Chapter 3: Smart Buildings: State-of-the-Art Methods and Data-driven Applications

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Nomenclature

BAS: building automation system

BEMS: Building Energy Management Systems

CCTV: closed circuit television

CMMS: computerized maintenance management system

CNN: convolutional neural network

DAE: denoising autoencoder

FDD: fault detection and diagnosis

GRU: gated recurrent unit

HVAC: heating, ventilation and air-conditioning system

IEQ: indoor environmental quality

IMU: inertial measurement unit

LSTM: long short-term memory

MPC: model predictive control

PCA: principal component analysis

XGB: extreme gradient boosting

1. Introduction

The rapid development of IoT technologies have enabled the collection of massive amounts of data during building operations, making it increasingly promising and feasible to devise data-driven methods for smart building management. As an example, comprehensive sets of sensors and actuators are being equipped in the heating, ventilation and air-conditioning system (HVAC) to achieve real-time monitoring and controls over different components, such as chillers, water pumps, cooling towers and air handling units. Such information is typically collected with high frequencies (e.g., 30-second or 1-minute), which can be of significant value to describe the complicated operating patterns and interactions among building services systems. At present, extensive research interests have been drawn from both the building industry and academia to utilize such information to devise data-driven solutions. Compared with conventional management methods which rely heavily on domain expertise and human labors, data-driven approaches are highly promising to enhance the efficiency and effectiveness of various building management tasks.

This chapter serves as an overview of the state-of-the-art research and applications for smart building management, using building energy system as an example. More specifically, section 2 introduces main characteristics of information collected during building operations, while emphasizing its compatibility with different kinds of data analytics. Section 3 introduces data preprocessing techniques for enhancing building operational data quality. Sections 4 to 6 describe representative data-driven applications in various building management tasks, i.e., fault detection and diagnosis, occupancy analysis and optimal controls. The state-of-the-art data-driven methods and associated challenges in practice have been discussed in-depth. It is believed that the contents of this chapter are helpful for grasping the status-quo and major research trends in the smart building field.

2. Major types and characteristics of building operation information

Buildings possess intrinsic geometric, parametric and physics-related information. In general, there are three types of information available for analysis in large-scale public buildings. The first type is image and video data collected through closed circuit television (CCTV) systems. Such information has unstructured formats and is typically of large amounts, which imposes great challenges for knowledge extraction and applications. Thanks to the development in deep learning and computer vision technologies, existing studies have developed advanced tools to utilize such information for object detection, image segmentation and classification tasks. For instance, Lee et al. developed deep learning models to identify human postures and behaviors in buildings, which in turns facilitated optimal controls of building services systems [1]. Ayala et al. proposed a deep learning approach for automatic fire alarms , which helps to achieve intelligent building safety management [2]. Another type of unstructured information collected during building operations is the textual data and it is typically system maintenance records generated by building management staffs . Existing studies mainly adopted text mining techniques to extract useful knowledge from such information. Gunay et al.puts forward a text-mining method to extract information about failure patterns in building systems and components from computerized maintenance management systems (CMMS) databases [3]. Ding et al. proposes a text mining-based methodology to gain insights from relevant literature on building energy saving [4].

Besides the abovementioned unstructured information, structured building operational data, which describe the operating conditions of building services systems, are also available and serve as the major resources for building data analytics. Building operational data are typically collected by Building Automation Systems (BAS) or Building Energy Management Systems (BEMS) through IoT technologies and stored in multi-relational databases. As an example, Fig. 1 presents an example two-dimensional data table for storing building operational data, where each column represents a data variable and the row represents data collected at a time step. The data collection intervals may range from seconds to hours, providing detailed electronic descriptions of building dynamic operations at various temporal scales. The data collected can be further divided into four major categories, i.e., energy consumptions, physical operating parameters, environmental conditions, and miscellaneous data.

(1) Energy consumption data: Energy meters are used to measure energy consumptions of different building systems and components, such as the electricity power consumptions of chillers, pumps and fans, and the gas consumptions of boilers or heaters. Such data are highly valuable for building energy performance assessment.

(2) Physical operating parameters: The operating conditions of building services components can be described through real-time measurements and control signals. As an example, the actual operating conditions of chillers can be described using physical measurements, such as chilled water temperatures, chilled water flow rates, compressor operating frequencies, on/off status, and etc. Such variables can be numerical or categorical, such as *ON* and *OFF* status. Numerical variables may present different scales and variations, which make data normalization or standardization a must before most predictive modeling tasks. In addition, some numerical variables can be represented as categorical variables due to the operating characteristics of different components. For instance, measurements on water flow rates are numerical values, yet their varying ranges may be quite limited, specifically when a constant-speed pump is used.

(3) Environmental conditions: Building operations are subject to both indoor and outdoor environmental conditions, such as the indoor and outdoor temperature and humidity, as well as the extreme fire environments. Such variables are valuable for building performance assessment and controls, as they are closely related to indoor comforts and

energy efficiency issues. At present, a wide variety of outdoor environment variables are publicly available and can be used to facilitate smart building management. For instance, outdoor illuminance data can be used for daylighting and renewable energy controls, CO_2 concentrations can be used to formulate optimal ventilation strategies, and smoke visibility can be used for fire emergency response.

(4) Miscellaneous data: Thanks to the rapid development in IoT and sensing technologies, more detailed building and occupant data are available in smart buildings. For instance, occupancy data of different spaces can be readily collected using smart entrance security or camera-aided technologies. Such information can be used to optimize HVAC control logics with the aim of enhancing indoor environment quality. Personal belongings, such as smart phones, smart bracelets and laptops, also provide information for smart controls. Smart phones or smart bracelets typically contain inertia measurement units, which can capture high-frequency and multi-axis acceleration data for human gesture identification. Laptops are typically connected with wireless networks and such information can be used to infer the relative locations of building occupants. It can be imagined that more detailed and fine-grained information will be available during operations, which further opens the opportunities for smart building controls and optimization.

