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Citation for final published version:

Zhang, Boyan, Rezgui, Yacine , Luo, Zhiwen and Zhao, Tianyi 2024. Fault detection research on novel transfer learning-based method for cross-condition, cross-system and cross-operation in public building HVAC sensors. *Energy* 313 , 133704. 10.1016/j.energy.2024.133704

Publishers page: <http://dx.doi.org/10.1016/j.energy.2024.133704>

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Fault detection research on novel transfer learning-based method for cross-condition, cross-system and cross-operation in public building HVAC sensors

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Abstract: Transfer learning (TL) has the inspiring potential for artificial intelligence in heating, ventilation and air conditioning (HVAC) system with insufficient data labels. However, traditional TL-based methods are limited when applied across different conditions, systems, and operations. Unfortunately, public building HVAC systems encounter challenges related to data acquisition and richness, making it difficult to obtain data from similar HVAC systems conditions, scenarios and operations. It proposes a novel TL-based method that combines energy and mass balance constraint equation (EBCe) to diagnose the sensor faults in HVAC systems across different systems, conditions and operations. Firstly, it utilizes laboratory data as the source domain data and constructs EBCe based on the common physical laws of HVAC system to reduce the data differences between laboratory and public buildings. Then, an laplacian kernel domain-adaptive neural network (LkDaNN) is proposed to generalize more efficiently feature differences between the source domain data and target domain data. Finally, experiment analyzes the non-fault and four control-sensors fault under both cross-operation and non-cross operation conditions. The experimental results demonstrate that the EBCe-LkDaNN method achieves satisfactory fault detection and diagnosis (FDD) performance. The overall FDD accuracy of proposed method can reach 90.72% and 88.64% under different cross-operation, respectively. Practical application of the EBCe-LkDaNN strategy for HVAC sensor FDD are discussed at last.

Keywords: HVAC sensor, Transfer learning (TL), Fault diagnosis and detection (FDD), public building, Energy and mass balance constraint equation (EBCe)

Nomenclature			
e	Constraint equation	T	Temperature
F	Flow	P	Pressure
η	Drive efficiency	V	Air velocity
O	Opening degree of air damper	E	Power
Y	Feature mapping in layer	x	Signals
K	Convolution kernel weight	W	Weight parameter
Subscripts			
co	Condenser outlet	ci	Condenser inlet
eo	Evaporator outlet	ei	Evaporator inlet
S	Supply air	c	Condenser
e	Evaporator		
Abbreviation			
MMD	Maximum mean discrepancy	EBCe	Energy and mass balance constraint equation
TL	Transfer learning	CNN	Convolutional neural networks
DANN	Domain adversarial neural network	DaNN	Domain-adaptive neural network

1. Introduction

1.1 Background

The International Energy Agency has reported that the global energy consumption is approximately 30% consumed attributed to the building sector[1]. In public buildings, heating, ventilation and air conditioning (HVAC) typically account for the largest fraction of their operational energy consumption[2]. To optimize energy consumption in buildings, modern HVAC system has been developed more complex control technologies[3]. It has integrated numerous sensors, actuators and control algorithms to monitor and control HVAC operation[4]. The actual performance of HVAC system heavily depends sensors measurement to control the actuators operation. Unfortunately, due to harsh operating environments, insufficient commissioning and equipment aging, HVAC sensor failure is the most common faults in HVAC failures[5]. Faulty sensors can cause HVAC control strategies to fail in achieving their anticipated performance. This leads to increased energy consumption and decreased thermal comfort in indoor environments. References[6]-[9] have proven that timely faulty sensor diagnosis can significantly reduce energy

wastage and improve indoor thermal comfort. Therefore, it is necessary to research on faulty sensor diagnosis methods for HVAC system.

1.2 Summary of studies on HVAC sensor fault diagnosis

Last decade, numerous researches have focused on the fault detection and diagnosis (FDD) of HVAC systems. Generally, there exist the following three mainstream approaches for FDD in HVAC sensors[10]: model-based methods, rule-based methods and data-driven methods. The model-based methods involve constructing precise mathematical models to diagnose faults by analyzing the redundancy between the actual operational state of the system and the physical model[11]. Based on the physical principles, model-based methods can effectively achieve accurate and reliable FDD in HVAC systems[12][13], including the detection of issues such as fouling[14], leaking[15] and stuck[16]. However, the increasing complexity of HVAC systems has led to excessive computational costs in constructing accurate mathematical models, which limits the application of model-based methods in large and complex HVAC systems[17]. Additionally, the high uncertainty of sensor failures pose a significant challenge when trying to achieve precise calculations through mathematical models[18][19]. Rule-based methods utilize pre-developed rules (either from empirical knowledge[20] or scientific principles[21]) to monitor sensor measurements and detect faults. However, HVAC systems have the characteristics of variable operating conditions. It is difficult to obtain all rules which largely depend on the expertise and knowledge of the developer[22]. To overcome the limitations posed by insufficient physical models and domain knowledge in HVAC sensor faults diagnosing. Current research has seen a significant focus on data-driven fault detection methods.

Unlike model-based and rule-based approaches, data-driven methods purely rely on sensor data. In recent years, building automation systems (BASs) have been widely used to collect HVAC data, which has led to the widespread application of data-driven methods in FDD of HVAC faulty sensors[23]. According to the complexity of data-driven algorithms, it can be classified into machine learning (ML) methods based on statistics, feature extraction and deep learning (DL) methods based on artificial neural networks (ANN)[24]. In earlier data-driven research, ML methods are proposed to apply in HVAC faulty sensor detection. Li[25] proposed a principal component analysis (PCA) based residual feature extraction method for HVAC faults detection. Nunzio[26] used PCA to

achieve feature extraction in soft fault outliers of chiller sensors. Considering the influence of uncertain factors such as weather conditions and intrinsic loads, Wang[27] proposed a conditional-based adaptive PCA method to mitigate the negative impact of these uncertainties. Despite its popularity in HVAC sensor FDD, PCA-methods not handle nonlinear and non-gaussian distributed datasets effectively. Unfortunately, the data characteristics of HVAC sensors are nonlinear and non-Gaussian distributed[18][28]. Therefore, Zhang[29] proposed the independent component analysis k-nearest neighbour (ICKNN) method to detect sensor faults in HVAC. Considering the impact of multi-operating conditions in large-scale commercial HVAC systems, Wen[30] proposed a method based on Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to identify different operating conditions in HVAC systems. Presented method enables the identification and localization of sensor faults in the system. Luo[31] proposed a novel K-means method for fault diagnosis of chiller sensors.

As research on ML methods advances, numerous multiple-ML based methods are increasingly applied to FDD for HVAC sensors. These multi-ML methods combine with each other to meet the demand for precise FDD in increasingly complex HVAC systems. For instance, Guo[32] proposed a FDD method that combines a feature extraction approach based on component analysis with Gaussian Mixture Models. Li[33] proposed a fault detection method based on Extreme Learning Machine (ELM) combined with K-Nearest Neighbors (KNN) for chiller faults detection. Experimental results demonstrated that the efficiency of fault detection with KNN improved by approximately 10% through feature extraction using ELM. Gao[34] proposed an enhanced fault detection method based on KNN combined exponentially weighted moving average independent component analysis.

Constrained by the principles of ML methods, it is challenging to achieve feature extraction and clustering of fault data faced with complex learning tasks in HVAC systems[35]. However, DL algorithms with more complex network structures and more parameters, can effectively extract features from historical data and thus more accurately diagnose fault types[36]. In recent years, DL-based HVAC sensor FDD methods, such as autoencoder[35][37], generative adversarial network[36] and deep recurrent neural networks[38][39], have attracted considerable attention. Elnour[37] proposed an auto-associate neural network to detect sensor faults in air handling unit (AHU). Experimental results indicate that compared to traditional ML methods, the FDD efficiency of

autoencoder neural networks has improved by 15%. In subsequent research, Ren[35] proposed the thermodynamic-law-integrated autoencoder as a fault diagnosis method for HVAC sensors. In the case study, compared with a conventional DL method, the proposed method increased the fault detection rate by 27.2%. In order to address the imbalance between normal and fault sample data, Ruan[36] proposed an improved conditional variational autoencoder-generative adversarial network. By converting time-series signals into image signals and generating fault samples using generative adversarial networks, a balance is achieved between normal and fault sample data. Guo[39] achieved fault diagnosis in HVAC systems through a deep belief network. Experimental results demonstrated a fault diagnosis rate of 97.7% using this method, representing an improvement of 5.05% compared to the benchmark method.

In both ML and DL-based methods, abundant and high-quality historical data is necessary to construct FDD models[24][40][41]. However, obtaining such data is impractical in some buildings, particularly newly constructed ones[41]. Furthermore, obtaining substantial, high-quality data on comprehensive normal operation and faulty conditions is often unrealistic[42]. Therefore, improving the generalizability and transferability of data-driven HVAC sensor FDD methods across different HVAC systems is essential.

1.3 Literature of transfer learning-based FDD research for HVAC

Transfer learning (TL) is a method that acquires knowledge for a new learning task (known as the *target domain*) by leveraging historical learning tasks (known as the *source domain*) from relevant domains[43]. It can help address the challenge of achieving task objectives in the target domain with limited availability of rich training data (labels)[44]. Early TL methods primarily consisted of principles based on sample-based, feature-based and model-based approaches[45][46]. As the continuous advancement of DL, TL methods based on DL have received extensive research attention[47][48], which primarily consists of fine-tuning (FT) and domain-based neural network[49][50].

In the field of HVAC fault detection base on FT, Fan[51] proposed a new image-based FT framework to constructed a transfer task between various different units to validate the proposed method in HVAC FDD. The FT-based cross-domain fault diagnosis method[52] is provided to address the limitation of incomplete labelled data, which is evaluated using an experimental HVAC

system and its simulation. An automated FDD method based on TL is proposed for chiller fault detection in Ref [53]. The experiment analysed 31 types of faults, including equipment performance degradation, sensor malfunctions and unreasonable setpoints. Compared to the contrastive methods, the results demonstrated that the FT method based on convolutional neural networks (CNN) reduced the diagnosis time by half and significantly improved the accuracy of fault detection.

The advantage of FT-based TL methods lies in their simple network structure[54]. However, FT-based methods require a higher degree of similarity between the source domain data and the target domain data, which limits their ability to handle situations where the training data and distribution of the target data differ significantly. Therefore, domain-based neural networks have attracted the attention in field of HVAC fault detection[55]. Ke[43] presented a physical model integrated with wasserstein generative adversarial network model for AHU FDD in scenarios with insufficient training data samples. Du[55] proposed a novel domain adaptation deep learning model and teacher-student networks for HVAC fault diagnosis. For the cross-condition tests, the proposed method achieved high accuracies of 88% and 98%, respectively. Zhu[56] developed a domain adversarial neural network (DANN) to transfer the knowledge from a data-rich source chiller to build a diagnostic model for new target chiller.

