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Unsupervised anomaly detection of industrial building energy consumption

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ABSTRACT

Detecting anomalies in building energy consumption can reduce unnecessary energy waste and improve energy efficiency. The role of anomaly detection has become particularly pivotal in industrial buildings because of their high energy consumption and the potential risks associated with abnormal events. Although extensive data collected through smart meters has indicated the advantages of anomaly detection using data mining techniques, labeled data are often unavailable in practical situations. Therefore, this study develops an ensemble framework that combines three unsupervised learning algorithms, including Local Outlier Factor, Deep Isolation Forest, and Anomaly Transformer, to identify anomalous power consumption with a focus on subsequence anomaly. The transformer-based network is established to precisely impute missing values and enhance the reliability of anomaly detection. The experimental results based on hourly cooling energy consumption in the two industrial buildings confirmed the effectiveness of the proposed method. To better interpret the anomaly detection results, the Extreme Gradient Boosting is applied to construct the relationship between influencing factors and anomalous consumption. The area under the Receiver Operating Characteristic curve is used as a metric for the classification task, and an average of over 0.96 indicates robust performance. Weekday and dew point temperatures are found to have significant impacts on the electricity usage pattern. The research findings provide valuable insights for developing effective solutions to identify unexpected trends in building energy consumption and support efficient energy management.

1. Introduction

Building operations are responsible for 30% of final energy consumption and 26% of energy-related emissions worldwide, emphasizing their significant potential for mitigating climate change [1]. Industrial buildings, in particular, play a crucial role in decarbonizing the building sector [2]. It is estimated that industrial buildings account for 25% of total electricity use in the EU and possess substantial opportunities to improve energy efficiency [3]. Many factors influence the energy use of buildings, and inappropriate operation and control strategies have been reported to result in considerable energy waste [4,5]. One of the most promising approaches for addressing this issue is anomaly detection [6].

Anomaly detection is the process of identifying an unusual or atypical observation that deviates greatly from the others in a data set [7,8]. For time-series data, these anomalies can be classified as point anomalies or subsequence anomalies. Point anomalies are individual data points that exhibit sudden behavior compared to their surrounding points. Subsequence anomalies constitute a consecutive set of data points whose joint behavior is abnormal, but individual data might not be anomalous [9]. For example, while each hourly reading in a daily record of energy usage may align with historical data, the cumulative daily pattern could still reveal unusual consumption trends. This has also been referred to as collective anomaly or pattern-wise anomaly in the existing literature [10].

In the field of building energy consumption, anomalies are typically the consequences of equipment malfunctions or unwanted behavior [11]. Such anomalies can result in unnecessary energy waste, especially in poorly maintained, outdated, or incorrectly managed systems [3]. For example, commercial buildings usually consume about 15% to 30% more energy than necessary because of improperly controlled systems [12]. In addition, anomalous behavior can lead to an expanded operation time beyond the norm and even trigger a permanent breakdown of the device. Once identified, these irregular consumption patterns can be reported to the building manager, who can subsequently adopt appropriate corrective measures [13]. In industrial buildings, the efficiency of manufacturing activities can be significantly compromised if anomalous

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Table 1
Summary of previous studies on anomaly detection of building energy with unsupervised algorithms.

Reference	Dataset	Approach	Anomaly type
[24]	A university office building	A hybrid neural net ARIMA model	Point anomaly
[26]	A smart campus (public dataset AMPds2)	Multi-agent-based unsupervised approach and ensemble model	Point anomaly
[25]	Three residential houses in British Columbia, Canada	Deep learning-based unsupervised techniques, including recurrent neural networks and quantile regression	Point anomaly
[3]	A German manufacturing company	Long Short-Term Memory based autoencoder	Point anomaly
[6]	An educational building in Hong Kong	Autoencoder-based ensemble method	Subsequence anomaly
[23]	Three office buildings in Chongqing	The density-based spatial clustering application with noise (DBSCAN) algorithm clustering technique	Subsequence anomaly

energy patterns, stemming from equipment faults or improper operations, are not properly detected. For instance, failing to meet the cooling energy demands of a production workshop can lead to equipment overheating or excessive humidity, potentially reducing equipment lifespan and compromising product quality. Therefore, anomaly detection is an essential part of building energy operations, and timely measures are required to diagnose and repair anomalies.