Building operational data have intrinsic high complexity due to interactions among various services components. Meanwhile, the relative low-quality issue makes it more challenging to ensure the reliability and validity of building data analytics. The quality of building operational data is restricted by the accuracy of sensors and suffers from deterioration due to measurement errors and transmission problems. The raw data collected during building operations may contain large amounts of missing values, outliers, drifting and stagnant measurements. In practice, it is a must to apply customized data preprocessing methods before the use of any machine learning and artificial intelligence algorithms.

Time	Energy consumption data	Physical operating parameters	Environmental conditions	Miscellaneous data
10:00	$\{X_{11},X_{12},\ldots,X_{1m}\}$	$\{Y_{11},Y_{12},\ldots,Y_{1n}\}$	$\{Z_{11},Z_{12},\ldots,Z_{1p}\}$	$\{L_{11},L_{12},\ldots,L_{1q}\}$
11:00	$\{X_{21},X_{22},\ldots,X_{2m}\}$	$\{Y_{21},Y_{22},\ldots,Y_{2n}\}$	$\{Z_{21},Z_{22},\ldots,Z_{2p}\}$	$\{L_{21},L_{22},\ldots,L_{2q}\}$
12:00	$\{X_{31},X_{32},\ldots,X_{3m}\}$	$\{Y_{31},Y_{32},\ldots,Y_{3n}\}$	$\{Z_{31},Z_{32},\ldots,Z_{3p}\}$	$\{L_{31},L_{32},\ldots,L_{3q}\}$
13:00	$\{X_{41},X_{42},\ldots,X_{4m}\}$	$\{Y_{41},Y_{42},\ldots,Y_{4n}\}$	$\{Z_{41},Z_{42},\ldots,Z_{4p}\}$	$\{L_{41},L_{42},\ldots,L_{4q}\}$
14:00	$\{X_{51},X_{52},\ldots,X_{5m}\}$	$\{Y_{51},Y_{52},\ldots,Y_{5n}\}$	$\{Z_{51},Z_{52},\ldots,Z_{5p}\}$	$\{L_{51},L_{52},\ldots,L_{5q}\}$
15:00	$\{X_{61},X_{62},\ldots,X_{6m}\}$	$\{Y_{61},Y_{62},\ldots,Y_{6n}\}$	$\{Z_{61},Z_{62},\ldots,Z_{6p}\}$	$\{L_{61},L_{62},\ldots,L_{6q}\}$

Fig.1 A typical example of structured building operational data

3. Data preprocessing tasks for building operational data

The general process of building data analytics has three key stages, i.e., data preprocessing, knowledge discovery, and knowledge applications. Data preprocessing is an indispensable step considering possible deficiencies in building data quality. There are five major tasks for preprocessing building operational data, i.e., data cleaning, data reduction, data scaling, data transformation and data partitioning [5].

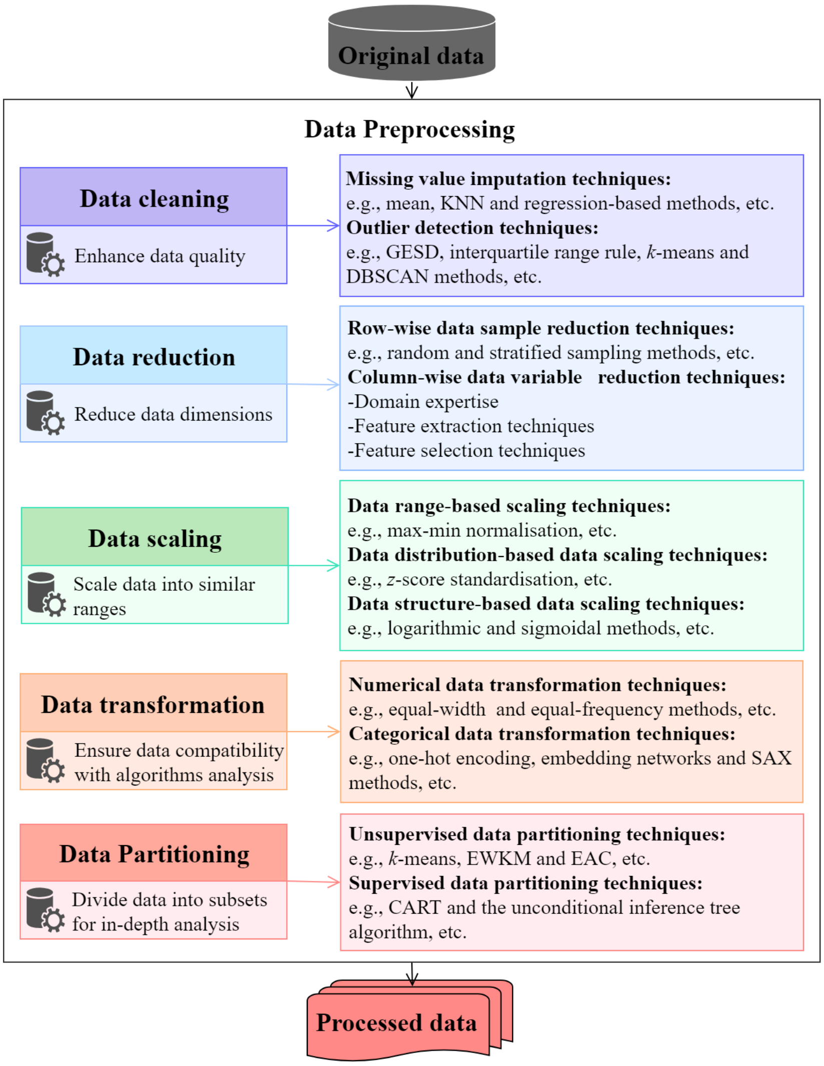

Fig. 2 Typical data preprocessing tasks for building operational data analysis [5]

Data cleaning addresses missing value and outliers, which may stem from errors in sensors, transmission, and storage systems. Missing values can be imputed through model-free and model-based methods. Model-free methods are easy to implement, which may use means or medians as estimate s for missing values. It should be noted that such methods are not effective when imputing missing values lasting for long time periods, as it cannot reflect dynamics in system operations. Model-based methods, such as regression-based methods, are more suitable for estimating continuous missing values, yet more efforts are needed for model development. Outliers in building operational data are typically identified through either univariate or multivariate approaches. The univariate approach assumes that a variable follows a certain distribution, based on the outliers that are identified from a statistical point of view, such as the 3-sigma method for normal distribution data. Such approach can only identify outliers with extreme values. By contrast, the multivariate approach considers possible correlations among multiple data variables for outlier identification. Existing studies mainly adopted unsupervised clustering analysis algorithms, such as k-means and density-based clustering methods, for applications.

