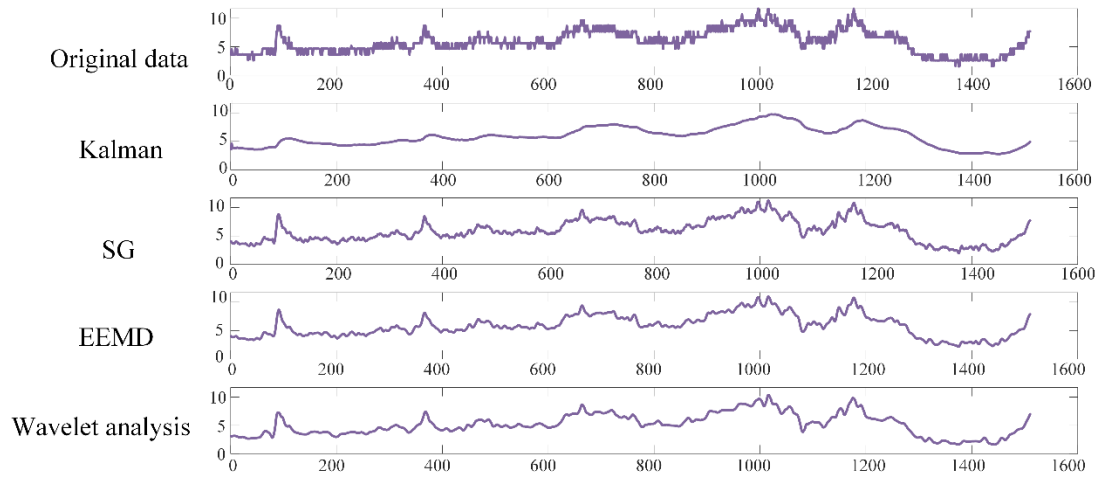
Sensors point	Kalman (%)	SG (%)	EEMD (%)	Wavelet analyze (%)
T1	93.50	93.69	93.67	93.21
C	41.57	43.41	42.59	41.72
H	58.82	60.27	59.53	59.09
PM	2.15	3.38	2.14	2.92
SP	13.78	14.76	13.70	13.12
S	0.26	1.56	0.23	0.17
T2	3.62	4.62	3.56	3.33
T3	57.93	58.30	57.85	56.68
T4	15.50	16.51	15.49	14.95
T5	99.14	99.08	99.07	98.96
P1	47.58	50.64	50.28	74.88
P4	39.73	42.94	42.45	82.82
P2	0.86	2.02	0.84	0.65
P3	0.16	1.32	0.13	0.07
F1	0.09	1.47	0.06	58.17

As shown in Fig. 8, the experiment compares the filtering performance of four major filtering methods for HVAC sensor signals. The comparison examines the signal power ratio of signals and noise power to the original signal and noise power for each control sensor in the HVAC system across different filtering methods. As shown in Table 8, a higher signal ratio indicates that the filtering method better preserves the original sensor signal. Table 9 displays the noise power ratio in the original signal before and after filtering. A lower noise ratio suggests a more effective noise reduction by the filtering method. Considering practical engineering applications, it is challenging to apply customized filtering methods for each sensor signal within the system. Therefore, when analyzing filtering methods, a unified approach should be selected based on the overall filtering efficiency across all sensors in the system.