Recognizing the critical role of anomaly detection, this study aims to (1) propose an unsupervised ensemble framework that integrates local outlier factor (LOF), deep isolation forest (DIF), and anomaly transformer (AT) to explore anomalous building energy consumption; (2) develop an Extreme Gradient Boosting (XGBoost) classifier by annotating data and quantitatively interpreting the identified anomalies with SHapley Additive exPlanations (SHAP) values; and (3) validate the effectiveness of the proposed method using energy data collected from energy monitoring platforms in two industrial buildings. Additionally, a transformer neural network is trained to accurately impute missing values during data preprocessing. The findings of this study can be summarized to support diagnostic tasks and energy management in industrial buildings.

The paper is structured as follows: Section 2 reviews the current research on anomaly detection. Section 3 introduces the framework of the proposed method and the principles of selected techniques. Section 4 discusses the results of subsequence anomaly detection conducted on experimental buildings. Finally, Section 5 presents the conclusions of this research.

2. Literature review

In recent years, the widespread adoption of machine learning–based anomaly detection has been attributed to the ability to handle massive and complex data, discover underlying patterns, and automatically adapt to new data. The proliferation of sensor devices has fueled data mining techniques and proven successful in various industries, such as credit fraud detection and intrusion detection in network systems [14,15]. In the building sector, a common way to detect anomalies is to use supervised learning to construct complex nonlinear relationships between operating parameters and state labels (e.g., normal, faulty, or low energy-efficiency states, etc.), and to determine the operation status of the system [16]. Literature [17] proposed a robust reference model for detecting anomalous energy consumption patterns in a transformer substation. The model achieved a prediction accuracy of 94.6% in terms of identifying anomalies in daily load profiles. Literature [18] focused on using automated methods to detect anomalies in the energy patterns of a city hall and campus, finding that global accuracy ranged from 80% to 90%. Literature [19] used the AdaBoost ensemble model combined with deep neural networks to detect electricity theft in building energy consumption data.

Although supervised anomaly detection techniques have demonstrated high accuracy in the current literature, real-world datasets rarely contain labeled anomalies. In other words, the distinction between normal and abnormal data is unclear. The reliance on well-annotated data for supervised models does not align with the actual needs of building managers [20]. This discrepancy underscores the importance of developing unsupervised algorithms for practical applications [21]. Table 1 summarizes previous research on unsupervised anomaly detection in building energy consumption. In related studies, it is assumed that abnormal patterns constitute a small portion of the dataset, typically less than 20% [22]. Unsupervised learning algorithms for anomaly detection can be built on density, clustering, neural networks, etc. Literature [23] focused on anomaly detection in three office buildings in Chongqing, using clustering of daily power consumption patterns. Their study identified average outdoor air temperature and day types as primary factors that distinguished typical electricity load behaviors. Literature [24] developed a hybrid neural net ARIMA model that detected anomalies through differences between real and predicted consumption. The model was tested using 17-week electricity consumption data from an office building. Literature [3] introduced a long short-term memory–based autoencoder for identifying anomalous energy consumption using unlabeled data from a German manufacturing company. To enhance the interpretability of the anomaly detection results, literature [25] combined recurrent neural networks and quantile regression to reveal connections between various quantile predictors and the target variable in residential buildings.

One concern with unsupervised methods lies in their effectiveness when labels are missing. To ensure reliable and precise anomaly detection, a few studies have developed ensemble frameworks that integrate various unsupervised algorithms. Literature [6] proposed an autoencoder-based ensemble method considering multiple autoencoder architectures and training schemes, and then designed a novel approach for estimating model performance. Literature [26] introduced a multiagent-based unsupervised approach for detecting energy consumption anomalies on a smart campus and evaluated its performance by labeling the data with ensemble models. This study aggregated individual predictions and finalized labels based on a majority voting system.