1.4 Challenge and contributions

To sum up, the above literature review demonstrates that extensive TL methods have been developed for sensor or equipment FDD in HVAC systems. However, existing research still has its limitations, and the following issues deserve in-depth study.

(1) Previous literature has extensively investigated FDD of HVAC sensors or system faults based on TL methods under conditions of similar operating conditions and systems. However, it neglects the difficult of finding an HVAC system with similar operating conditions and systems in real-world applications. However, lower similarity could cause negative transfer phenomenon[57]. The low similarity between source domain and target domain data significantly limits the practical application of TL methods

(2) With the increasing number of HVAC sensors, the computational cost will experience exponential growth[58]. FDD in numerous sensors using pure data-driven methods is not feasible. Furthermore, not only TL models but also entirely data-driven methods constructed solely from

HVAC sensor data may result in insufficient model interpretability.

The main contributions of this research can be summarized as follow:

- ◆ This validation experiment conducted research on HVAC sensor FDD in a large public building, despite having insufficient historical training data. The historical operational data of HVAC sensors from a room was used as the source domain. The research explored the application of TL for HVAC sensor fault diagnosis across systems, operating conditions and scenarios.
- ◆ Considering the differences in data across systems, operating conditions and scenarios in the source and target domains, as well as the complexity of HVAC system conditions in real-world applications, an energy and mass balance constraint equation (EBCe) is constructed based on energy conservation and mass conservation within the HVAC system. EBCe enhances the interpretability of data-driven methods. Simultaneously, it reduces the data dissimilarity between the source and target domains across different systems, operating conditions and scenarios.
- ◆ It proposes the laplacian kernel (Lk)- domain-adaptive neural network (DaNN), which enhances the kernel function to improve the FDD performance of HVAC faulty sensors across different systems, operation and scenarios. Across various systems, operating conditions and scenarios, the LkDaNN demonstrates higher fault detection accuracy compared to contrastive methods.

1.5 Organization

The rest of this paper is organized as follows: Chapter 2 introduces the methodology of this research and includes three parts: the construction of the Energy and Mass Balance constraint equation, the structure of the LkDaNN method, and an overview of the research methods. Chapter 3 describes the equipment installation: Section 3.1 presents the subject of the study, Section 3.2 analyzes the control loops and related sensors, Section 3.3 describes the setup of fault sensor locations and Section 3.4 introduces the classification of operational conditions based on energy consumption. Chapter 4 provides analysis and discussion of the experimental results: Section 4.1 introduces the research methods and comparison methods, Section 4.2 evaluates the overall performance of the fault diagnosis model, Section 4.3 discusses the fault identification rate of the

EBCe-LkDaNN under different fault scenarios, Section 4.4 evaluates the fault diagnosis model in terms of the F1 score, Section 4.5 analyzes the impact of EBCe on LkDaNN in HVAC sensor FDD, Section 4.6 evaluates the fault diagnosis models from the perspective of domain adaptability and Section 4.7 discusses the limitations of the current research. Chapter 5 presents the conclusions.

2. Energy and mass balance constraint-integrated transfer learning method for HVAC sensor FDD

2.1 Structure of Energy and mass balance constraint equation (EBCe)

In fault diagnosis research based on TL methods, the cross-condition, system and operation significantly constrain the efficiency and applicability of transfer learning methods. As shown in Fig 1, EBCe is proposed to reduce the variability of HVAC sensor data caused by different scenarios and operating conditions. Unlike physical formulas that express the operating principles of the HVAC system, the purpose of constraint equations is to construct characteristic equations that capture shared relationships between HVAC systems using energy consumption parameters and sensor measurements. These constraint equations reflects the energy and mass conversion processes within HVAC systems. The transformation process correlates sensor measurements in HVAC systems, enabling fault detection without the need for redundant sensor installations. The e used in the construction of the constraint equation is a dimensionless number that principle lies in utilizing TL methods to analyze the numerical variations in fault and non-fault states for the purpose of fault diagnosis.

Eq. (1) exhibits the EBCe on the chiller side, which is derived from the energy conversion process between the evaporator and condenser of the chiller unit. T_{co} , T_{ci} and F_c represents respectively the outlet temperature, inlet temperature, and chilled water flow rate on the condenser side. T_{ei} , T_{eo} and F_e represents the inlet temperature, outlet temperature and evaporator water flow rate on the evaporator side. COP stands for coefficient of performance, which measures cooling efficiency, respectively.

$$e_1 = \left(\frac{(T_{co} - T_{ci}) \cdot F_c}{(T_{ei} - T_{eo}) \cdot F_e} \right) / COP \quad (1)$$

Eq. (2) describes the constraint relationship between variable frequency pump energy

consumption and physical quantities. $(P_{eo}-P_{ei})$ represents the pressure difference between the inlet and outlet of the pump, where P_{eo} is the pump outlet temperature and P_{ei} is the pump inlet temperature. E_t represents the power of the pump on the evaporator side. $(n_1/50)$ represents the ratio of the actual frequency n_1 to the rated frequency, where the pump's rated frequency is 50Hz. F_e represents the flow rate. The pump efficiency is composed of the pump efficiency η_j , transmission efficiency η_c , motor efficiency η_m and variable frequency drive efficiency η_{VFD} . The formula for calculating the total efficiency of the pump is $\eta = \eta_j\eta_c\eta_m\eta_{VFD}$. Among them, η_j is describes as $\eta_j = b_0 + b_1F_e + b_2F_e^2$, b_0, b_1, b_2 is system constant in η_j . Transmission efficiency is minimally affected by the operation of the pump and can be considered as a constant. The motor efficiency of the pump remains above 0.9 across the entire frequency range, therefore, it can be treated as a constant. The variable frequency drive efficiency can be expressed as: $\eta_{VFD} = d_0 + d_1(\frac{n}{50}) + d_2(\frac{n}{50})^2 + d_3(\frac{n}{50})^3$. It ignores the low-order terms that can be simplified as $\eta_j = b_2F_e^2$. Since $0 < \frac{n}{50} < 1$, η_{VFD} can be approximated as $\eta_{VFD} = d_0 + d_1(\frac{n}{50})$. In summary, the constraint equation Eq. (2) can be derived based on the power calculation formula for the variable frequency pump.

$$e_2 = \frac{(P_{eo} - P_{ei})}{E_t \cdot (\frac{d_0}{d_1} + \frac{n_1}{50}) \cdot F_e} \quad (2)$$

As shown in Eq. (3), the constraint equation e_3 is constructed based on the energy conversion relationship between the AHU and the user-side water system. During summer conditions, the cooling load borne by the AHU coil is calculated based on the enthalpy difference between the mixed return air and the supply air. The relative humidity of air within the HVAC system experiences minimal fluctuations in steady-state operation. Therefore, the constraint equation is performed based on temperature differentials in Eq. (3).

$$e_3 = \frac{(T_{es} - T_{er}) \cdot F_h}{(T_s - T_r) \cdot o_f \cdot V_s \cdot D_r + (T_s - T_f) \cdot o_r \cdot V_s \cdot D_f} \quad (3)$$

T_{es} and T_{er} represent the supply water temperature and return water temperature of the AHU coil, respectively. T_s , T_r and T_f represent respectively the supply air temperature, return air temperature, and outdoor air temperature in the AHU. O_f and O_r represents respectively the opening

degrees of the outdoor air damper and the return air damper. D_f and D_r represent respectively the cross-sectional areas of the outdoor air duct and the return air duct within the AHU.

The power of air system E_w is composed of the power of the air pump E_a and the exhaust fan E_e . In winter conditions, the exhaust valve is closed and the exhaust fan stops working (i.e. $E_e=0$). That means $E_w=E_a$. In summer conditions, as the energy consumption of the air pump significantly outweighs that of the exhaust fan, it can be approximated that the energy consumption of the fan is roughly equal to the energy consumption of the air pump (i.e. $E_w \approx E_a$). E_w is positively correlated with the supply air static pressure P_s , which can be defined as shown in Eq. (4).

$$e_4 = \frac{P_s}{E_w} \quad (4)$$

The supply air static pressure P_s is calculated as: $P_s = P_f - P_m$, P_f is the supply air total pressure, P_m is the dynamic pressure of air supply. Among them, $P_f = a_0 w^2 + a_1 w(VD_h) + a_2 (VD_h)^2$ and $P_m = \frac{1}{2} \rho V^2$. a_0 , a_1 and a_2 are all coefficients, where w represents the ratio of the actual fan speed to the rated speed, D_h represents the cross-sectional area of the duct, and V represents the supply air velocity. Thus, the supply air static pressure can be expressed as: $P_s = a_0 w^2 + a_1 w(VD_h) + a_2 (VD_h)^2 - \frac{1}{2} \rho V^2$. Considering that higher-order variables have the most significant impact on the equation, we construct the constraint equation as: $P_s \approx V^2 (a_2 D_h^2 - \frac{1}{2} \rho)$. Since sensor fault monitoring typically only considers steady-state conditions, we can omit the term $(a_2 D_h^2 - \frac{1}{2} \rho)$ when constructing the constraint equation. F_h represents the supply air flow rate. To sum up, Eq. (5) can be derived as follow:

$$e_5 = \frac{P_s}{(F_h / D_h)^2} \quad (5)$$

As shown in Eq. (6), e_6 constructs the constraint equation between the evaporator side water flow rate F_e and the evaporator side pump power E_t .