The second task is data reduction, which aims to reduce data analysis complexity through row-wise or column-wise reduction methods. The row-wise data reduction methods focus on reducing the total number of data samples. As an example, random sampling can be applied to create a subset for analysis. Stratified sampling, which considers the proportions of data classes, is more suitable when class proportions are desired to be the same. For instance, the energy profiles of commercial buildings may present huge differences between weekdays and weekends. Random sampling may not strictly preserve the proportions between weekdays and weekends, while stratified sampling can be applied to maintain such information between the original and sampled data. The column-wise data reduction methods aim to select useful variables for in-depth analysis. Both domain expertise-based, statistical-based feature selection (e.g., correlation-based filters [6]) and feature extraction (e.g., principal component analysis [7] or autoencoders [8]) methods, can be applied for this purpose.

The third task is data scaling, which transforms variables with different scales to similar ranges for predictive modeling. The max-min normalization and z-score standardization methods are most used in the building field. The former transforms a variable to a range between zero and one, while the latter creates a variable with a mean of zero and a standard deviation of one. In practice, the latter may provide more flexibility as it is less sensitive to extreme values. Additionally, data structure-based methods, such as logarithmic methods, can be applied when variable distributions are highly skewed.

The fourth task is data transformation, which deals with mapping between numerical and categorical variables to ensure the compatibility with learning algorithms. Most building operational data are numerical variables. However, some learning algorithms, such as the A-priori algorithm for rule mining, only work with categorical variables. In such a case, the equal-width or equal-frequency methods can be applied to transform numerical variables into categorical ones. Meanwhile, categorical variables need to be transformed into numerical ones for predictive modeling. One-hot encoding is the most common way to transform a *k*-level categorical variable into *k*-1 encoding vectors. When k is too large, embedding networks can be applied to create numerical embeddings for efficient representations. It should be mentioned that some variables in building operational data, even though stored as numerics, should be treated as categorical variables. As an example, the *Month* or *Daily Hour* are typically stored using numerical values, yet they should be treated as categorical variables as their intrinsic orders are not meaningful for predictive modeling.

The fifth task is data partitioning, which aims to divide building operational data into subsets to ensure the sensitivity and reliability of data analysis results. For instance, unsupervised learning methods, such as clustering analysis, can be applied to identify typical operating conditions of chiller systems [9]. Such clustering results can be used for data partitioning, based on which more fine-grained knowledge can be discovered across various operating conditions. Supervised methods, especially decision tree-based methods, can also be applied for data partitions. The main idea is to select a variable as outputs, while using operating schedule-related variables (e.g., *Year*, *Month*, and *Day type*) as inputs for predictive modeling [10]. In such a case, the resulting decision tree splitting rules can be used for data partitioning.

All the above-mentioned data preprocessing methods can be integrated for enhancing the quality of building operational data and ensuring the reliability of data analysis results. In the later sections, various learning techniques which can be applied to extract useful knowledge for building management tasks, such as building services system modeling, fault detection and diagnosis, occupancy identification, and etc, are discussed.

4. Data-driven fault detection and diagnosis methods for building systems

4.1 Basic unsupervised and supervised learning-based FDD methods

From the data perspectives, operating faults in building systems can be regarded as data outliers or anomalies. Both supervised and unsupervised learning methods have been developed for fault detection and diagnosis (FDD) tasks. As an example, scholars have used the unsupervised principal component analysis method to decompose and reconstruct the original operational data, and then established diagnostic indicators based on the reconstruction error for fault identification [11]. The other popular approach is to use clustering analysis for fault identification. Clustering analysis-based methods assume that the operation data under similar working conditions will form a relatively close cluster in the multi-dimensional space. Therefore, possible faults can be identified by calculating the relative distance or density distributions between each data sample and cluster centers [12].

Unsupervised learning-based methods, to some extent, can avoid possible decision-making malpractices caused by the over-dependence on subjective experience. However, the analysis results from the unsupervised algorithms are usually inexplicable and redundant. As an alternative, supervised learning is a more direct and effective approach, which in essence tackles the fault diagnosis task as multi-classification problems. It requires the data to be labeled and such labels are used to describe the actual conditions of different data samples (such as *Normal*, *Valve leakage fault*, *Fan failure fault*). The most widely used approach is to use machine learning algorithms to capture the complicated relationships between input and output variables at the same time step. Once developed, such models can be applied for real-time fault identification. Existing studies have shown that ensemble methods, such as random forest, light gradient boosting machine (LightGBM) and extreme gradient boosting (XGB), typically result in the best fault diagnosis performance [13]. Considering that building systems have intrinsic dynamics, time-series modeling approaches have also been explored to enhance the fault diagnosis performance. On the one hand, users can introduce additional input variables to represent measurements at previous few time steps for more accurate fault modeling. In such a case, the learning algorithm stays unchanged. On the other hand, users may directly apply advanced temporal modeling algorithms for analyzing temporal building operational data. The main techniques used in this field are recurrent neural networks, such as the gated recurrent unit (GRU)-based and the long short-term memory (LSTM)-based models [14].

4.2 Transfer learning-based FDD methods

Supervised learning-based FDD methods are straightforward to use, yet the high requirement in labeled data makes them less feasible in practice. At present, researchers have proposed various approaches to handle the potential data quality problem for reliable fault modeling. Transfer learning, which has gained great success in computer vision , has provided a promising approach to tackling the data shortage problem. As shown in Fig. 3, the main goal of transfer learning is to migrate the knowledge learned from the source domain to solve new tasks in the target domain. In terms of building FDD problems, the main intuition is to integrate operational data collected from information-rich source buildings to facilitate the fault modeling in the information-poor target building.