Another concern about the performance of anomaly detection algorithms is the presence of missing values, which have to be addressed prior to data analysis. Simple imputation methods to fill missing data include mean-filling, priors filling, interpolation, etc. [27]. Although these methods are straightforward to implement, they tend to underestimate the variability in the data and can produce large errors in case of nonrandom missingness. Comparatively, machine learning approaches for imputation can model complex dependencies in time series data and provide more accurate predictions. Literature [28] constructed a softmax ensemble network composed of multilayer perceptrons to fill in missing values in electric energy consumption data with explanatory variables. Literature [29] developed a transformer network integrated with the k-means algorithm to compensate for missing electricity data of two residential houses. Capturing long-term dependencies in time series, their experimental results showed great improvements compared

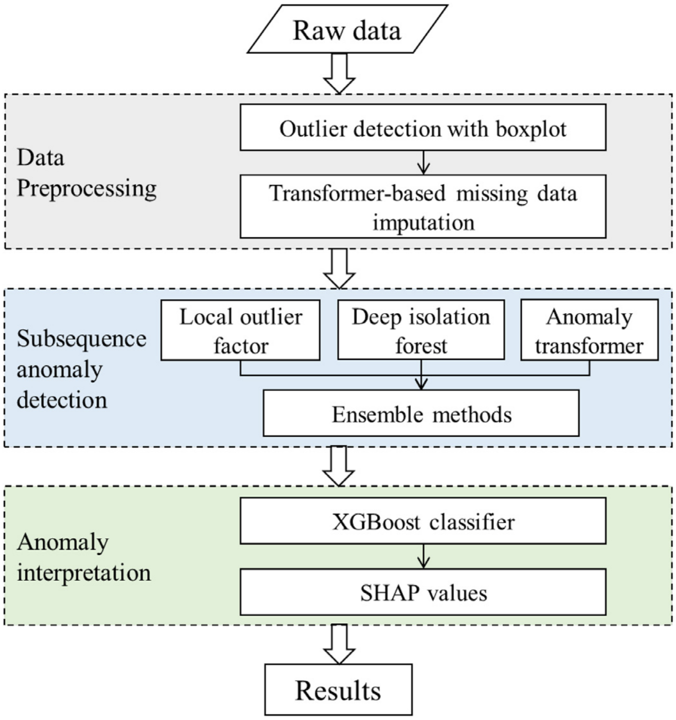


Fig. 1. Research outline.

to other commonly used imputation techniques. Recognizing the effectiveness of transformer architecture, literature [30] proposed Dual Transformer-based Imputation Nets for imputing missing data in multivariate time series, which not only improves data imputation accuracy but also enhances the applicability of models in real-world scenarios.

To summarize, unsupervised methods are highly valuable for anomaly detection because obtaining actual labels to indicate whether observations are abnormal can be unrealistic. Although growing attention has been paid to this field, studies on these methods are still scarce, especially when it comes to subsequence anomalies [9]. Besides, many of these studies lean on a single anomaly detection method; while no method exists that can perfectly detect all anomalies. For example, deep learning-based approaches can comprehend large-scale data and adapt to the surge in complexity [21]; however, they possess relatively low interpretability. Although several related studies can detect anomalies without prior information, they primarily offer qualitative explanations for the causes of these anomalies, lacking interpretability regarding what constitutes normal versus abnormal behavior [20]. Moreover, there has been insufficient emphasis on anomaly detection within industrial building energy systems [3]. Failure to promptly identify abnormal events in energy use not only undermines energy efficiency but also risks incurring economic losses stemming from operational failures. Finally, the importance of missing data imputation is often neglected in related research, thereby compromising the reliability of anomaly detection.