$$e_6 = \frac{F_e}{E_t} \quad (6)$$

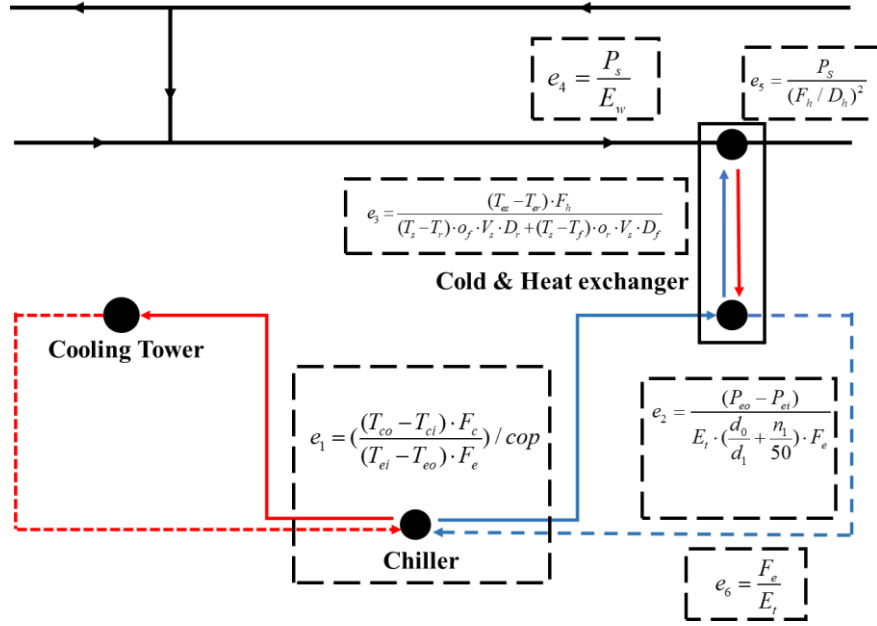


Fig 1. The schematic of energy and mass balance constraint equation in HVAC

The EBCe is based on the physical relationships of energy and mass within HVAC systems. In the process of fault diagnosis, corresponding expert rules are constructed based on the changes caused by deviations in fault data through multiple constraint equations. For instance, when a bias fault occurs at the evaporator outlet temperature, the measured value will be higher than the actual value. In this case, e_1 in the EBCe equation will increase, while the temperature difference between the supply and return water on the evaporator side will decrease. To maintain a constant cooling capacity, the water flow rate on the user side will increase, causing e_2 to rise. As the power also increases accordingly, e_6 will remain within the normal range, while e_2 will rise. However, when a fault occurs in the user-side water flow sensor, assuming its measured value is lower than the actual value, e_1 will also increase. However, e_6 will adjust the pump variable frequency drive speed, leading to an increase in E_t , which will cause e_6 to decrease. To sum up, by constructing relevant expert rules through the EBCe and combining the numerical changes among multiple constraint equations, fault diagnosis for control-related sensors within the HVAC system can be achieved. These e values will serve as inputs to the TL methods, with their corresponding labels as outputs.

2.2 Theoretical background of laplacian kernel domain-adaptive neural network (LkDaNN)

In cross-system, cross-condition and cross-operatin scenarios, significant differences exist in the data distribution characteristics and ranges between the source domain data and the target

domain data. In addition, during actual system operations, the operating efficiency of the equipment may not necessarily remain constant. Traditional domain adaptation neural networks may be negatively affected by this. Therefore, improving the domain generalization performance of transfer learning methods is a crucial prerequisite for their practical application. Based on the excellent domain generalization performance of domain-adaptive neural network (DaNN) [55], this paper proposes the laplacian kernel (Lk)-DaNN model for HVAC sensor fault detection. The structure of the proposed LkDaNN is illustrated in Fig 2. LkDaNN consists of a feature extractor, kernel mapping, classification layer, cross-entropy loss and maximum mean discrepancy (MMD) loss. LkDaNN belongs to the feature-based TL model, which aims to minimize the distribution difference between the source and target domains, thereby achieving feature alignment between the two domains. Subsequently, the performance of FDD model is enhanced in the target domain by leveraging the known information from the source domain data.

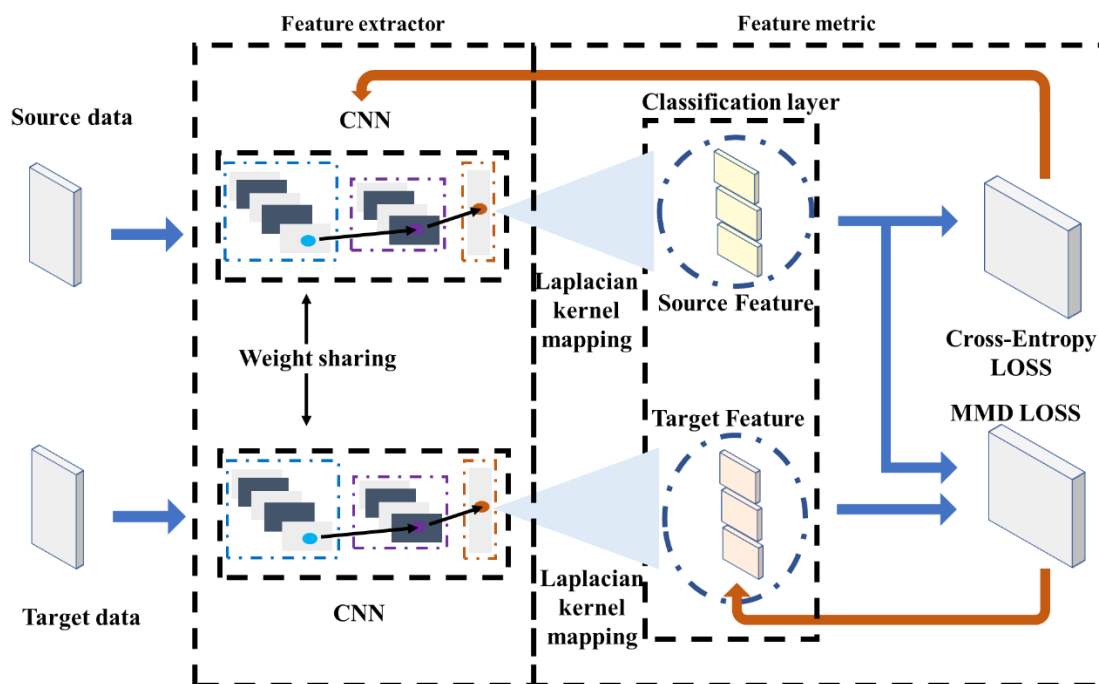


Fig 2. The structure diagram of LkDaNN

Due to its strong feature learning capabilities, convolutional neural network (CNN) is widely used as a feature extractor in TL[59]. As shown in Eq. (7)-(9), CNN will be used as the feature extractor for the transfer learning neural network. As shown in Fig 3, the basic structure of CNN

consists of the input layer, the hidden layer and the output layer[60]. Among them, the hidden layer includes three parts: the convolutional layer (CL), pooling layer and full connected layer (FCL)[61]. Firstly, the purpose of the CL is to learn features from the input samples and then feed them into the pooling layer. Then, to enhance computational efficiency, the pooling layer can reduce the spatial size of the data while retaining essential feature information. Finally, after multiple rounds of convolution and pooling operations, the feature information of the data will be inputted into fully connected layers to complete feature extraction[62].

Eq. (7) illustrates the process of signal x being fed into the CL for convolutional operations:

$$Y_j^l = \sum_{i \in M_j} x_i^{l-1} * K_{ij}^l + b_j^l \quad (7)$$

Where Y_j^l is the j th feature mapping in layer l . M is the CL. K is the convolution kernel weight, and b is the bias.

The pooling process in the max-pooling layer is illustrated after the convolutional layer. S is the pooling area, taken as 2×2 [24]. That is illustrated as Eq. (8):

$$Y_{pool} = \max_s \{Y_j^l\} \quad (8)$$

Assume fcl_j^{l+1} is the activation value of the j -th neuron at the $(l+1)$ -th layer, W is the weight parameter between neurons i and j . The fully connected layer integrates the feature data through Eq. (9):

$$fcl_j^{l+1} = \sum_{i=1}^n W_{ij}^l Y_i^l + b_j^l \quad (9)$$

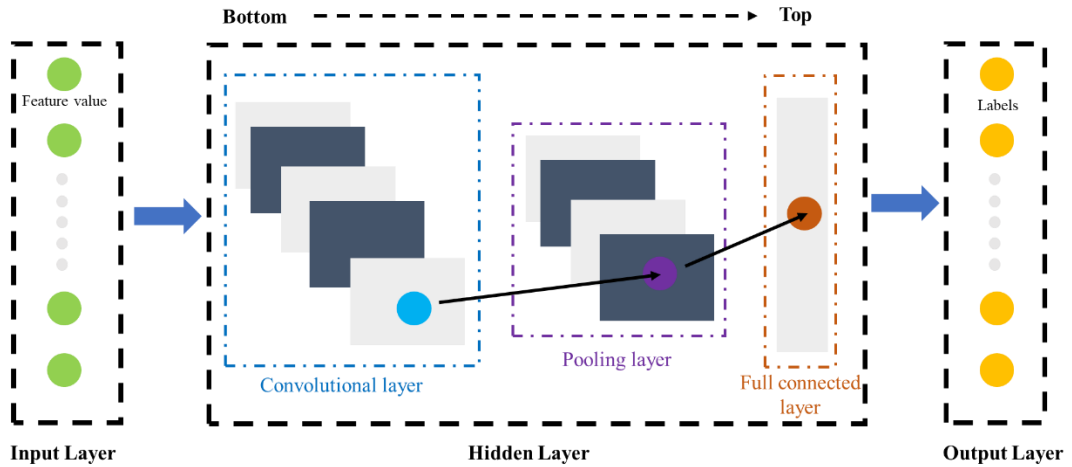


Fig 3. Schematic of CNN

The distribution characteristics and ranges of the source domain and target domain are different.

It is necessary to map the data to the same renewable kernel Hilbert feature space H_k , so that the feature distributions of the source domain data and target domain data are close [63]. Considering the differences between the source domain and target domain, we adopt the MMD to measure the distance between different correlated distributions, as shown in Eq. (10):

$$d_k^2(p, q) = \left\| E_{x \sim p}[\varphi(x)] - E_{x \sim q}[\varphi(x)] \right\|_{H_k}^2 \quad (10)$$

where, $d_k(p, q)$ represents the MMD between the source domain and target domain, $d_k^2(p, q)$ can be equivalently interpreted as the distribution distance of the average embeddings on H_k between two probability distributions. The mapping function $\varphi(\cdot)$ defines the mapping of original data from the original space to H_k . The kernel function $k(x_s, x_t)$ is defined as the inner product of the mapping, i.e., $k(x_s, x_t) = \langle \varphi(x_s), \varphi(x_t) \rangle$. If the feature distributions of the source domain data x_s and the target domain data x_t are the same, then $d_k(p, q) = 0$. In contrast, the feature distributions between the source domain and the target domain are different, then $d_k(p, q) \neq 0$.

Considering the significant differences in feature distributions between the source domain data and the target domain data across systems, operating conditions, and scenarios. Therefore, it is expected that the kernel function $k(x_s, x_t)$ should exhibit higher sensitivity to long-distance MMD. Traditional kernel functions exhibit slow decay rates, leading to lower sensitivity to long-distance MMD. However, the Laplacian kernel (Lk) has a faster decay rate, making it more efficient than other kernel functions, especially in capturing local features of the data in over long distances MMD. Therefore, as shown in Eq. (11), it adopts the Lk function for the aforementioned application. σ represents the width of the kernel function.

$$k(x_s, x_t) = e^{-\frac{\|x_s - x_t\|}{\sigma}} \quad (11)$$

During the backpropagation coordination process of LkDaNN, the optimal objective function L of the neural network is represented through the reconstruction loss L_C of the source domain data features and the Maximum Mean Discrepancy loss L_{MMD} , indicating the error in feature distribution between the source domain and the target domain [64]. This is constructed as shown in Eq. (12):

$$L = L_C + L_{MMD} \quad (12)$$

L_C and L_{MMD} is represented by Eq. (13) and Eq. (14), respectively:

$$L_C = \min \left[\frac{1}{n_s} \sum J(\theta(x_i^s), y_i^s) \right] \quad (13)$$

$$L_{MMD} = \sum_{i=l_1}^{l_2} d_k^2(D_s^l, D_t^l) \quad (14)$$

where, $J(\cdot; \cdot)$ is the cross-entropy loss, and $\theta(x_i^s)$ represents the probability of assigning the source sample x_i^s to the y_i^s class. D_s^l and D_t^l represent the l -th layer feature representations of the source domain and target domain samples, respectively. As shown in the feature metric content of Fig. 2, the fusion of source domain and target domain features is achieved through Eq. (10)-(14).