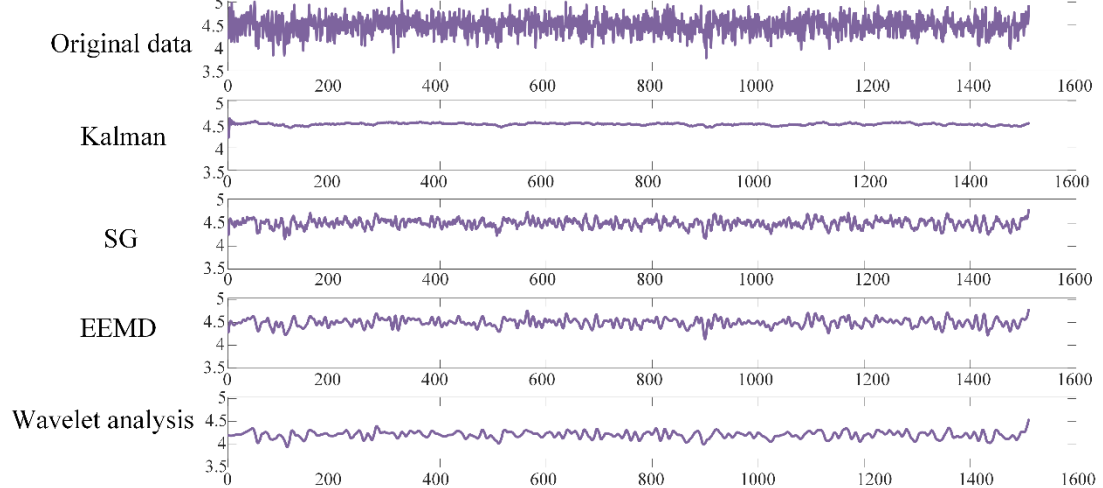




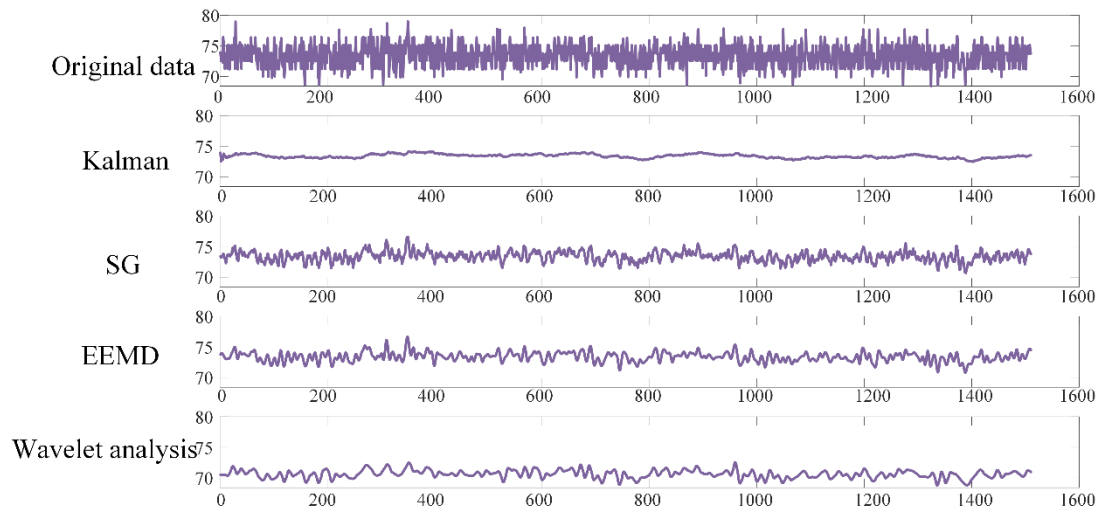
(c) Supply air humidity



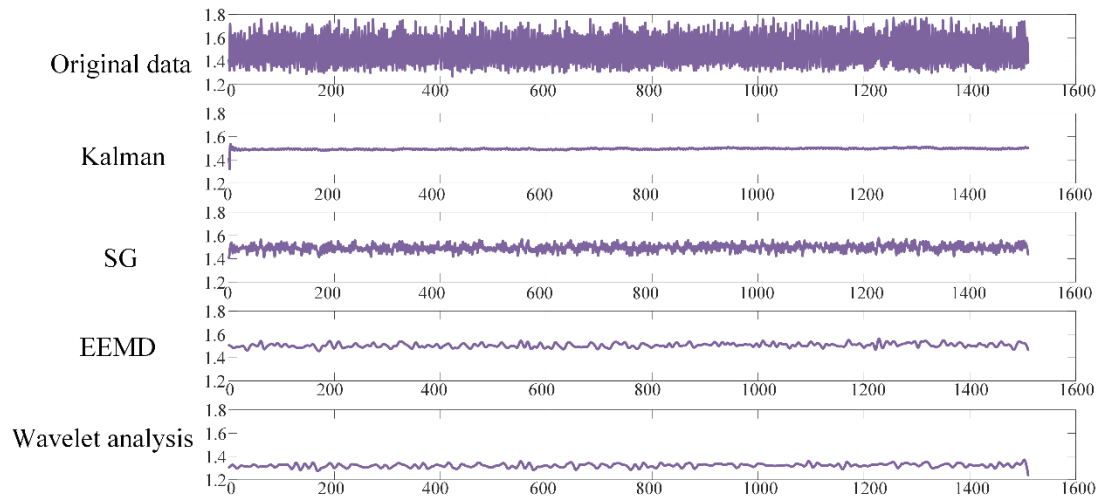
(d) Supply air PM2.5 concentration