3. Methodology

The research framework is displayed in Fig. 1. First, this study used the boxplot rule to detect the point anomalies that deviate so much from other observations, treated these anomalies as missing values, and then constructed a transformer-based neural network model to fill in the missing values. Second, three algorithms were applied for independent subsequence anomaly detection, with the detection ratio set at 10% for each algorithm [6,20,22]. This is built on the consideration that a ratio too low may overlook some anomalies, while one too high can misclassify normal data as anomalies. The difference between point anomaly and subsequence anomaly is further shown in Fig. 2. The final detection results were determined using majority voting, based on the frequency with which each category was voted on. Third, the XGBoost classifier was built with finalized labels that represent whether or not the energy consumption at each timestamp was normal. The SHAP was then used to analyze the influence of time and weather factors on the occurrence of anomalous behaviors.

3.1. Boxplot rule

The boxplot is a popular graphical tool used to identify point anomalies in data [31]. This plot establishes the upper and lower bounds; data points beyond these bounds are identified as point anomalies. The lower bound is calculated as the first quartile (Q1) minus k times the interquartile range (IQR), and the upper bound is the third quartile (Q3) plus k times the IQR. The IQR is the difference between Q3 and Q1. When adopting the boxplot rule, it is important to determine an appropriate value of k based on the research objectives and data distribution [32,33]. While $k = 1.5$ is generally recommended, it carries the risk of overestimating the prevalence of genuine anomalies [34,35]. Setting k to 3, which is also frequently used, helps ensure that only values with extreme deviations are considered anomalous. The boxplot serves as an effective tool for anomaly identification—it provides a clear visualization of data spread, central tendencies, and potential point anomalies.

3.2. Transformer-based imputation

Transformer is a model architecture that utilizes an attention mechanism to construct global dependencies between input and output in the time-series dataset. The model architecture is composed of encoder and decoder stacks, attention functions including scaled dot-product attention and multi-head attention, position-wise feed-forward networks, embeddings and softmax, and positional encoding. The encoder maps an input sequence from symbol representations to continuous representations. The decoder then generates an output sequence of symbols to present one element each time. The model is auto-regressive and consumes symbols that are previously generated as additional input for the next generation. This model eliminates the need for recurrent or convolutional layers, enables parallelization, and reduces training time significantly [36,37].

To validate the accuracy of prediction results, root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are selected as evaluation metrics. The corresponding equations are as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2} \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right| \tag{2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100\% \tag{3}$$

Where y_i and $\hat{y}_i$ represent the actual values and the predicted value, respectively.

3.3. Local outlier factor

LOF is a well-established method for anomaly detection, recognized for its ability to effectively identify abnormal data points within a dataset [38]. This algorithm computes the local density of each data point based on its k-nearest neighbors. Then, the LOF value for a point is determined by comparing its local density to the average local density of its neighbors. When the LOF value surpasses a predefined threshold, the data point tagged as abnormal. The LOF algorithm can adjust to datasets with varying density regions, but its performance may be impacted by noisy data.

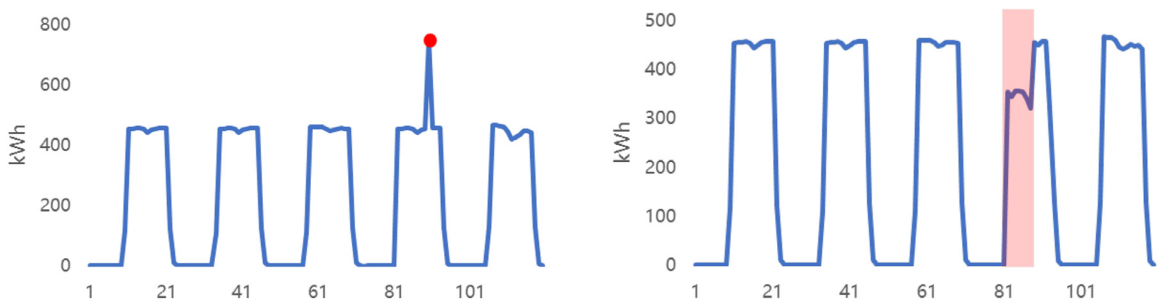


Fig. 2. Examples of point anomaly and subsequence anomaly.