The hyperparameters of LkDaNN are listed in Table 1. It can be seen that the table includes three ‘‘Conv’’ blocks and two FC layers. Every ‘‘Conv’’ block is composed of the Convolution layer, batch normalization (BN) and max-pooling layer. To fuse local features into global features before transmitting the features from the CL layer to FC layer, it is necessary to flatten the high-dimensional feature map into low-dimensional vectors for weighted summation in the FC layer.

Table 1

Model parameters of LkDaNN

Type of layer	Structure	In channels/Out channels/Stride/Kernel	Input size	Output size
Inputs	-	-	-	[32×1×6]
Conv-1	CL1	1/32/1/2	[32×1×6]	[32×32×7]
	BN1	-	[32×32×7]	[32×32×7]
	Max-pooling1	-/-/2/2	[32×32×7]	[32×32×3]
Conv-2	CL2	32/64/1/2	[32×32×3]	[32×64×4]
	BN2	-	[32×64×4]	[32×64×4]
	Max-pooling2	-/-/2/2	[32×64×4]	[32×64×2]
FC-1	128×64	-	[32×128]	[32×64]
FC-2	64×32	-	[32×64]	[32×32]
FC-3	32×8	-	[32×32]	[32×8]
Classification	8×5	-	[32×8]	[32×5]

2.3 Overall methodology

Fig 4 shows the diagnostic process of the HVAC fault model proposed in this study, validating the effectiveness of the LkDaNN model based on CEBE. Firstly, it is necessary to collect operational data from both source domain and target domain. Considering that HVAC systems may not accurately reflect their operational states through sensor data under transient conditions[29].

Moving window statistical method is used in the data pre-processing to filter out transient data from both source domain and target domain. Then, as shown in Fig 4 (Light green section), sensor data and energy consumption data from HVAC system are used to construct constraint equations. Considering the difficulties in unifying the data characteristics of HVAC systems in different systems, scenarios, and operating conditions, the distinctions in these data characteristics are primarily reflected in the distribution ranges, waveforms, and periodic variations of sensor signals. Therefore, this study constrains the data discrepancies between different systems by constructing EBCe. The principle of EBCe is based on the similarity in the laws governing the flow of energy and mass within HVAC systems, which adhere to the relevant thermodynamic laws[35]. These constraint equations are used as units for data normalization, which ensures all the data is normalized using the same set of constraint equations.

Although EBCe constrains the differences between the source and target domains, feature transfer still needs to be achieved through TL methods. As shown in Fig 4 (light blue section), it proposes the LkDaNN as a fault diagnosis model. The constraint equation data is incorporated into LkDaNN for training. During the training process, weight sharing mechanism of LkDaNN enables the transfer learning of source domain features to target domain features. Finally, learning strategies are evaluated for different operating conditions and sensor faults based on the target domain test data. The evaluation assesses the performance and effectiveness of proposed model under various scenarios and fault conditions.

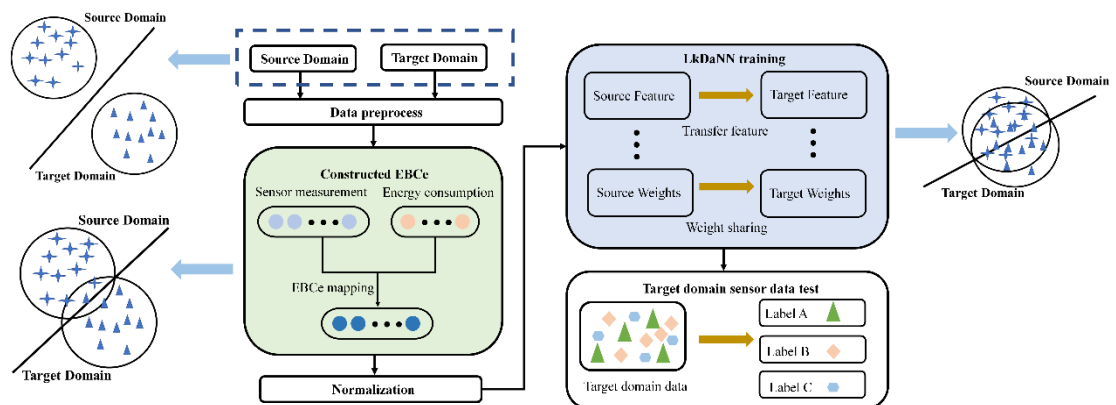


Fig 4. The flowchart of CEBe based LkDaNN for HVAC sensor FDD

3. Experiment installation

3.1 Descriptions of research object

Fig 5 illustrates the basic HVAC information of the source domain and target domain. The source domain system is the experimental platform of the Dalian University of Technology's Institute of Building Energy, and the target domain system is a public music hall in Dalian City. Therefore, the experimental purpose is to conduct HVAC sensor FDD research targeting large-scale public buildings across system, condition and operation using laboratory equipment. Table 2 introduces the application scenario, system equipment and equipment parameters of the source domain and target domain. The main energy-consuming equipment of HVAC consists of chiller unit and AHU. In the source domain, the rated cooling input power of chiller is 4.8kW and cooling capacity of that is 19kW. Meanwhile, the cooling capacity of AHU is 30kW and that power is 1.1kW. In the target domain, one chiller unit has a rated cooling input power of 104.4kW and cooling capacity of 626.4kW. And one AHU has a cooling capacity of 137kW and a power of 15kW. As shown in Table 2, target domain respectively has 2 chillers and 2 AHUs. During the actual operation in the target domain, it includes 2 identical AHUs running simultaneously. One AHU serves the stage area inside the music hall, while the other serves the seating area inside the music hall. This study simulated a fault using only one of the AHUs as the experimental subject.

Table 2.

The introduction of HVAC equipment in the source domain and target domain

	Source domain	Target domain
Application scenario	Indoor area: 75.2m ² , Height: 4 m	Indoor area: 1184 m ² , Height: 20 m
System equipment	1 unit of chiller, COP: 4.20,	2 unit of chiller, COP: 2.77
	2 Variable frequency chilled water pumps	3 Variable frequency chilled water pumps
	2 Variable frequency cooling water pumps	3 Variable frequency cooling water pumps
	1 Water distributor and collector	1 Water distributor and collector
	1 AHU	2 AHUs
	1 Cooling tower	1 Cooling tower.
Equipment	Chiller	Chiller

parameters	Rated cooling input power 4.8 kW Cooling capacity 19 kW Chilled water pump Rated power: 0.37 Kw Rated frequency: 50 Hz Chilled water pipe diameter: 40 mm Cooling water pump Rated power: 0.55 kW Rated frequency: 50 Hz Pipe diameter: 40 mm AHU Air supply volume: 5000m ³ /h Cooling capacity: 30kW Power: 1.1kW Duct cross-sectional area: 0.65m×0.32m	Rated cooling input power 104.4 kW Cooling capacity 626.4 kW Chilled water pump Rated power: 15 Kw Rated frequency: 50 Hz Chilled water pipe diameter: 250 mm Cooling water pump Rated power: 15 kW Rated frequency: 50 Hz Pipe diameter: 250 mm AHU Air supply volume: 25000m ³ /h Cooling capacity: 137kW Power: 15kW Duct cross-sectional area: 1.20×0.80m
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NOTE: In both the source and target domains, there is one standby circulating water pump