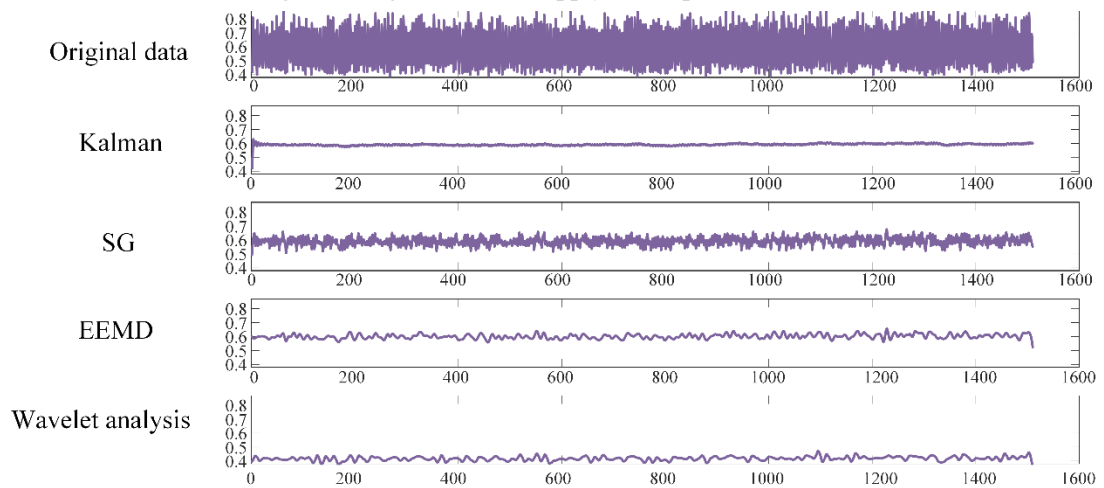
(e) Supply air static pressure



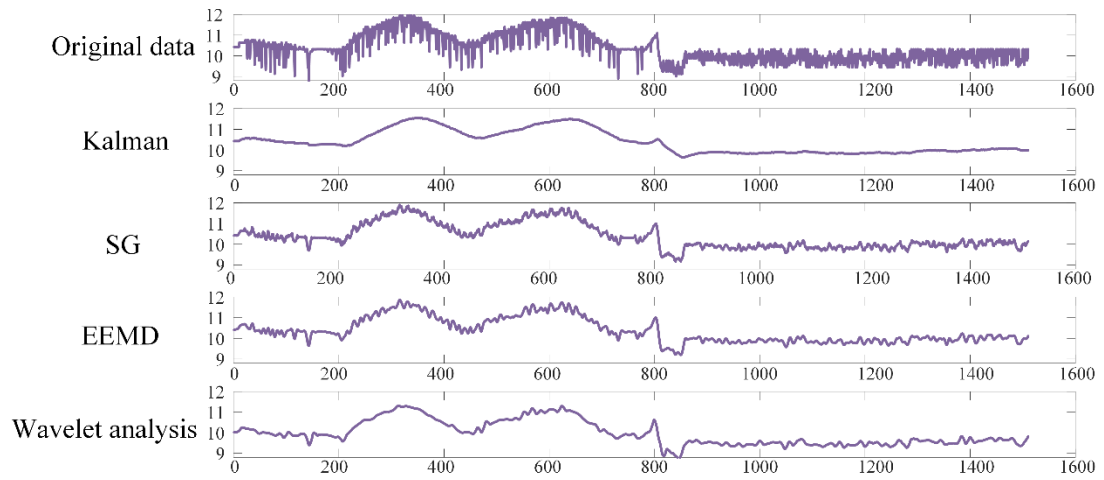
(f) Supply air speed



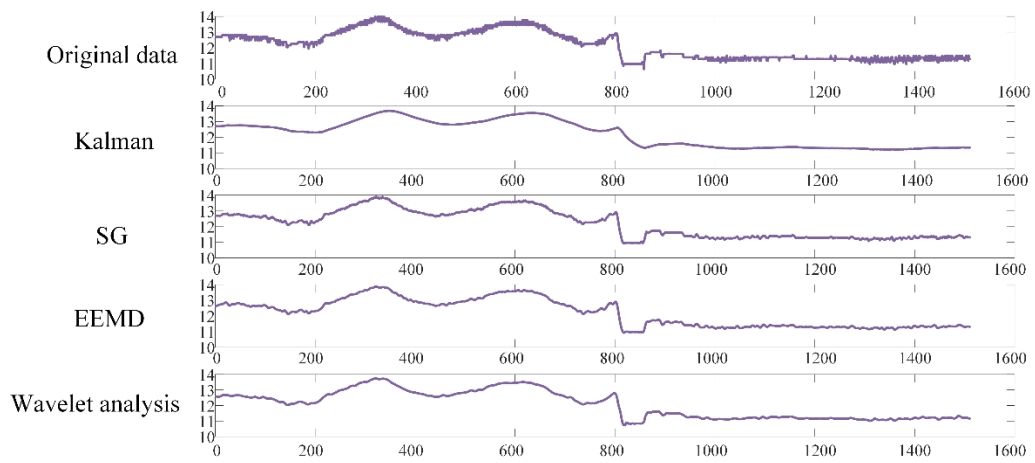
(g) Cooling tower-side supply water pressure