Although the Euclidean distance in the general LOF model can handle single anomalies, it is ineffective at detecting collective anomalies in time-series data due to its method of calculating distance. Therefore, dynamic time warping (DTW) distance is adopted to replace Euclidean distance in the LOF algorithm, enabling more efficient calculation of distances between two time-series subsequences [20,39]. When there are two time-series data X $\{x_1, x_2, x_3, \cdots, x_i\}$ and Y $\{y_1, y_2, y_3, \cdots, y_i\}$, the DTW distance is defined as follows:

$$D_{dtw}(X, Y) = d\left(x_1, y_1\right) + \min\left(D_{dtw}(Rest(X), Rest(Y))\right) \tag{4}$$

Where $d(x, y) = ||x - y||_p$, $Rest(X) = \{x_1, x_2, x_3, \cdots, x_i\}$, $Rest(Y) = \{y_1, y_2, y_3, \cdots, y_i\}$.

When integrating DTW into the LOF algorithm, the modified method treats time-series data as a special point to determine their density compared to the surrounding points. In this way, LOF is enhanced and can extract abnormal data segments, compare two unequal-length time series, and remain unaffected by the synchronization of time-series data.

3.4. Deep isolation forest

Isolation forest (iForest) is an unsupervised anomaly detection algorithm that uses the isolation method to randomly partition feature space and detect anomalies from complex data [40]. iForest is composed of several isolation trees (iTree), each constructed by randomly selecting a feature and a split value to partition the data. The process starts with a random sample of the data at the top node and continues dividing until each piece of the data is isolated or a certain depth is reached. During this process, an anomaly score is calculated, which represents the path length from the root to the leaf in the iTree. A shorter path to isolate a sample indicates a higher likelihood of being abnormal. Assume iTree is $\mathcal{T} = \{\tau_i\}_{i=1}^{T}$, and the anomaly score of the data object O is calculated based on the average path length over all iTrees in the iForest:

$$\mathcal{F}_{iForest}(O|\mathcal{T}) = 2^{-\mathbb{E}_{\tau_i \in \mathcal{T}} \frac{|p(o|\tau_i)|}{C(T)}} \tag{5}$$

where $C(T)$ is a normalizing factor [41].

The linear axis-parallel isolation method employed by iForest is limited in addressing complex anomalies, as it considers only one dimension at a time. Extensions such as hyperplane-based isolation also adhere to linear partitions, potentially introducing algorithmic bias constraints and struggling with anomalies that require non-linear isolation strategies. To tackle these challenges, the DIF algorithm constructs deep neural networks and employs random axis-parallel isolation for data partitioning. In this approach, an ensemble of random representations is generated by optimization-free neural networks, which require no optimization and only necessitate simple initialization. This approach enhances flexibility when partitioning the original data. Furthermore, each feature in the new representation space arises from non-linear interactions among the original features, thus overcoming linear limitations and facilitating the isolation and identification of complex anomalies.

3.5. Anomaly transformer

The Anomaly transformer stacks Anomaly-Attention blocks and feed-forward layers, where Anomaly-Attention comprises a two-branch structure containing prior-association and series-association. This stacking structure is efficient in understanding the underlying associations from deep multi-level features. The series-associations are calculated by the self-attention of transformers and captures the actual observed associations from the raw data. The prior-associations use a learnable Gaussian kernel to capture the expected normal behavior of time points according to adjacent relationships [42]. Furthermore, this method is particularly adept at modeling pairwise associations and pointwise representations simultaneously, which is crucial for understanding complex temporal dynamics in time-series data.