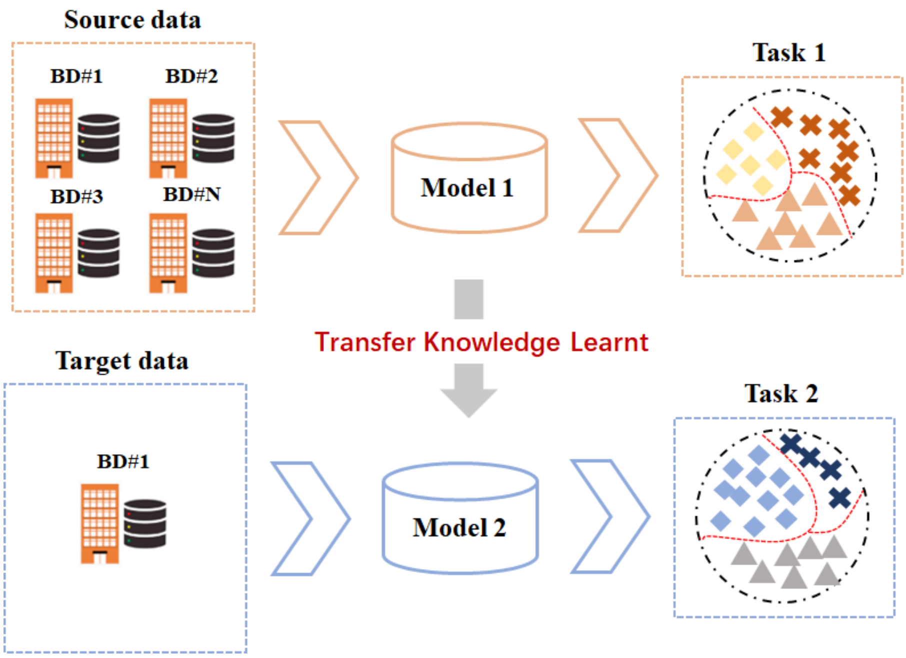

Fig. 3 Schematic diagram of transfer learning process.

As an example, Liu et al. achieved knowledge transfer between two chiller systems using convolutional neural networks (CNNs) [15]. A temporal dimension was manually inserted to convert tabular building operational data into 2D image data. CNNs were developed based on the rich operational data collected from the source chiller, and customized to the target chiller using limited operational data. Experimental results showed that transfer learning helped to enhance the fault diagnosis accuracy by up to 8.18%~12.63%. In practice, different building systems or components may collect completely different data variables. Advanced solutions are therefore needed to tackle the heterogeneous data challenge for source data integration and unification. Fan et al. proposed a novel image-based transfer learning framework which provides a format-compatible, information-expanding data basis for building operational data analysis [16]. The main idea is to apply the t-SNE algorithm to obtain the 2D coordinates of each variable, based on which an image can be generated for each data sampling using their measurements as pixel values. In this study, two strategies have been explored for effective knowledge transfer. One is called the freezing strategy, which utilizes the pre-trained model for image feature extraction. In such case, some or all convolutional layers for feature extractions using the source domain data are frozen, while the rest are trained using the target domain data. The other is the fine-tuning strategy, which adopts the pre-trained model for weight initialization and all the model weights are fine-tuned using target domain data. The research results indicated that the fine-tuning strategy was more efficient for cross-domain FDD knowledge transfer in the building field.

4.3 Semi-supervised learning-based FDD methods

Transfer learning-based methods assume the availability of source domain data for pre-trained model development, which is a rather heavyweight solution for individual buildings. A natural question arises as if there is no such source domain data, what approaches should the user take to enhance the reliability of data-driven models. It turns out that individual buildings typically have sufficient amounts of operational data, yet only a small subset of them are labeled and compatible with supervised learning algorithms. As a solution, semi-supervised learning methods, which aims to explore and utilize the information hidden in unlabeled data for predictive modeling, have gained increasing interests in the building field.

In general, there are four approaches for semi-supervised classification, i.e., generative model-based, low-density separation-based, graph-based, and self-labeling approaches [17]. The first two types have specific assumptions about the distributions of unlabeled data and decision boundaries, which may limit their potential in analyzing real-world data. As an example, Li et al. proposed a semi-supervised data-driven fault diagnosis method for chiller systems based on semi-generative adversarial networks [18]. It used semi-generative adversarial networks to learn the information on unlabeled data distributions, based on which the quality of supervised fault classification models was enhanced.

The third approach relies on the graph theories for semi-supervised learning. It is mainly used to analyze unstructured data (e.g., images or text) and usually requires larger amounts of computational resources. By contrast, the fourth approach, i.e., the self-labeled approach, is more popular for its simplicity and flexibility in practical implementation. The main idea is to firstly adopt the supervised learning paradigm to train a basic model using labeled data alone, and iteratively update model parameters using high-quality pseudo-labels generated from unlabeled data. Fig.4 illustrates the self-training process for developing semi-supervised neural networks for fault diagnosis. It consists of five major steps, i.e., initial fault diagnosis model development using labeled data alone, pseudo label generation from unlabeled data, customized pseudo label data selection, and iterative updates of the fault diagnosis model for improved performance [19]. Such a learning framework is compatible with various supervised learning algorithms, making it a promising candidate for analyzing building operational data. The research results validated the value of semi-supervised learning in FDD tasks, indicating that the utilization of unlabeled data can lead to an accuracy increase of over 20% given limited labeled data.