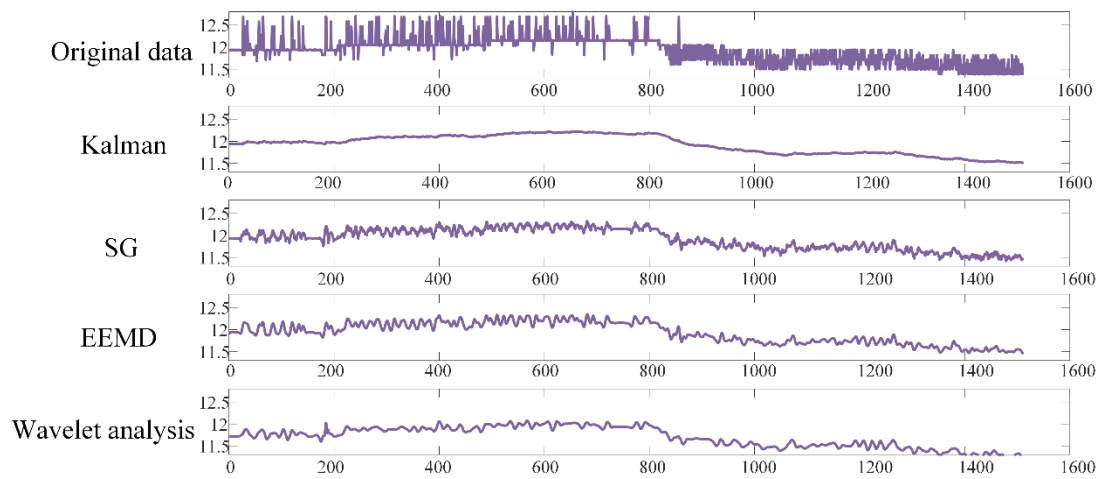
(h) Cooling tower-side return water pressure



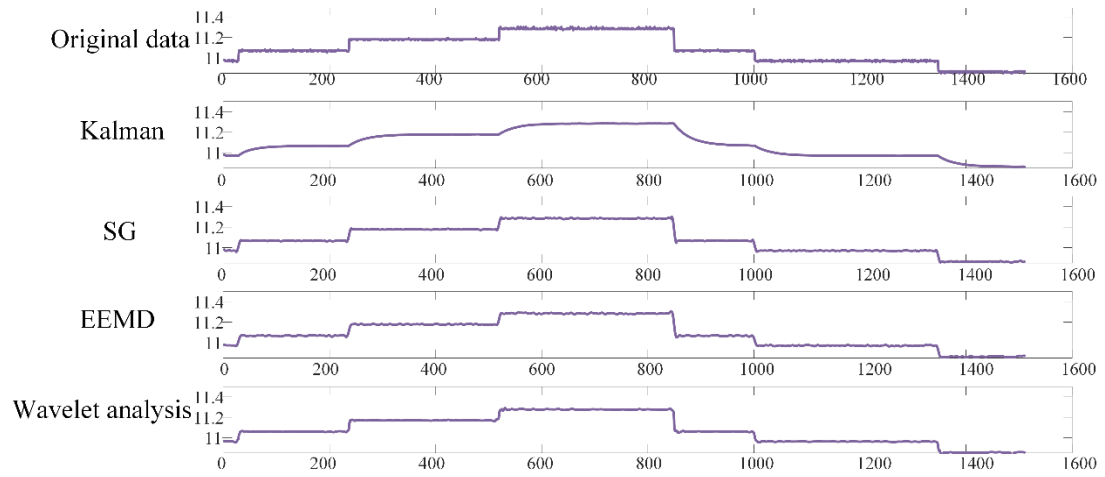
(i) User-side water supply water temperature



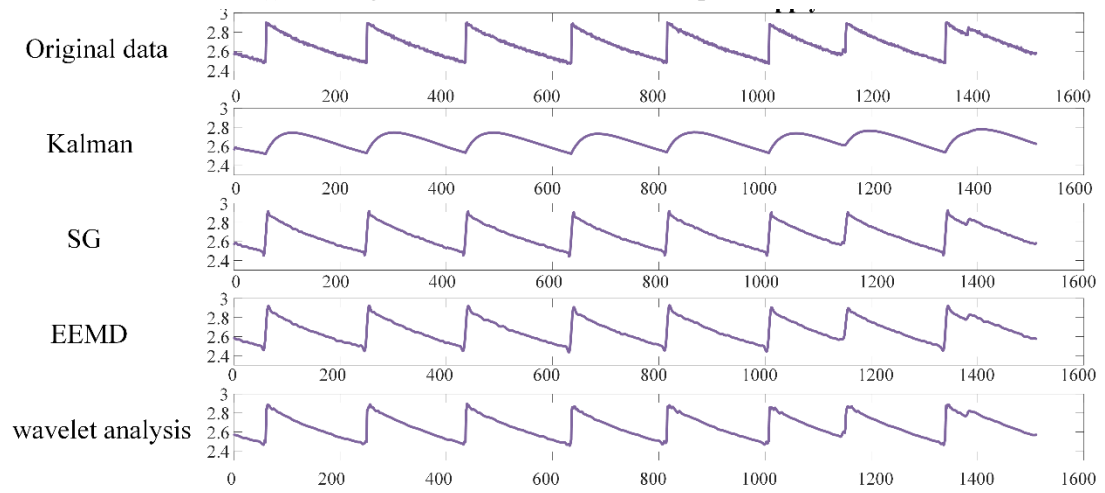
(j) User-side water return water temperature