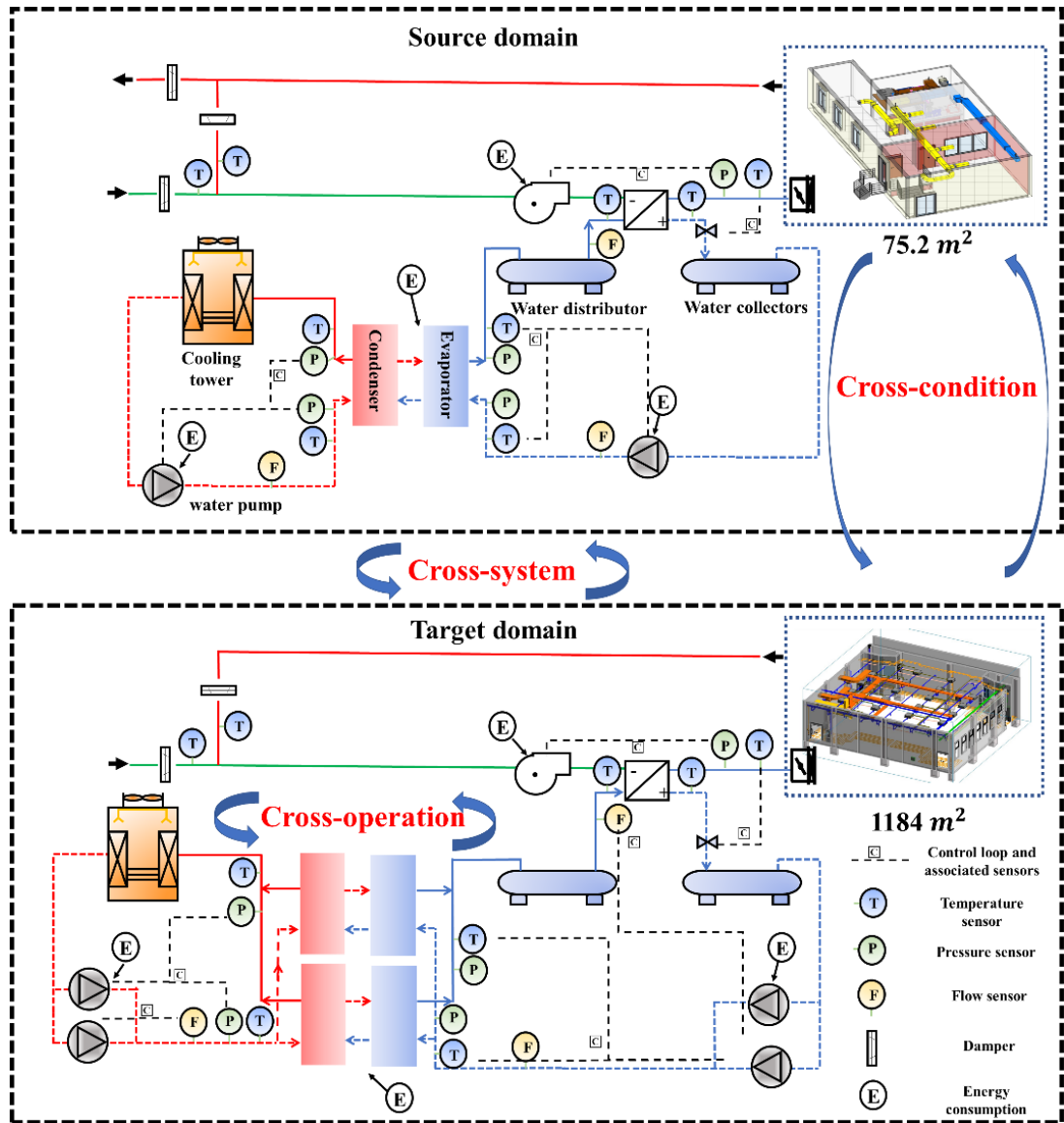


Fig 5. Research object introduction: source domain and target domain

3.2 The control loop and relevant sensors

PID controller, based on sensor measurements, adjusts the operating parameters of the HVAC system to the desired values by controlling actuators through the control loop[6]. One of the primary purposes of HVAC is to ensure thermal comfort in indoor environments. Dynamic adjustment of supply air temperature and airflow is an important means to ensure indoor thermal comfort. Fig 5 illustrates the main control loops for ensuring indoor thermal comfort in both the source domain and the target domain, respectively. The control loops in the source domain and target domain are not entirely identical. Sensors directly involved in the control loop are designated as control sensors, while sensors indirectly involved or not involved in the control loop are designated as monitoring

sensors[65]. Faults in control sensors have a greater negative impact on the HVAC control system. Therefore, it receives higher attention in FDD compared to measurement sensors. The control sensor of source domain and target domain is shown in Table 3, respectively. In comparison to the source domain, the evaporator and condenser flow sensors in the target domain are also considered control sensors. This is because the HVAC in the target domain has a higher cooling load demand. Therefore, the flow sensors of the evaporator and condenser need to calculate the frequency and number of operating pumps based on the deviation between the measured values and set values. Table 4 introduces the specific parameters of sensors at various locations in both the source domain and target domain. Due to different measuring objects in HVAC sensors, their measuring range, precision, and principle also vary. As a result, sensitivity to faults varies from sensor to sensor, leading to widely varying efficiency when using the same FDD method to diagnose different fault sensors [6].

Table 3

Control sensors in the source domain and target domain

Sensor Name	Source domain	Target domain
Static pressure of supply air	✓	✓
Temperature of supply air	✓	✓
Temperature of fresh air	×	×
Temperature of return air	×	×
Temperature of heat exchanger inlet water	×	×
Temperature of heat exchanger outlet water	×	×
Flow of heat exchanger water	×	✓
Temperature of condenser inlet	×	×
Temperature of condenser outlet	×	×
Flow of condenser water	×	✓
Temperature of evaporator inlet	✓	✓
Temperature of evaporator outlet	✓	✓
Flow of evaporator water	×	×
Pressure of condenser inlet	✓	✓

Pressure of condenser outlet	✓	✓
Pressure of evaporator inlet	×	×
Pressure of evaporator outlet	×	×

Note: ✓ represents control-based sensors, × represents monitor-based sensors

Table 4

The basic parameters of various sensors in source domain and target domain

Description	Unit	Range	Precision	principle
Temperature of supply air	°C	-20-50	±0.1°C	Resistive
Temperature of return air	°C	0-50	±0.1°C	
Temperature of fresh air	°C	0-50	±0.1°C	
Temperature of evaporator inlet	°C	-30-130	±0.1°C	
Temperature of evaporator outlet	°C	-30-130	±0.1°C	
Temperature of condenser inlet	°C	-30-130	±0.1°C	
Temperature of condenser outlet	°C	-30-130	±0.1°C	
Temperature of heat exchanger inlet	°C	-30-130	±0.1°C	
Temperature of heat exchanger outlet	°C	-30-130	±0.1°C	Ultrasound
Flow rate of evaporator water	m ³ /h	0-10	±1.0%	
Flow rate of heat exchanger water	m ³ /h	0-10	±1.0%	
Flow rate of condenser water	m ³ /h	0-10	±1.0%	Capacitance
Static pressure of supply air	Pa	0-250	±0.075%	
Static pressure of evaporator inlet	Bar	0-9	±0.05%	
Static pressure of evaporator outlet	Bar	0-9	±0.05%	
Static pressure of condenser inlet	Bar	0-9	±0.05%	
Static pressure of condenser outlet	Bar	0-9	±0.05%	

3.3 Setting of Faulty sensor points

Table 5 shows the fault points and severity of HVAC sensor in both source domain and target domain. Experiment discussed four faulty sensors within the HVAC: evaporator inlet temperature sensor, heat exchanger water flow sensor, supply air temperature sensor, and supply air static pressure sensor. The purpose to select the above sensors is that all of them are control sensors. If these sensor fault, it is possibility have a negative impact on the HVAC system control loop. Among them, the heat exchanger water flow sensor is a control sensor in the target domain, while it is a

measurement sensor in the source domain. Meanwhile, the monitored physical quantities of above sensors could cover all the physical quantities related to indoor thermal comfort control loops within the HVAC. In the research of HVAC faulty sensor detection, the utilization of a sensor reading bias generator to introduce various sensor biases into the sensor measurements has been widely employed in the study of HVAC sensor faults [67]. In experiment, the temperature, humidity, differential pressure, and flow rate sensors are connected to the controller through the expansion module. Then the expansion module is connected to the upper computer operation platform through the RS-485[68]. Sensor faults are added to the corresponding sensor data via the upper computer operating platform to simulate sensor faults. The historical measurements are transmitted to the collector. Hence, during the experiment, the experimenter can gain a clear understanding of the health status of each data group and assign fault labels to different types of faults. In this research, the fault detection process is conducted offline. To simulate sensor faults more accurately, the fault settings in the research referenced relevant findings in Ref [69]. The specific sensor fault statuses in both the source domain and target domain are shown in Table 5.

During the data collection process, the operating conditions of the source domain system were set to summer conditions, with data collected from May 25, 2023 to June 1, 2023, at an interval of 5 min. The operating conditions of the target domain system were also set to summer conditions, with data collected from June 11, 2023 to June 28, 2023, at an interval of 5 min. After sorting the obtained experiment data, the moving window statistical method is used to filter the transient data[66]. To ensure the randomness of the experiment under two operating conditions, both the testing and training datasets are randomly sampled from the original dataset. The number of samples taken is shown in Table 6 and Table 7. Both the training datasets in the source domain and target domain have been labeled. All models are trained and tested on the same datasets[70].

Table 5

Sensor fault severity under the source domain and target domain

NO.	Measured points	Fault severity level
S1	Temperature of evaporator inlet	0.80-2.10
S2	Flow of heat exchanger water	0.70
S3	Temperature of supply air	1.00-1.40
S4	Static pressure of supply air	5.20-11.70
T1	Temperature of evaporator inlet	1.30-1.40-

T2	Flow of heat exchanger water	5.00-5.10
T3	Temperature of supply air	1.70-1.80
T4	Static pressure of supply air	25.10-27.60
D1	Temperature of evaporator inlet	1.20-1.50
D2	Flow of heat exchanger water	14.80-15.10
D3	Temperature of supply air	1.60-1.78
D4	Static pressure of supply air	25.10-27.30

Note: “S” represents the source domain, “T” represents the target domain under single-chiller operation, “D” represents the target domain under dual-chiller operation

Table 6

The training and testing dataset in single-chiller operation

Fault points	Training dataset in source domain	Training dataset in target domain	Testing dataset in target domain
Normal	637	80	456
Temperature of evaporator inlet	634	80	500
Flow of heat exchanger water	635	80	300
Temperature of supply air	635	80	500
Static pressure of supply air	634	80	700

Table 7

The training and testing dataset in dual-chiller operation

Fault points	Training dataset in source domain	Training dataset in target domain	Testing dataset in target domain
Normal	637	80	456
Temperature of evaporator inlet	634	80	1000
Flow of heat exchanger water	635	80	400
Temperature of supply air	635	80	500
Static pressure of supply	634	80	732

3.4 The energy consumption-based operation condition division

The HVAC will adaptively adjust the cooling capacity and the number of operating chillers based on indoor conditions to precisely match the indoor cooling demand. Ref [71] analyzed the energy consumption proportions of different equipment in the same HVAC system under various operating conditions. The conclusion indicates that under different conditions, the energy consumption of the chiller unit accounts for 87.94% to 92.78% of the total energy consumption. Therefore, it is feasible to use chiller energy consumption as the criterion for distinguishing HVAC operating conditions. Among them, the number of chiller units operating is the most prominent distinguishing feature for chiller energy consumption. To sum up, it uses the number of operating chiller units in the HVAC system as the criterion for dividing operating conditions. Fig 6 explains the process of TL-based method for faulty sensors diagnosis under cross-operation conditions. The feasibility of FDD used CBCe-LkDaNN is discussed under cross-operating condition and non-cross-operating conditions.

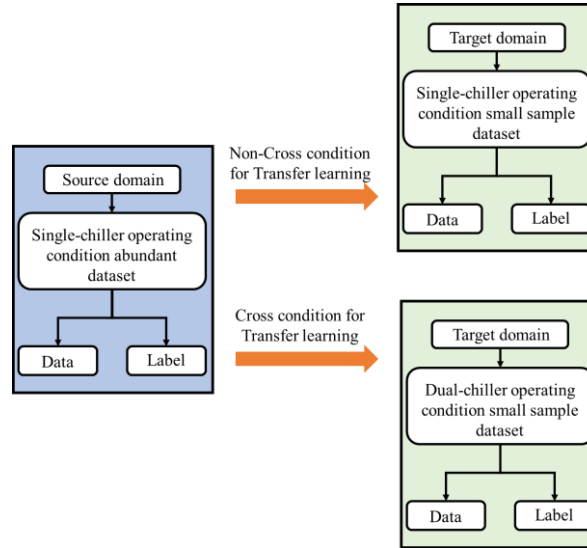


Fig 6. Illustration of the cross-operation FDD process

4. Result analysis and discussion

The evaluation criteria for fault diagnosis are typically assessed from two perspectives: diagnostic rate and false alarm rate. Additionally, the F1 score is an important metric for evaluating data-driven models. Furthermore, the feature fusion efficiency of TL methods serves as the

theoretical basis for validating the efficiency of transfer learning in fault diagnosis. And it will also discuss the limitations of the current research. Lastly, this section will analyze and discuss the results based on the aforementioned metrics.