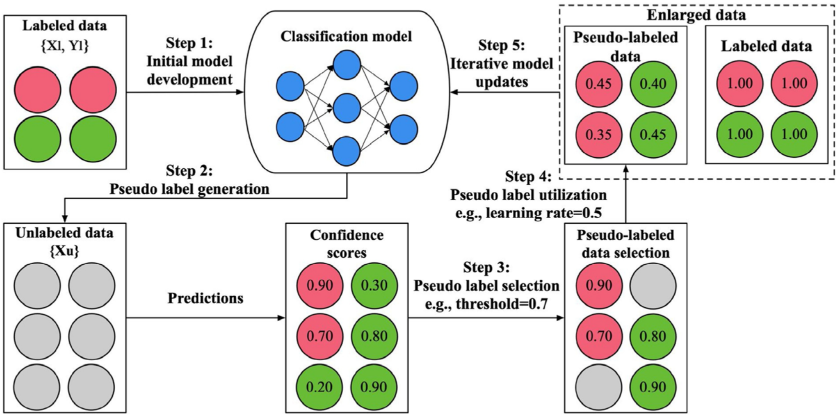

Fig. 4 The self-training strategy for semi-supervised neural network development [19].

4.4 Self-supervised learning-based FDD methods

Semi-supervised learning enables the integration between unlabeled and labeled data for predictive modeling. One possible limitation is that semi-supervised learning may suffer from overfitting and poor generalization performance given extremely labeled data. Taking the self-labeled approaches described in Section 4.3 as an example, the base model is developed through the supervised learning protocol using labeled data alone. Given limited labeled data, such a model may have rather poor performance, which may severely affect the quality of pseudo labeled data generated from unlabeled data, making it an ineffective semi-supervised learning process. To tackle the labeled data challenges associated, existing studies have resorted to self-supervised learning to unlock the potential of large amounts of unlabeled building operational data. In general, self-supervised learning consists of two key steps. The first is to develop pre-trained models based on user-defined tasks (also known as pretext tasks) to learn useful data representations from unlabeled data, and the second is to customize pre-trained models for specific predictive modeling tasks through transfer learning protocols.

Self-prediction and contrastive learning are two major approaches of self-supervised learning. The former focuses on reconstructing a data sample or predicting one part of the data sample given other parts, while the latter aims at learning data invariant embeddings given different data transformations. Self-supervised learning has been widely used in natural language processing and computer vision fields [20]. Existing self-supervised learning frameworks are mainly designed for analyzing sequential or image data [21]. Considering that building operational data are in essence tabular data, customized solutions are needed to implement self-supervised learning methods in the building field. As shown in Fig.5, the data reconstruction-based self-prediction methods are the most direct route to self-supervised tabular data learning. The main idea is to develop denoising autoencoders (i.e., DAEs) to reconstruct unlabeled building operational data from their noisy versions. A mask matrix, which has the same dimension as the unlabeled data, is defined through random 0-1 sampling to indicate the position of added data noise . Such data noise can be generated through a certain noise injection method, such as Gaussian noise , swap-noise , and etc. Besides data reconstruction, pre-trained models can be developed for both data reconstruction and noise location prediction. If trained properly, these encoder models should learn meaningful embeddings which are robust to data noises and can be transferred to downstream predictive modeling tasks[22]. Contrastive self-supervised learning methods can also be applied for analyzing tabular building operational data. As shown in Fig.6, one possible approach is to use data augmentation techniques to generate positive and negative pairs for each data sample, and then develop Siamese encoder models to learn meaningful latent embeddings to classify whether two data samples are similar or dissimilar to each other.

In previous studies [cite], a lightweight transformer architecture has been proposed to analyze tabular building operational data and data experiments have been conducted to investigate the value of self-supervised learning in FDD tasks. The experimental results demonstrated the value of the self-supervised learning in fault classification, especially when limited labeled data are available for fault modeling. The results indicate that self-prediction pretext tasks with 10-20% swap-noises levels are more suitable for tabular building operational data analysis. By contrast, contrastive learning is more sensitive to hyperparameter settings, making it less feasible for practical applications in the building field.

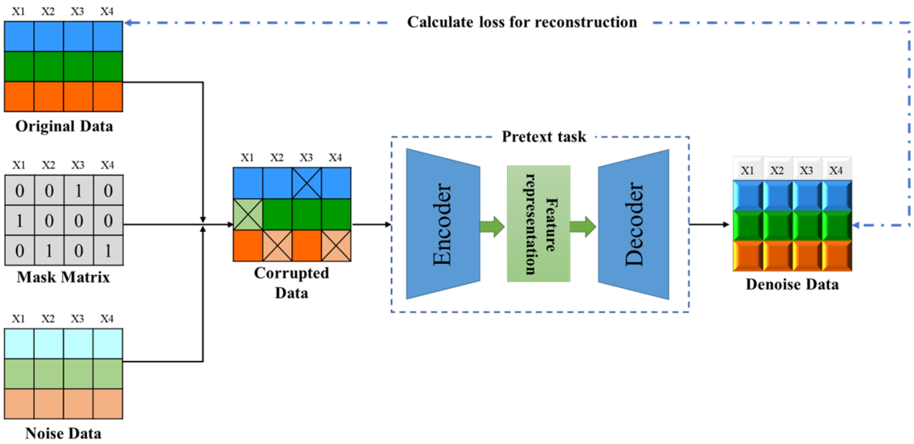

Fig. 5 Illustration of self-prediction pretext tasks for tabular building operational data

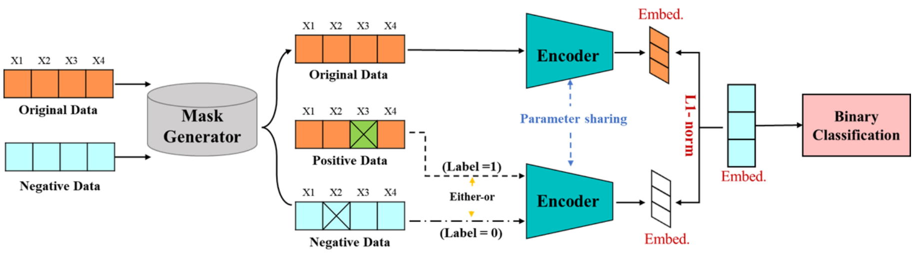

Fig. 6 Illustration of contrastive learning pretext tasks for tabular building operational data