The method incorporates the concept of association discrepancy, which is designed to efficiently detect anomalies by capitalizing on the observation that anomalies often struggle to form strong associations with the overall series compared to normal points. Due to their rarity and distinctiveness, anomalies tend to be associated with data points that are more localized to adjacent time points. A minimax strategy is then employed to enhance the discriminative power of the association discrepancy. This strategy amplifies the differences between normal and abnormal behaviors, thereby making anomalies more detectable. In this way, anomaly transformers can identify anomalies in complex systems where labeling data is impractical or impossible. The integration of the Anomaly-Attention mechanism and the use of association discrepancies provide a robust framework for identifying both subtle and overt anomalies in diverse time-series applications [43].

3.6. Majority voting ensemble

A majority voting ensemble aggregates the predictions of multiple models to produce a more robust final prediction (Fig. 3). Each classification model independently evaluates the data points, categorizing them as either normal or abnormal. The final prediction is determined by the consensus of more than half of the individual models. This voting process creates an approximate ground truth by labeling the data points based on the consensus of multiple models. Previous studies have utilized labeled data obtained through majority voting to evaluate the performance of newly proposed anomaly detection algorithms [26]. Moreover, the classifier ensemble built on majority voting was found to outperform individual models by aggregating prediction results [44].

3.7. XGBoost

XGBoost is a highly efficient and advanced implementation of gradient boosting that has been widely applied in energy-related studies, such

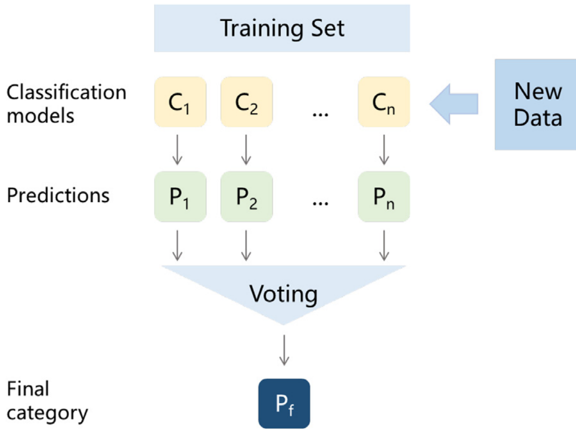


Fig. 3. A schematic illustration of the majority voting ensemble.

as the prediction of energy consumption [45,46]. It utilizes sophisticated techniques, such as tree pruning, regularization, and the handling of missing values, to enhance speed and performance. Therefore, it is a powerful data mining tool that has fast computational speed, high accuracy, and robustness. The algorithm efficiently constructs boosted trees and supports parallel computation. Each new tree corrects errors made by the previous trees, reducing bias and variance and improve model accuracy. In this study, XGBoost was utilized to classify data points into their respective classes. The algorithm is proficient at handling large datasets and adaptable to various data types. In addition to its computational efficiency and flexibility, XGBoost incorporates regularized boosting techniques to mitigate overfitting.

Evaluation metrics are crucial for assessing classification problems. Class imbalance often occurs in datasets where the number of positive and negative samples varies significantly, and the distribution of these samples may change over time [47]. The receiver operating characteristic (ROC) curve is composed of the true positive rate (TPR) and the false positive rate (FPR) at different classification thresholds, with AUC representing the area under the curve. The AUC ranges from 0.5 to 1, and a larger value indicates better performance. Compared to metrics such as accuracy and precision, AUC offers advantages in handling imbalanced datasets, as it remains unaffected by class distribution and integrates model performance across various thresholds. In this study, where there was a low proportion of anomalous data, the AUC was used to assess model performance.

3.8. SHAP

SHAP is a method for explaining machine learning model predictions. Built upon the Shapley value concept from game theory, it quantifies the contribution of each feature to predictions. SHAP values offer an intuitive and interpretable approach to understanding the reasons behind individual predictions as well as overall performance. The computation of SHAP values involves predicting all possible subsets of features and calculating the contribution of each subset to the prediction. This method enables the identification of features that play a key role in model predictions, thereby enhancing the interpretability of machine-learning algorithms. SHAP values have been widely employed to explain various types of models, including XGBoost, providing valuable insights for decision-makers and domain experts [48].