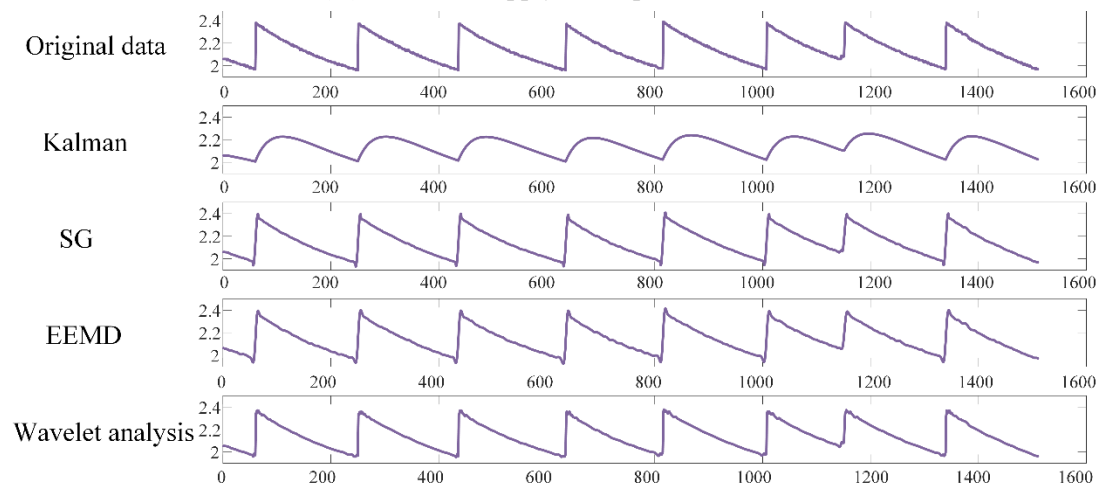
(k) Cooling tower-side supply water temperature