5. Data-driven human behavior identification for building systems

Building is designed to provide a comfortable indoor environment for building occupants and ensure their safety in case of an emergency. For example, the accurate and real-time identification of human behavior is essential for preventing unnecessary energy uses while maintaining high levels of indoor comfort. Data-driven methods have been developed to facilitate human behavior identification tasks. More specifically, existing studies differ in their data sources, machine learning techniques used, and occupant-centric applications. To summarize, four types of data have been adopted for human occupant behavior studies, i.e., environmental data, smart meter data, video camera data, and physiological data. Environmental data are measurements on indoor and outdoor environments, such as air temperature, humidity, carbon dioxide concentration, luminosity, and noise level. Previous studies have utilized temperature, relative humidity and carbon dioxide concentration data as inputs for forecasting the number of occupants in buildings [23]. Smart meters, which track energy consumptions of different building systems, such as HVAC systems, lighting systems, and socket systems, can also be used as proxies for occupant modeling [24]. Video cameras can collect massive amounts of image data on human activities and serve as the most straightforward approach for occupant behavior identifications. The video data from Kinect have been adopted for detecting various human discomfort poses, such as wiping sweat, shaking T-shirt, and shoulder shaking [25]. Despite its high accuracy, such approach requires large amounts of computing resources and may violate occupant privacy. By contrast, the physiological data collected through wearable devices have gained increasing interests in the past few years. Such data cover a wide range of physiological indices, such as the heart rate, blood oxygen, skin temperature, and movement acceleration. Previous studies have utilized such data to predict thermal comfort and thereby, enabling the detailed description of individual-level thermal preferences across different spaces[26].

In terms of the human behavior modeling methods, existing studies have used both supervised learning and unsupervised learning algorithms for analysis. Supervised learning-based methods focus on developing regression or classification models on indoor occupancy presence [27], occupant number [28], occupant activities [29], thermal comfort levels [30]. Unsupervised learning-based methods, such as clustering analysis, which have been developed with the aim of differentiating thermal preferences based on longitudinal environmental and physiological data [31], while principal components analysis (PCA) were frequently adopted to reduce data dimensionality for further analysis [32].

From the application perspectives, existing studies can be divided into three types, i.e., occupancy detection, occupants number prediction, and human thermal comfort identification. Occupancy detection determines whether someone is in the room and serves as the basis of occupant-centric control logics, e.g., whether the lighting and HVAC systems in a space should be turned on. Occupant number prediction focuses on estimating the occupant numbers. It can be regarded as a regression problem and the predictions can be integrated with control logics for more energy-efficient operations, e.g., determine the fresh air volume for air conditioning systems [33]. Thermal comfort identification aims to identify the thermal preferences of indoor occupants given different HVAC operating conditions. Data-driven models have been developed for such purposes using the air temperature, relative humidity, and air velocity as model inputs [34].

To further illustrate the usefulness of data-driven methods in human behavior identification, two examples on occupant detection and thermal preference identification have been provided in below figures. The first is to utilize multi-source environmental data to achieve non-invasive occupancy detection [35]. Fig. 7 presents the pairwise plot between environmental and time variables collected in a meeting room. The blue dots signify that the room is being occupied, while the red dots signify that the meeting room is vacant. When there is a discernible distinction between the red dots and the blue dots in the row and column of an input variable, it demonstrates that this input variable has a great potential in detecting occupancy. Conversely, this input variable has limited efficacy in indoor occupancy detection. For example, a marked divergence between the red dots and the blue dots can be observed in the row and column of the indoor light intensity. It indicates that the indoor light intensity has the capability to distinguish the indoor occupancy. After initial data exploration, machine learning models can be developed for occupancy detection and occupant number prediction tasks. As shown in Fig. 8, a fairly high occupancy detection accuracy of 97.09% can be achieved using the indoor temperature, outdoor temperature, indoor relative humidity, indoor carbon dioxide concentration, indoor noise level, indoor light intensity and hour as inputs to extreme gradient boosting (XGB) model.

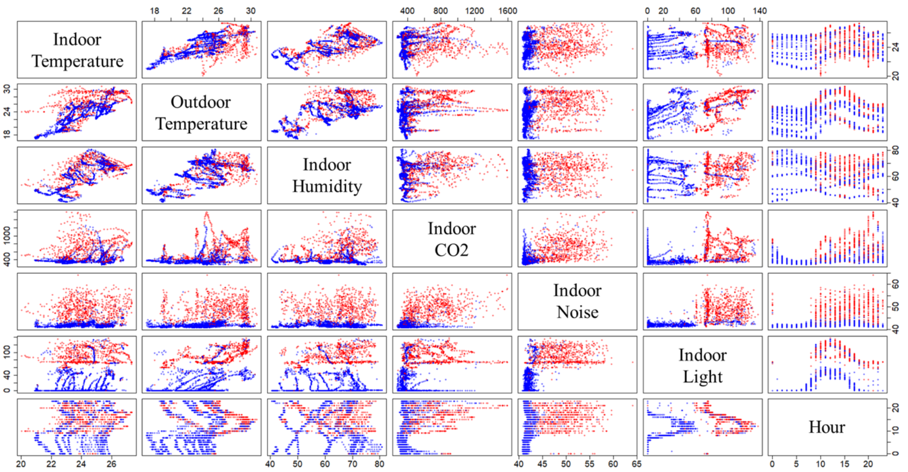

Fig 7. The pairwise plot of environmental and time variables given different occupancy states[35]