4.1 Comparison methods

To analyse the FDD performance of the combined EBCe-based LkDaNN for faulty sensor in HVAC systems under different operating conditions, three different FDD methods are compared. Due to previous research[55][72] demonstrates that TL-based FDD models have higher FDD efficiency in cases where the data from the target domain are insufficient. Therefore, it only considers the TL-based FDD model as comparison methods. Then, although the fine tune (FT)-based model structure is simpler. Numerous researches on TL-based FDD have indicated that fine tune (FT)-based FDD model is suitable in cases where the similarity between the source domain and target domain is low[73][74][75]. To sum up, this research adopts the following methods for comparison: DANN[76], DaNN[55] and radial basis function (RBF)-DaNN.

4.2 Overall evaluation of FDD performance

Fig 7 compares the performance of fault detection rate and fault alarm rate from the proposed method and different TL-based methods combined with EBCe. Overall, it can be found that the performance of different methods is significantly different. Especially, the fault diagnosis efficiency of target data under cross-operating (Dual-compressor operation condition) is slightly lower than that of the target domain data under non-cross-operating conditions (Single-compressor operation condition). For instance, compared to non-cross-operating conditions, the fault diagnosis rate of LkDaNN decreased by 2.08%, while the fault alarm rate increased by 3.07%. Experimental results demonstrate that EBCe-LkDaNN exhibits stronger stability in the scenario of HVAC sensor fault diagnosis under cross-operating conditions.

Overall, it demonstrates that the TL methods based on DaNN outperform the TL method based on DANN in the experiment. This is because TL methods based on DANN typically introduce adversarial loss between the source domain and target domain data, which may lead to training instability or convergence difficulties when the low similarity between the source domain and target domain data[77]. Under the comparison of TL methods based on the DaNN, due to the faster decay

rate of LK, it is more sensitive to capturing data features when there is a large difference between the source domain and target domain data, compared to the linear kernel (DaNN) and Gaussian kernel (RBF-DaNN) of DaNN. Similarly, experimental results that EBCe-LkDaNN exhibits higher fault detection efficiency compared to other DaNN-based methods in different scenarios. In the experimental analysis of fault alarm rate indicators, LkDaNN has the lowest fault alarm rate. However, due to the negative impact of cross-operation, that fault alarm rate is higher than that in the non-cross-operation scenario.

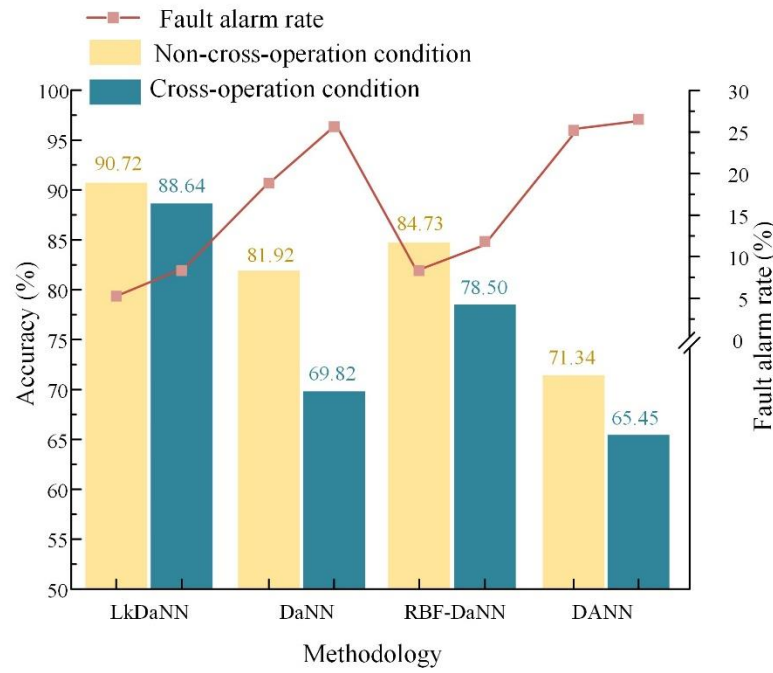


Fig. 7 The overall diagnosis performance of TL-based methods combined with EBCe

4.3 FDD results analysis combined with EBCe

The experimental analysis focused on the FDD research of four different control sensors in HVAC systems under limited data conditions based on TL. Section 4.3.1 analyses the non-cross-operating scenario across systems, while Section 4.3.2 analyses the cross-operating and cross-system scenarios. The four control sensors encompass the main measured physical quantities of HVAC systems: evaporator inlet temperature sensor (Ts1), condenser flow sensor (Ts2), supply air temperature sensor (Ts3), and supply air static pressure sensor (Ts4).

4.3.1 FDD results analysis of non-cross operation scenario

Fig 8 shows the FDD results of non-fault and four fault scenarios in non-cross operation by the

proposed method and compared methods. In non-fault scenarios, LkDaNN achieves the highest fault diagnosis rate compared to the comparison methods, reaching 94.74%, which can effectively reduce the personnel maintenance costs caused by fault alarms.

In the scenario of the evaporator inlet temperature sensor (Ts1), the FDD accuracy based on DaNN is higher than that based on DANN. Specifically, the fault diagnosis rate of LkDaNN and DaNN is 83.40%. Previous studies[29] have shown that the evaporator inlet temperature sensor is subject to strong noise. Noise will harm distinguishing fault characteristics. Therefore, the fault diagnosis rate of the evaporator inlet temperature sensor has not reached the expected level of over 90%. Similarly, due to the interference from uncertain factors such as the outdoor environment[71], the fault diagnosis rate of the supply air temperature sensor (Ts3) in both the proposed and comparison methods is also below 90%. However, the fault diagnosis rate of LkDaNN is still overall higher than that of the comparison methods in the sensor of evaporator inlet and supply air temperature. In the sensor fault scenarios of flow rate of heat exchanger (Ts2) and static pressure of supply air (Ts4), LkDaNN consistently exhibits great fault detection efficiency, which is 92.00% and 96.43%, respectively.

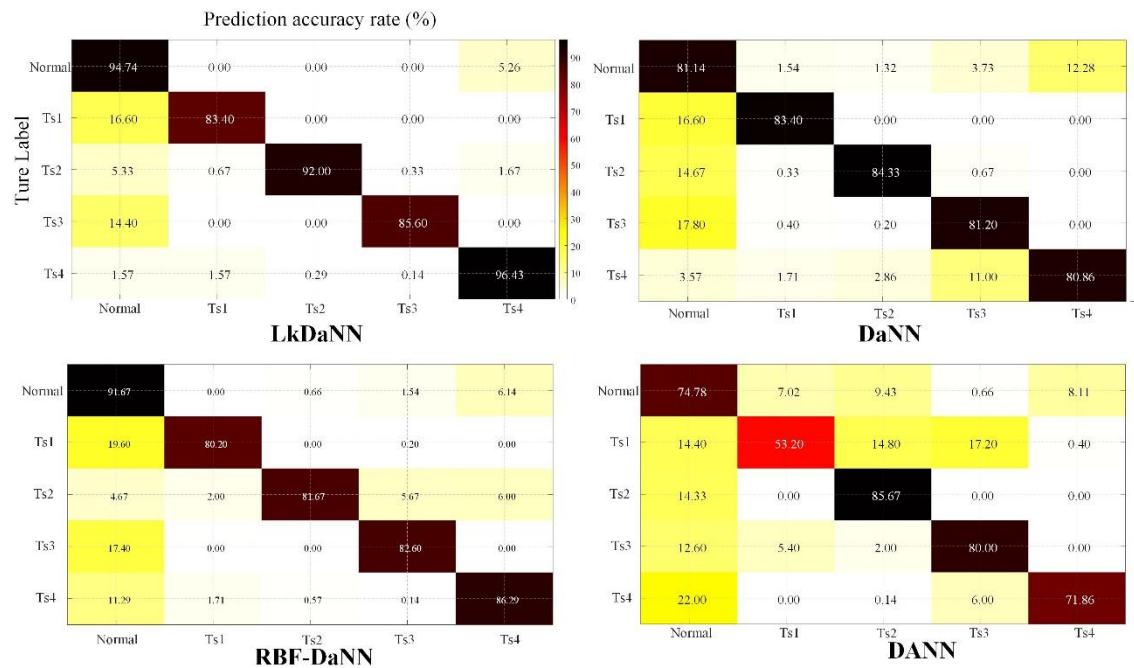


Fig. 8 The confusion matrix of FDD methods under non-cross-operation (single chiller operation)

4.3.2 FDD results analysis of cross-operation scenario

Fig 9 shows the FDD results of non-fault and four fault scenarios in cross-operation by the proposed method and compared methods. Considering the challenges that cross-operating conditions pose to the TL-based method, the accuracy of LkDaNN in non-fault states is 91.67%, which is a decrease of 3.07%. In the scenario of the evaporator inlet temperature sensor fault, LkDaNN achieves an accuracy of 96.80% under cross-operation conditions, which is better than fault diagnosis results in non-cross operation. As shown in Fig 10, the range of the evaporator inlet temperature based on EBCe in the target domain under different operating conditions is influenced by the fluctuation sensor data. The fluctuation range of the sensor data under single-chiller conditions is greater than that under dual-chillers conditions. Therefore, the fault diagnosis efficiency of Ts1 under cross-operating is higher than that under non-cross-operation conditions. Due to the high uncertainty of the measured data of air-side sensors and the negative impact of cross-operating conditions, the diagnostic efficiency in Ts3 and Ts4 scenarios is only 77.00% and 77.46%, respectively.