(l) Cooling tower-side return water temperature



(m) User-side supply water pressure



(n) User-side water return water pressure

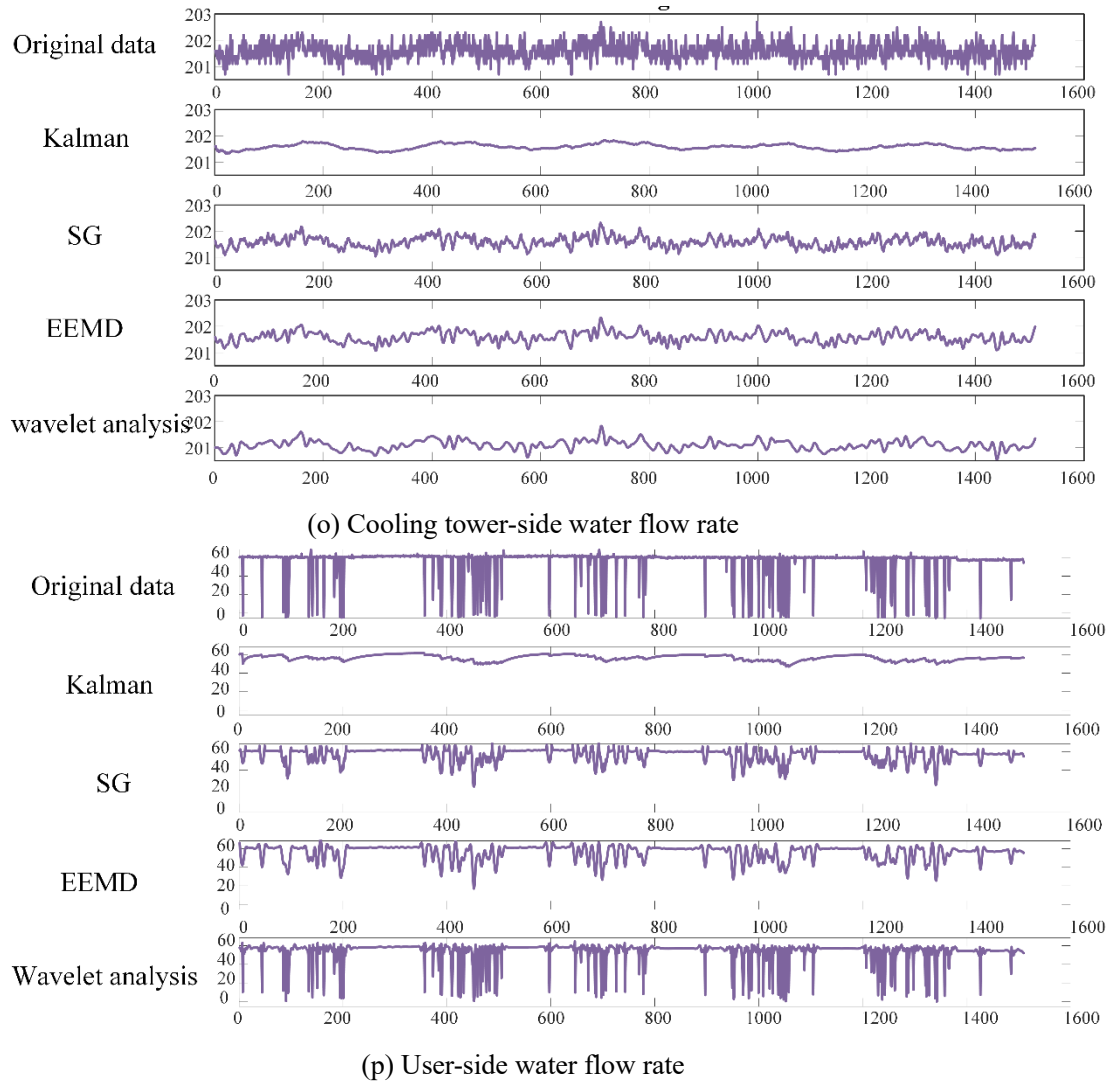


Fig 8. The filter analysis of HVAC sensors in different methods (top to bottom): original data, Kalman, SG, EEMD and wavelet analysis

EEMD filtering method achieves a signal retention rate of 98.66%–100% in AHU. From the perspective of noise filtering efficiency, the SG filter performs slightly less efficiently than the Kalman and EEMD methods. As shown in Fig 8, the Kalman filtered signal has a smoother waveform compared to the rest of the filtering methods from the data waveform. The Kalman method has a slightly lower signal retention rate compared to the SG and EEMD methods. However, in terms of noise retention rate, the performance of the Kalman filter is similar to that of the EEMD method, with a difference of less than 0.5%. It indicates that the smoothed data signal after Kalman filtering may be due to signal distortion.

As shown in Table 9, the higher the signal-to-noise ratio of the sensor signal, the higher the percentage of noise after filtering. For instance, the SNR of supply air temperature sensor is 47.97, yet the percentage of noise power after denoising remains between 93.21% and 93.69% of the original signal's noise power. It may indicate a low noise content within the signal. Setting the cutoff frequency for signals at one-third to one-fifth of the sampling frequency might not align with the noise characteristics of such sensor signals. For sensors with low signal-to-noise ratios, various filtering methods demonstrate strong filtering effectiveness. Similarly, EEMD achieves optimal

signal retention in the water system. The signal retention rate after EEMD filtering for relevant sensors in the water system reaches between 96.15%-100%, with most control sensors in the water system achieving 100% signal retention. Additionally, EEMD exhibits a lower noise percentage compared to other methods, demonstrating its superior filtering capability. In summary, overall, EEMD shows greater filtering efficiency in the signal filtering of HVAC system control sensors.

5. Conclusion and Limitations

5.1 Conclusion

The study analyzes the signal characteristics of various control sensors within the system and examines the interrelationships among these sensors. Additionally, it evaluates the filtering effectiveness of current mainstream signal filtering methods on different control sensors in HVAC system. The specific conclusions are as follows:

(1) First, research analyzes the time-domain characteristics of various control sensors in HVAC system, and three types of signal characteristics are defined: time-decay type, unstable time-periodic type and non-time-series type. Among them, time-decay type sensors are mainly concentrated on the AHU (excluding sensors related to airflow) and on return water temperature sensors in the chiller. The unstable time-periodic sensors demonstrate strong temporal correlations, but with a slower decay rate over time, such as: supply water temperature sensors in the user-side and cooling tower-side. Finally, the measurements of non-temporal sensors are mostly related to measurements by fans and pumps in HVAC system. Experiment indicates that the time-domain characteristics of sensors are not directly related to the measured physical quantities but are rather associated with the control strategies of the quantities being measured. Therefore, before constructing filtering and feature extraction methods based on temporal characteristics, the control strategy of the sensor measurements should be discussed first.

(2) Then, it analyzes the frequency-domain sensors characteristics in HVAC by PSD. The research indicates that sensors such as supply air speed, user-side water flow and cooling tower return water pressure in the HVAC system have higher noise content. The research conclusion reveals that the SNR of above sensors are 22.17, 16.18 and 19.53, respectively. Given the practical challenges of applying customized filtering methods for each sensor signal in a system, it is crucial to select a unified filtering method based on the overall filtering efficiency of all sensors in the HVAC system. Based on the overall system or focusing solely on the water system, the EEMD method performed slightly better than the Kalman, SG, and wavelet analysis methods, with an average signal retention rate of 99.63% and an average noise removal rate of 64.02%. However, when focusing solely on the AHU as the monitoring target, the SG method demonstrated slightly better overall performance compared to the other three methods. Therefore, when selecting a filtering method for signal processing, the research focus should first be determined.