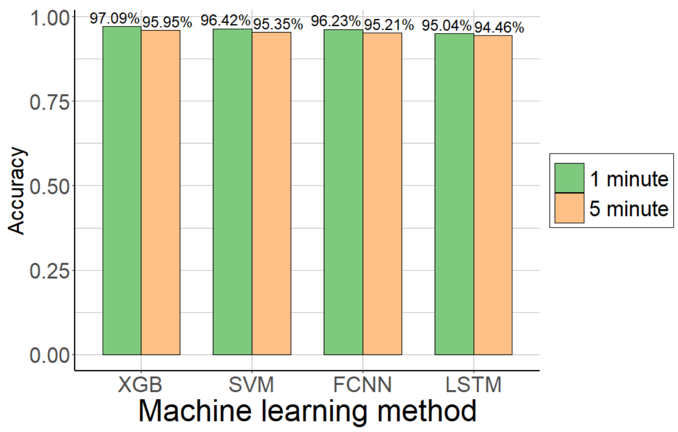

Fig 8. Accuracy of different classification methods with different data collection frequencies[35]

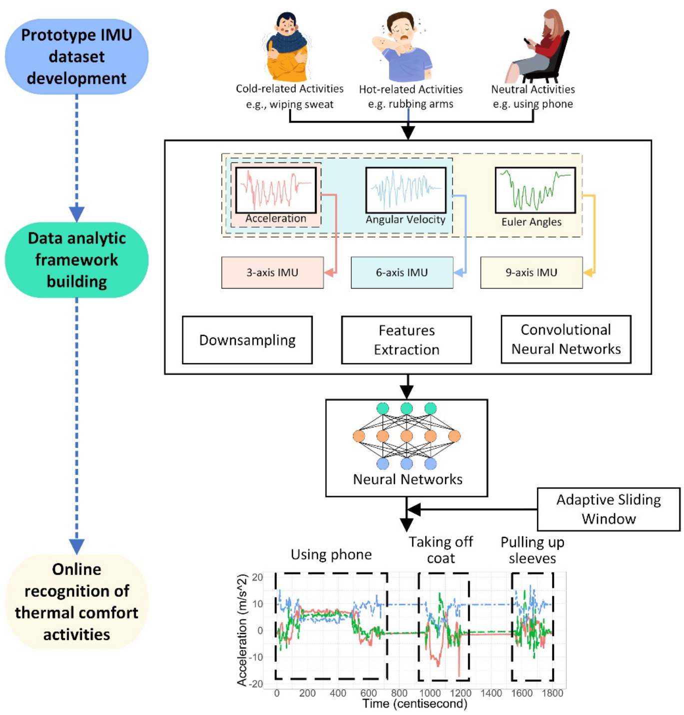

Fig 9. A framework of thermal comfort inference using human IMU data

As another example, the high-frequency Inertial Measurement Unit (IMU) data collected through wearable devices can be utilized to infer human thermal comfort. The main idea is that humans may perform certain activities when feeling either hot or cold, and the resulting IMU data can be used to identify thermal comfort-related activities. As shown in Fig. 9, in our previous studies, a framework for analyzing human IMU data has been proposed for human thermal comfort identification. Firstly, a prototype IMU dataset was created containing 30 prototype activities, i.e., 10 cold-related (e.g., rubbing hands, wearing coat), 10 hot-related (e.g., wiping sweat from face, taking coat off), and 10 neutral (e.g., using phone, typing) activities. Secondly, data preprocessing steps on features extraction and variable selection are conducted to prepare the IMU data into suitable inputs for predictive modeling. Finally, an online thermal comfort activity recognition method was developed based on machine learning algorithms. Fig.10 presents the resulting confusion matrix on thermal comfort-related activity identification. No. 1 to 10 are cold-related actions, No. 11 to 20 are hot-related actions, and the others are neutral actions. The results indicate relatively high identification performance with an accuracy of 86.2%. Such prediction results can be integrated with HVAC system control logics to achieve customized and energy-efficient operations.

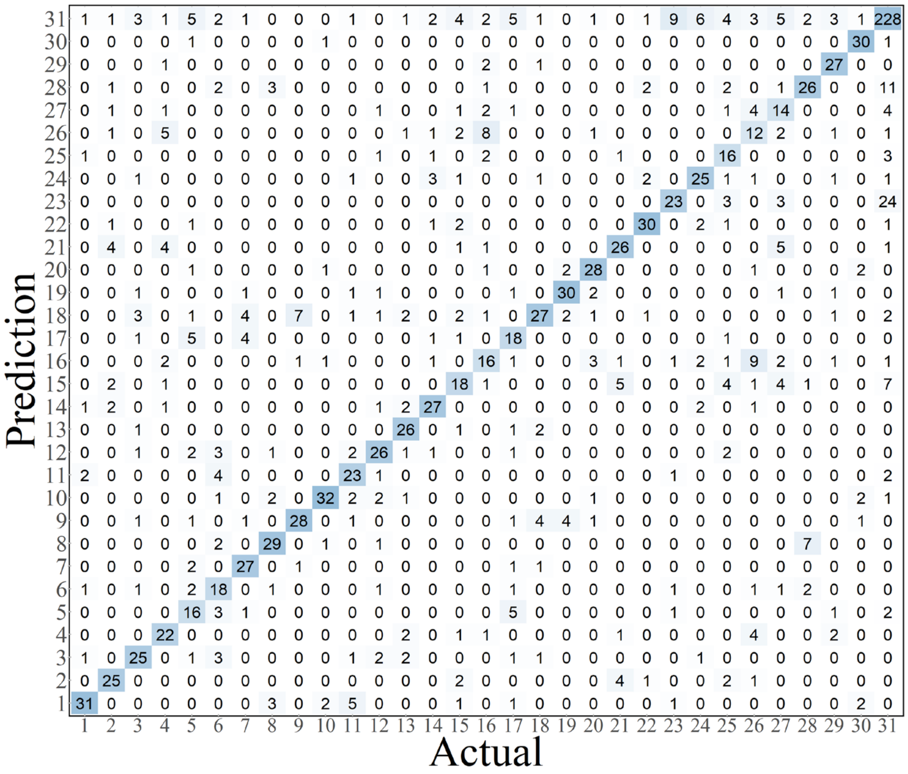

Fig. 10 Confusion matrix of thermal comfort activities recognition

6. Data-driven optimal control methods for building systems

Data-driven technologies have been used in three main types of optimal control methods in the building field, i.e., model predictive control (MPC), rule-based control, and reinforcement learning control.