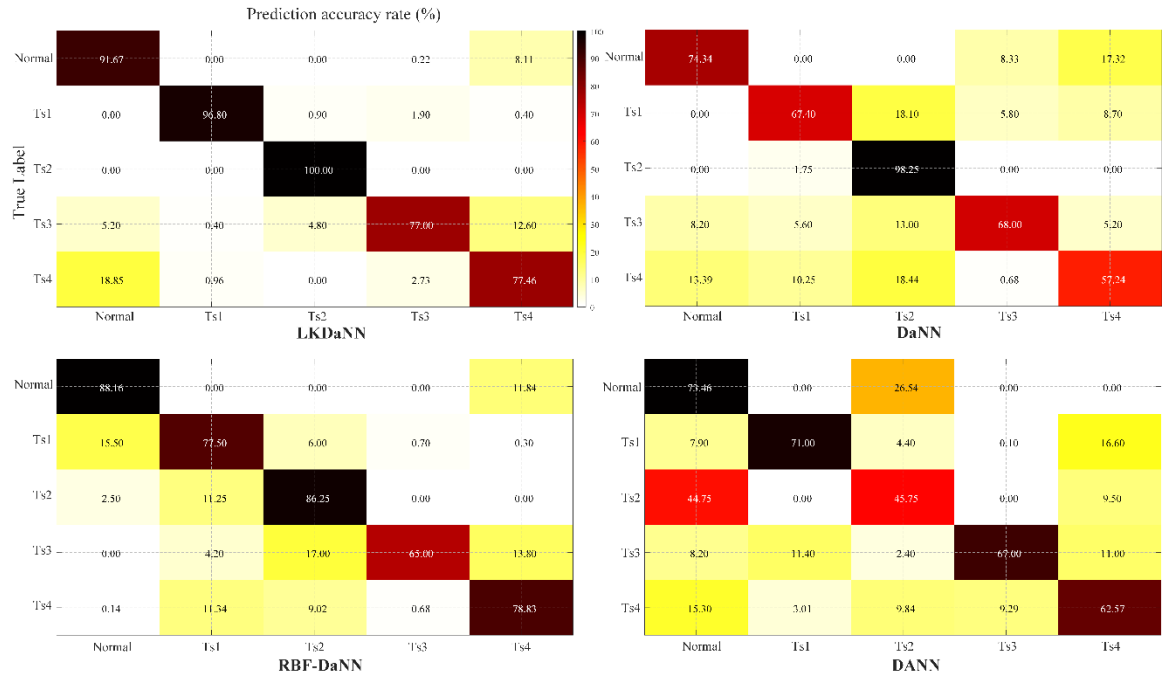


Fig. 9 The confusion matrix of FDD methods under dual-chiller operation

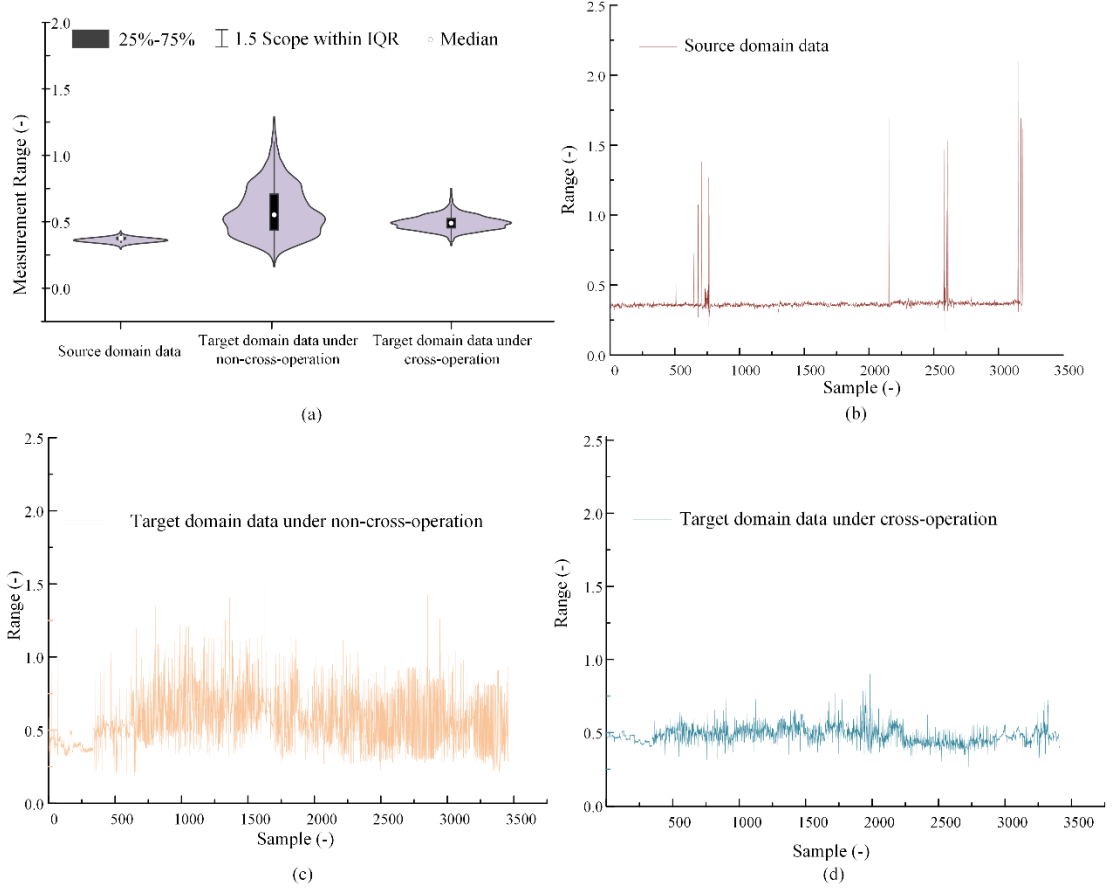


Fig. 10 Taking the evaporator inlet temperature sensor as an example: (a) The violin plot of data distribution; (b) The signal of source domain data; (c) The signal of target domain data under non-cross-operation; (d) The signal of target domain data under cross-operation

4.4 F1 performance evaluation metrics

To better evaluate fault detectability by methods, several evaluation metrics, including precision, recall rate and F1 score, are considered, respectively [34]. Precision denotes the rate at which an HVAC sensor fault is detected under normal operating conditions. This measures the stability of the proposed method. The recall rate denotes the number of actual detections or isolations identified through the methods divided by the number of actual fault samples. The F1 score is defined as the harmonic mean of precision and recall[78]. Among them, True positive (TP) and true negative (TN) are respectively defined as normal and faulty samples correctly classified in the confusion matrix. And, false positives (FP) and false negatives (FN) denote incorrect classification. The definitions are presented in Eqs. (15)-(17)[29].

$$precision = \frac{TP}{TP + FP} \quad (15)$$

$$recall = \frac{TP}{TP + FN} \quad (16)$$

$$F1 = \frac{2 \cdot precision \cdot recall}{precision + recall} \quad (17)$$

Due to the lack of practical significance of F1 scores performance when it is low. F1 scores lower than or equal to 0.65 are set to the origin for a more intuitive representation of the F1 parameter performance of different methods in Fig 11. As shown in Fig 11, LkDaNN outperforms the comparison methods in terms of F1 performance in both cross-operating and non-cross-operating scenarios. Through F1 scores performance, it can be proven that DANN is not suitable for applications across systems, scenarios, and operating conditions.

Compared to DaNN and RBF-DaNN, LkDaNN exhibits superior F1 scores. The possible reason could be that during the training process of the TL, the laplacian kernel possesses a faster decay rate, which makes it more sensitive when there are significant differences in features between the source domain and the target domain.

Unfortunately, LkDaNN is not perfect. Overall, the evaluation score of LkDaNN is relatively low in the analysis of the recall. This indicates that LkDaNN has a higher probability of diagnosing fault data as non-fault conclusions when diagnosing faults in the fault interval, leading to a higher misdiagnosis rate. The reasons may include two points: (1) The classifier of LkDaNN still needs optimization. (2) The noise and uncertainty of sensor data hurt the fault diagnosis efficiency.

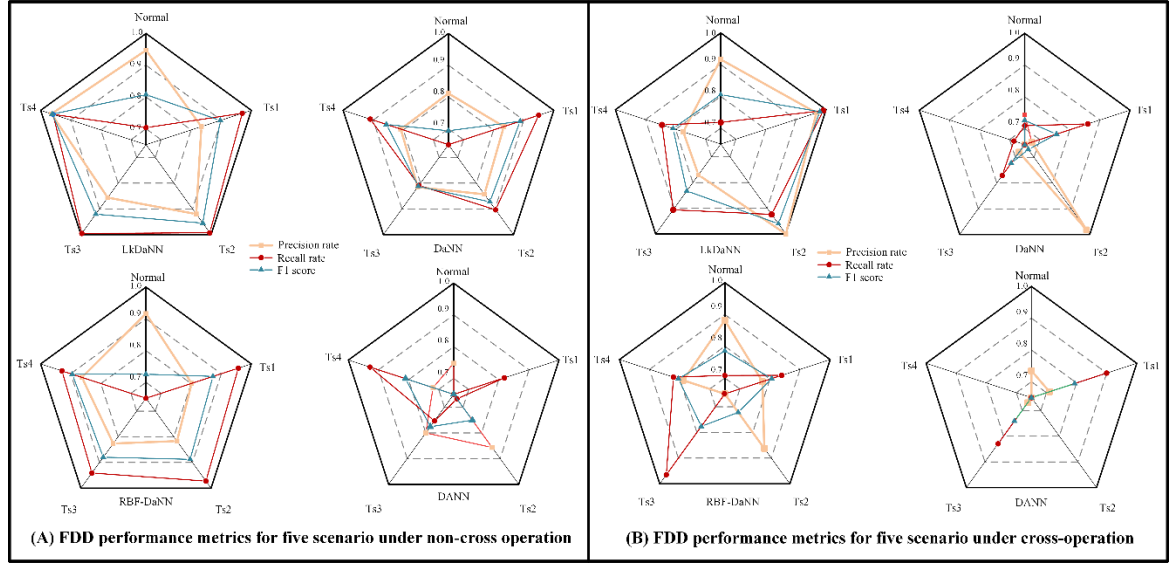


Fig. 11 FDD performance metrics of five scenarios in F1 scores

Table 8

The F1 performance of average score and statistics

	LkDaNN		DaNN		RBF-DaNN		DANN	
	Statistics	Average	Statistics	Average	Statistics	Average	Statistics	Average
Non-cross operation	0.0622	0.9082	0.0785	0.8245	0.0712	0.8521	0.0883	0.7170
Cross-operation	0.0855	0.8771	0.0524	0.6995	0.0341	0.7787	0.1419	0.6329

As shown in Table 8, it demonstrates that LkDaNN combined with EBCe outperforms the other considered methods in different scenarios and tasks. In conjunction with the average and statistic (standard deviation) of F1, it discusses the differences in FDD performance of the evaluation methods. If the average of F1 is low, it proves that the evaluation method is not sensitive to the HVAC sensor's fault. Meanwhile, the low statistic of F1 reflects the applicability of the evaluated method. Compared with other methods, the statistic of the LkDaNN F1 score is 0.00622 and 0.0855 under non-cross operation and cross-operation, respectively. To sum up, the evaluation metric of LkDaNN is better stability of other TL-based methods under different scenarios and tasks.

4.5 Impact of EBCe for LkDaNN in HVAC sensor FDD

It analyzes the FDD performance of LkDaNN based on EBCe and original data under both

cross operation and non-cross operation conditions in validation. As shown in Fig 12, the fault diagnosis rate of LkDaNN based on EBCe is overall higher compared to LkDaNN based on original data, with increases of 21.87% and 24.88% in non-cross operation and cross operation scenarios, respectively. Among them, the accuracy of LkDaNN combined with EBCe improves by 23.67%-40.13% in non-cross operation. However, the accuracy of LKDaNN combined with EBCe decreased by 0.2% compared to LkDaNN combined with the original data in the scenario of the evaporator inlet sensor (Ts1) failure. It can be approximately interpreted as EBCe having no effect on the detection of Ts1 in the non-cross operation scenario. Because the data distribution of the evaporator inlet temperature sensor is similar in the non-cross operating condition. As shown in Fig 12(b), the FDD accuracy of LkDaNN combined with EBCe increased by 29.50% under the Ts1 scenario in the cross-operation scenario. Overall, the fault diagnosis accuracy of LkDaNN combined with EBCe improved by 24.88%, with the fault diagnosis rates under different fault scenarios increasing by 6.60% to 51.50% in the cross operation scenarios.