(3) Finally, the study analyzes the inter-sensor correlations in the HVAC system. Based on the correlation coefficients of various control sensors within the HVAC system and the dynamic relationships of energy and mass, the study defined two categories of correlated sensors: first-class (I) correlated sensors and second-class (II) correlated sensors. The experiment demonstrated that natural or indoor environmental factors and the dynamic relationship of energy and mass within the HVAC system are significant factors affecting the correlation between sensors. And, the correlation is not influenced by control factors.

5.2 Limitations

It analyzes the signal characteristics of control sensors in public building's HVAC under

summer operating conditions. However, the research only focuses on summer conditions and does not examine the signal characteristics of control sensors under winter operating conditions. Additionally, factors such as sensor accuracy and measurement principles are also potential contributors to signal characteristics. It primarily explores the relationship between sensors and the system, lacking a microscopic examination of the sensors themselves. In future research, the team will standardize the HVAC system and control logic variables to compare the differences in signal characteristics among control sensors with varying measurement principles and accuracies.

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Reference

- Abbott, A.** (1991). Title of the work. *Journal Name*, Volume(Issue), Page Range.
- Akari, N., Shi, S., Miyata, S., Akashi, Y., Momota, M., & Sawachi, T.** (2024). Design-operation gap caused by parameter variance in HVAC system control sequences: A simulation-based study on energy efficiency and temperature controllability. *Journal of Building Engineering*, 87, 109112.
- Azarbani, A., & Abbasi, R.** (2019, November). Optimal state estimation of air handling unit system without humidity sensor using unscented Kalman filter. In 6th International Conference on Control, Instrumentation and Automation (ICCIA) (pp. 1–6). IEEE.
- Cheng, D., Zhang, W., & Liu, J.** (2017). Window-varying particle filter for parameter identification of space thermal model. *IEEE Transactions on Instrumentation and Measurement*, 66(1), 1–12.
- Choi, S., & Jiang, Z.** (2006). A novel wearable sensor device with conductive fabric and PVDF film for monitoring cardiorespiratory signals. *Sensors and Actuators A: Physical*, 128(2), 317–326.
- Cotrufo, N., & Zmeureanu, R.** (2016). PCA-based method of soft fault detection and identification for the ongoing commissioning of chillers. *Energy and Buildings*, 130, 443–452.
- Du, Z., Chen, L., & Jin, X.** (2017). Data-driven based reliability evaluation for measurements of sensors in a vapor compression system. *Energy*, 122, 237–248.
- Du, Z., Fan, B., Chi, J., & Jin, X.** (2014). Sensor fault detection and its efficiency analysis in air handling unit using the combined neural networks. *Energy and Buildings*, 72, 157–166.
- Du, Z., & Jin, X.** (2008). Multiple faults diagnosis for sensors in air handling unit using Fisher discriminant analysis. *Energy Conversion and Management*, 49(10), 3654–3665.
- Fan, B., Du, Z., Jin, X., Yang, X., & Guo, Y.** (2010). A hybrid FDD strategy for local system of AHU based on artificial neural network and wavelet analysis. *Building and Environment*, 45(2), 2698–2708.
- Gangiseti, R., et al.** (2016). Title of the work. *Journal Name*, Volume(Issue), Page Range.
- Guo, J., He, Q., Zhen, D., Gu, F., & Ball, A. D.** (2024). Multiscale cyclic frequency demodulation-

based feature fusion framework for multi-sensor driven gearbox intelligent fault detection. *Knowledge-Based Systems*, 283, 111203.

Guo, Y., Li, G., Chen, H., Hu, Y., Li, H., Xing, L., & Hu, W. (2017). An enhanced PCA method with Savitzky-Golay method for VRF system sensor fault detection and diagnosis. *Energy and Buildings*, 167–178.

Hu, Y., Li, G., Chen, H., Shen, L., Li, H., Hu, M., Liu, J., & Sun, K. (2018). Chiller sensor fault detection based on empirical mode decomposition threshold denoising and principal component analysis. *Applied Thermal Engineering*, 144, 21–30.

Huang, W., Gao, C. X., Luo, D., Wang, Y., Zheng, X., Liu, C., Wang, Y., Li, Y., & Qian, H. (2024). Risk evaluation of venue types and human behaviors of COVID-19 outbreaks in public indoor environments: A systematic review and meta-analysis. *Environmental Pollution*, 341, 122970.

International Energy Agency (IEA). (2022). Technology and innovation pathways for zero-carbon-ready buildings by 2030. IEA, Paris.

Jin, Q., & Duanmu, L. (2016). Experimental study of thermal sensation and physiological response during step changes in non-uniform indoor environment. *Science and Technology for the Built Environment*, 22(2), 237–247.

Kelso, J., & Smith, T. (1998). Title of the work. *Journal Name*, Volume(Issue), Page Range.

Khalilnejad, A., French, R. H., & Abramson, A. R. (2020). Data-driven evaluation of HVAC operation and savings in commercial buildings. *Applied Energy*, 278, 115505.