MPC is a constrained optimal control strategy that can calculate the optimal control action by maximizing/minimizing a given objective function based on the prediction of the controlled object's future behavior. For example, the objective of building control could be to maximize the thermal comfort and indoor environmental quality (IEQ) for occupants considering temperature, humidity, CO_2 concentrations, illuminance, etc. In addition, minimizing monetary costs under time-varying energy prices is also a popular objective because energy markets are undergoing massive changes to increase their flexibility by demand side management.

The model predictive control framework mainly includes three parts, model prediction, rolling optimization, and model correction [36], as shown in Fig.11. The data-driven technology can be used for training the prediction model. Here is a typical example. A data-driven model is used to predict building cooling load based on disturbances (e.g., weather conditions). Then according to the cooling load, the rolling optimization can be conducted to determine the optimal chilled water outlet temperature setpoint for achieving minimal monetary costs. In fact, this prediction model could also be other types of models, such as the white or gray box models. However, compared with the white box model, the computation load of the data-driven model is relatively low which is more proper to be used for online optimal control. Compared with gray box models, the prediction accuracy of the data-driven model could be more satisfied with the development of many advanced machine learning technologies. Although data-driven models normally require a large amount of training data, it becomes less problematic with the rapid development of IoT and sensing technologies. It should be mentioned that many advanced machine learning technologies that can obtain high accuracy are non-linear, which then can cause non-convex problems in the rolling optimization process. Although this problem can be solved by heuristic numerical optimization, it still faces the risk of divergence [37].

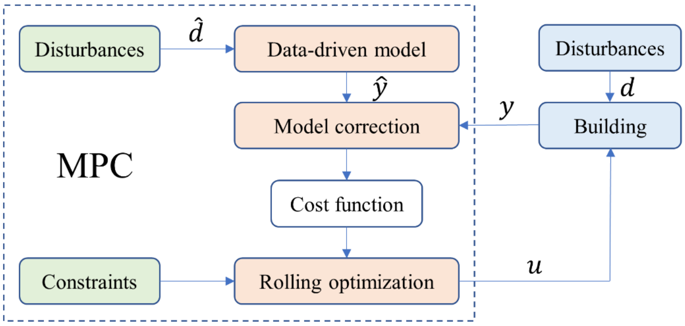

Fig. 11 Data-driven model for model predictive control (MPC)

For rule-based control, data-driven technology can be used to extract rules from the results of other advanced control strategies [38], e.g., the MPC mentioned above. Therefore, the control action (u shown in Fig.11) can be obtained directly according to the disturbances ($\hat{d}$ shown in Fig.11). One typical example is that it can directly find the relationship between weather conditions and the optimal chilled water outlet temperature setpoint based on the control actions of MPC in the training stage. In this way, the process of cooling load prediction and online optimization is not required in the operation stage, which can save the cost of IT infrastructure both in terms of hardware and software. On the other hand, rule-based control can only obtain near-optimal control, which means that it can only mimic MPC but not be able to obtain the same results as MPC. In addition, after these rules are extracted and used in the operation stage, it is normally difficult for them to be amended , as the training dataset is fixed. It indicates that the control performance will be degraded when the practical cases are outside of the predefined conditions. Therefore, the rule-based control has relatively low adaptability.

Reinforcement learning control can also map disturbances ($\hat{d}$ shown in Fig.11) to control actions (u shown in Fig.11). However, different from the rule-based control, the learning process is based on a trial-and-error procedure [39]. It means that the reinforcement learning control agent will try different chilled water outlet temperature setpoints and calculate the reward (monetary cost) under different weather conditions. Then gradually, this agent can find the optimal chilled water outlet temperature setpoint according to the weather conditions for obtaining the most reward (minimal monetary cost). Compared with rule-based control, it has high adaptability as it can be trained and updated at every step in the operation stage. On the other hand, safe operation (especially in the initial phase) should be noted in real applications because of the trial-and-error procedure mentioned above. This could be accomplished by a suitable modification of the trial procedure. For example, instead of making use of heuristic trial methods that are blind to the risk of actions, the initial learning phase could be guided by the available prior knowledge of the problem [40]. In addition, the long training periods could also be an obstacle to solve before the real application of this control method.

7. Conclusive remarks

Buildings are becoming not only energy-intensive, but also information-intensive. The massive amounts of building operational data have provided an ideal platform to devise data-driven solutions for smart building management. This chapter presents the overall picture of building data analytics together with their applications for building energy management. Focusing on the structured tabular data collected by Building Automation Systems (BAS), data analytics have been designed for data preprocessing, knowledge discovery and knowledge applications. More specifically, data preprocessing techniques have been developed with the aim of enhancing original data quality while ensuring the validity and sensitivity of data analysis results. Data-driven applications have been developed to facilitate typical building operation management tasks, such as fault detection and diagnosis, occupancy recognition, and optimal controls.

It is realized that the main obstacle in practice is the data quality problem, which may severely affect the applicability of learning algorithms and validity of data analysis results. As a prominent example, an essential premise of supervised learning algorithms is that sufficient labeled data are available for model training. However, the acquisition of data labels can be time-consuming and labor-intensive. As a result, most building operational data are unlabeled and not compatible with advanced machine learning algorithms. Therefore, to further enhance the applicability and feasibility of data-driven methods, advanced learning paradigms should be adopted in the building field to tackle potential data shortage problems, such as transfer learning, semi-supervised learning, generative modeling and self-supervised learning. At present, the research in these fields is still at their preliminary stages and more research efforts for comprehensive analysis are needed. Despite possible challenges, it can be foreseen that with the advances in building data analytics, data-driven innovations will become more prevalent in the building to facilitate building energy saving and smart energy management.

Acknowledgement

The authors gratefully acknowledge the support of this research by the National Natural Science Foundation of China (No. 52278117), the Philosophical and Social Science Program of Guangdong Province, China (GD22XGL20) and the Shenzhen Science and Technology Program (No. 20220531101800001 and 20220810160221001).

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