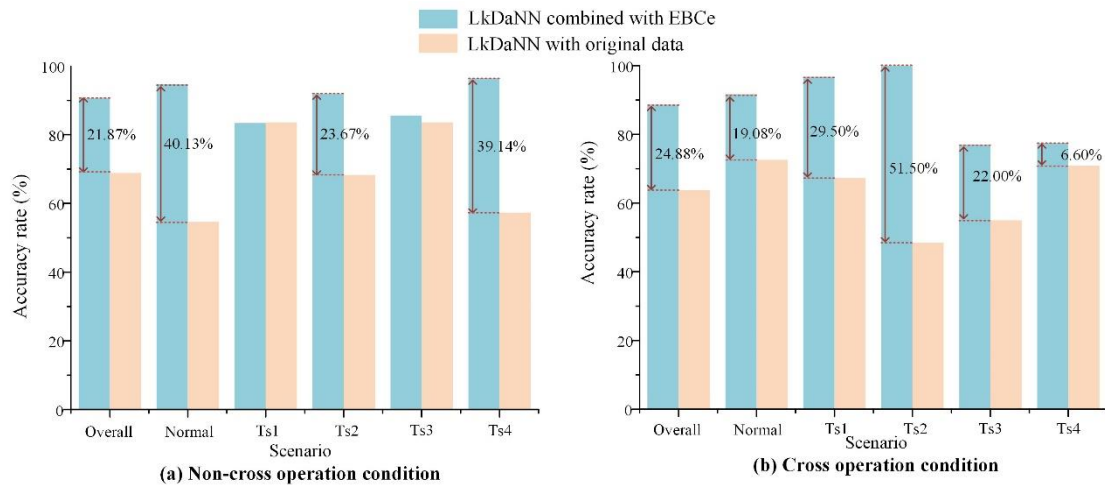


Fig 12. The performance analysis of EBCe-based HVAC sensor's FDD

Fig 13 analyzes the impact of EBCe on the LkDaNN method from the evaluation metrics of ML. In different fault scenarios under both cross operation and non-cross operation conditions, EBCe has improved the FDD performance of LkDaNN compared to the original data. EBCe can significantly improve the fault recognition capability of LkDaNN in different fault scenarios through reducing the differences between source and target domain data caused by cross-system, cross-condition and cross-operation conditions. It demonstrates that TL methods are more sensitive

to the differences between source and target domain data. In practical engineering applications, reducing the differences between source and target domain data can effectively improve the fault diagnosis efficiency for TL-based methods.

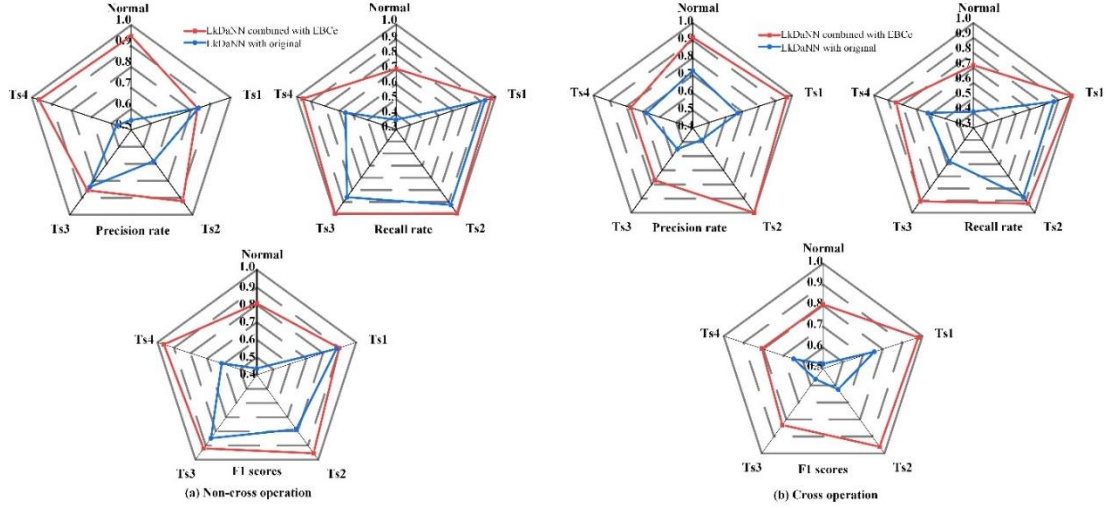


Fig 13. The analysis of F1 scores between original data and EBCe

4.6 Domain adaptation analysis

The domain fusion capability is an important criterion for assessing the feature transfer ability of TL methods. It employs statistical significance analysis to evaluate LkDaNN and comparison methods. As shown in Fig. 14, the P-value analyzes the degree of feature fusion between the source and target domains after completing transfer learning. The P-value ranges from $[0,1]$, indicating the ability to distinguish between source and target domain data. When $P < 0.05$, it can be concluded that there is a significant difference between the features of the source and target domains. Conversely, when $P \geq 0.05$, it indicates poor domain adaptation between the features of the source and target domains. A larger P-value suggests better domain adaptation performance for that feature between the source and target domain data.

The number of features for the four methods is 128. Among them, in the count of features with $P < 0.05$ (high significance), the proportion of features for LkDaNN is 0.78%, which is significantly lower than the other three comparative methods. In the statistics for high P-values ($P \geq 0.5$), the proportion of RBF-DaNN is slightly higher than that of LkDaNN. However, considering its performance in high significance, it can be demonstrated that the global optimization capability of LkDaNN's kernel parameters is better to that of RBF-DaNN. In the high significance range, the

feature proportions of RBF-DaNN and DaNN are similar. For DANN, the distribution of feature P-values further confirms that it is not suitable for the research scenario presented in this study.

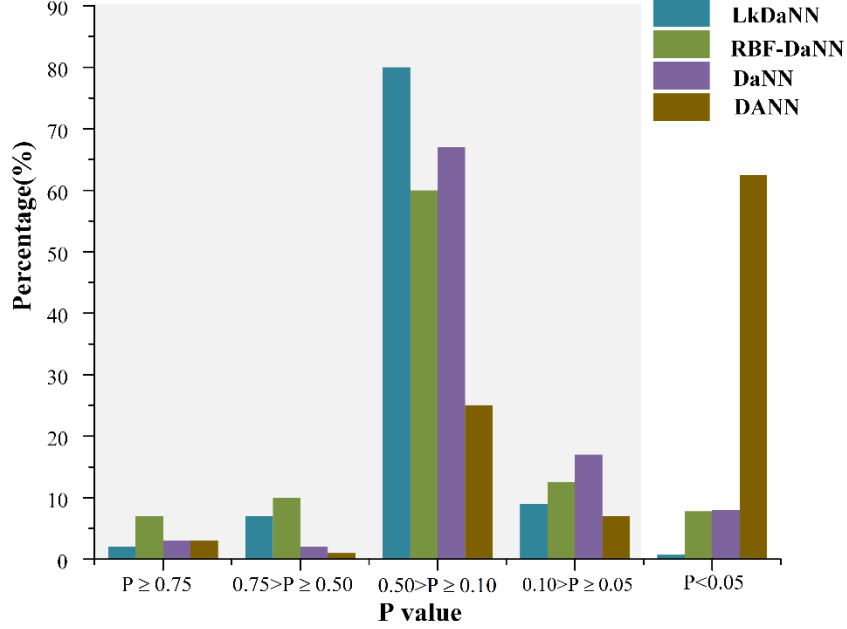


Fig 14. The analysis of domain adaptation by P value

4.7 Limitations

It investigates the feasibility of achieving FDD under conditions of significant differences in equipment, application scenarios and operating conditions. The goal is to propose an HVAC sensor FDD method for detection under cross-system, cross-condition and cross-operation. However, it can be seen that there is still great room for improvement in the FDD capability of EBCe-LkDaNN from the conclusions of the experiment conclusion. First, the current accuracy of fault identification still needs improvement in the fault diagnosis efficiency. In future work, efforts will focus on enhancing fault feature extraction and feature metrics in TL models to improve both fault mining and fusion capabilities, thereby increasing the efficiency of existing TL models in fault identification. Secondly, the training data for the target domain still requires a small amount of fault label data. Therefore, finding ways to reduce reliance on fault label data will also be a key focus of future research.

5. Conclusion and Prospects

To address the challenges of insufficient labeled samples and the difficulty in obtaining similar HVAC system data for sensor FDD in large public buildings, it proposes a TL-based fault diagnosis model using laboratory data under cross-condition, cross-system, and cross-operating scenarios. The specific conclusions are as follows:

(1) To address the differences in data feature between the HVAC system in public buildings and laboratory rooms, this paper proposes the EBCe-LkDaNN. By leveraging the energy consumption levels of the HVAC system, automatic classification of HVAC system operating is achieved. Experimental results demonstrate that the EBCe-LkDaNN achieves an overall fault diagnosis rate of 90.72% in non-cross-operation scenarios and 88.64% in cross-operation scenarios.

(2) EBCe is developed to reduce the data feature differences between the source domain and the target domain, and to automatically categorize operations. In non-cross-operation scenarios, the fault diagnosis rate of EBCe-enhanced LkDaNN, considering both normal and four sensor fault states, increased by 21.87% to 40.13%. In cross-operation scenarios, the fault diagnosis rates of EBCe-enhanced LkDaNN increased by 6.60% to 51.50%.

(3) LkDaNN is proposed to address the challenge of capturing structural features caused by the large distribution differences between source and target domain data in cross-condition and cross-system scenarios. Compared to other TL-based methods, LkDaNN achieved an improvement in fault diagnosis rates ranging from 5.99% to 19.38% and 10.14% to 23.19%, respectively.

Acknowledgement

The work described in this paper was supported by the National Natural Science Foundation of China (Grant No. 52078096), the Natural Science Foundation Joint Fund of Liaoning Province (Grant No. 2023-MSBA-023), 2023 Dalian University of Technology-Cardiff University Cooperation and Exchange Foundation Project, 2023 International Exchange Foundation Project of "Co-Creation of Excellence Program" from Dalian University of Technology (Grant: DUTIO-ZG-202307), the Key Project of DUT for International Students Studying and Researching in China: Innovation and Practice of Talent Cultivation Model in the Field of Smart Buildings for the "Belt and Road" Initiative (Grant No. 1103-82120001).

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