Li, G., Hu, Y., Chen, H., Shen, L., Li, H., Hu, M., Liu, J., & Sun, K. (2016). An improved fault detection method for incipient centrifugal chiller faults using the PCA-R-SVDD algorithm. *Energy and Buildings*, 116, 104–113.

Li, G., Yao, Q., Fan, C., Zhou, C., Wu, G., Zhou, Z., & Fang, X. (2021). An explainable one-dimensional convolutional neural networks based fault diagnosis method for building heating, ventilation and air conditioning systems. *Building and Environment*, 203, 108057.

Li, J., Wang, P., Li, Y., Rezgui, Y., Yoon, S., & Zhao, T. (2024). Analysis of sensor offset characteristics in building energy systems based on redundant sensors: A case study on variable air volume system. *Energy & Buildings*, 306, 113957.

Li, S., & Wen, J. (2014). A model-based fault detection and diagnostic methodology based on PCA method and wavelet transform. *Energy and Buildings*, 68, 63–71.

Liang, W. (2014). Modeling and control of AHUs in building HVAC system. University of California, Merced.

O'Neill, Z., & Niu, F. (2017). Uncertainty and sensitivity analysis of spatio-temporal occupant behaviors on residential building energy usage utilizing Karhunen Loeve expansion. *Building and Environment*, 115, 157–172.

Pang, Z., Guo, M., O'Neill, Z., Smith-Cortez, B., Yang, Z., Liu, M., & Dong, B. (2025). Long-term field testing of the accuracy and HVAC energy savings potential of occupancy presence sensors in a single-family home. *Energy and Buildings*, 328, 115161.

Salehi, S. S., Kalamees, T., Kurnitski, J., & Thalfeldt, M. (2024). New typical meteorological year generation method based on long-term building energy simulations. *Building and Environment*, 256, 111502.

Shadi, M. A. H., Pavlak, G. S., & Bahnfleth, W. P. (2022). Model-based testbed for uncertainty quantification in building control systems with advanced sequences of operation. *Journal of*

Architectural Engineering, 28(2), 1–12.

Shi, Z., & O'Brien, W. (2019). Sequential state prediction and parameter estimation with constrained dual extended Kalman filter for building zone thermal responses. *Energy and Buildings*, 183, 538–546.

Sun, B., Luh, P. B., Jia, Q.-S., O'Neill, Z., & Song, F. (2014). Building energy doctors: An SPC and Kalman filter-based method for system-level fault detection in HVAC systems. *IEEE Transactions on Automation Science and Engineering*, 11(1), 1–12.

Vanus, J., Kubicek, J., Vilimek, D., Penhaker, M., & Bilik, P. (2023). A innovative wavelet transformation method optimization in the noise-canceling application within intelligent building occupancy detection monitoring. *Heliyon*, 9(1), e1614.

Wang, J., & Gong, C. (2006, June). Sensing induced voltage of electromagnetic flow meter with multi-electrodes. In 2006 IEEE International Conference on Information Acquisition (pp. 20–23). IEEE.

Wen, S., Zhang, W., Sun, Y., Li, Z., Huang, B., Bian, S., Zhao, L., & Wang, Y. (2023). An enhanced principal component analysis method with Savitzky–Golay filter and clustering algorithm for sensor fault detection and diagnosis. *Applied Energy*, 337, 120862.

Xie, K., Ning, X., Wang, X., Xie, D., Cao, J., Xie, G., & Wen, J. (2023). Recover corrupted data in sensor networks: A matrix completion solution. *Journal Name*, Volume(Issue), Page Range.

Yan, B., Li, X., Malkawi, A. M., & Augenbroe, G. (2017). Quantifying uncertainty in outdoor air flow control and its impacts on building performance simulation and fault detection. *Energy and Buildings*, 134, 115–128.

Yan, K., Ji, Z., & Shen, W. (2015). Online fault detection methods for chillers combining extended Kalman filter and recursive one-class SVM. *Neurocomputing*, 228, 205–212.

Yoon, S., Yu, Y., Li, H., Choi, Y., & Hong, Y. (2022). Improved energy balance calculation of unitary air conditioners via virtual in-situ calibration. *Journal of Building Engineering*, 45, 103464.

Zhang, B., Wang, P., Liu, G., Ma, Z., & Zhao, T. (2024). AHU sensor fault diagnosis in various operating conditions based on a hybrid data-driven model combined energy consumption. *Journal of Building Engineering*, 87, 109028.

Zhang, B., Wang, P., Liu, G., Li, J., & Zhao, T. (2023). Diagnosis of single and multiple-source faults of chiller sensors using EWEEMD-ICKNN by time sequence denoising and non-Gaussian distribution feature extraction. *Energy & Buildings*, 113572.

Zhao, T., Zhang, B., Li, M., Liu, G., & Wang, P. (2023). Handling fault detection and diagnosis in incomplete sensor measurements for BAS based HVAC system. *Journal of Building Engineering*, 80, 108098.