In summary, this section presents the core principles of various methods employed at each stage of anomaly detection, along with their respective advantages. First, during data pre-processing, the classic boxplot method is applied to identify extreme outliers, followed by the construction of a transformer model to accurately impute missing values. Next, three unsupervised algorithms are used to detect anomalous periods in the electricity data, with a voting mechanism incorporated to enhance result reliability. Finally, an XGBoost model is trained based on the detected anomalies, and SHAP is employed to explain the underlying causes of these anomalous periods.

4. Results

4.1. Data preprocessing

This study investigates two manufacturing companies in China: one producing medical devices in Guangzhou and one working on electronic products in Xiamen. In both buildings, central air conditioning was utilized for cooling, with energy management platforms installed to monitor energy consumption. According to building managers, maintaining the smooth functioning of the cooling system is crucial for production activities. If cooling system malfunctions are not properly detected and addressed, they could result in industrial equipment overheating or excessive humidity, thereby affecting product quality and lifespan. Additionally, sustaining appropriate temperature and humidity levels can enhance employee work efficiency and productivity.

The data originates from the energy monitoring platforms of individual buildings and primarily includes two types: (1) cooling energy consumption, consumed in the form of electricity and collected through smart meters; and (2) operational parameters of the cooling system, such as the on/off status of equipment. Although the latter is not the target of data-driven anomaly detection in this study, it can support the analysis of causes of anomalies, such as whether abnormal periods are caused by equipment malfunctions. Cooling energy consumption, which is the main source of energy use in investigated industrial buildings, is collected through smart meters installed in the buildings at a frequency of 3 min. Building A boasts a floor area of 24,000 square meters, and the energy data for building A covers the period from June 6, 2022 to October 15, 2022. Building B, located in Xiamen and spanning 60,000 square meters, had its consumption data collected from July 1, 2022 to September 29, 2022. Weather parameters were sourced from ECMWF Reanalysis v5 (ERA5) [49]. Hourly data for atmospheric temperature and dew point temperature were used in this study.

After obtaining the raw dataset, data preprocessing was conducted. First, the data was converted from a 3-minute frequency to an hourly frequency. During the process, energy consumption was aggregated by summing the values for each hour, while weather parameters were averaged. Then, boxplots were utilized to exclude extreme point anomalies, minimizing the interference of values that deviated significantly from the normal range in subsequent analysis. Anomalies were defined as values falling outside the range $[Q1 - k^{*}IQR, Q3 + k^{*}IQR]$, where k was set to 3 to capture extreme values. The proportions of identified points in the two buildings were 0% and 0.40%, respectively. The detected anomalies were treated as missing values.

Owing to transmission congestion and network failures, the occurrence of missing data is sometimes unavoidable. To enhance the accuracy of predictions for these missing values, a transformer network is trained on the energy data of each building, and its performance is compared to that of simple imputation methods. In forward filling and backward filling, the missing values are replaced with the last or the next observed data respectively. Linear interpolation estimates the missing values by fitting a straight line between two known data points and then interpolating the missing data on this line. Spline interpolation uses piecewise polynomial functions to assess missing values, providing a more flexible and smoother estimate than linear interpolation. Specifically, a non-missing interval is randomly selected from the dataset and artificially rendered as missing. A three-hour duration is chosen for testing because it corresponds to the average period of missing data. Then the performance of various imputation strategies is quantified using MAPE, RMSE, and MAE that calculate the discrepancies between the predicted values and true values. This procedure is repeated iteratively 20 times for each method.

Table 2
Evaluation metrics of missing value imputation of two industrial buildings.

Imputation method	Building A			Building B		
	MAPE	RMSE	MAE	MAPE	RMSE	MAE
Forward filling	18.7%	45.9	38.5	3.0%	52.5	41.3
Backward filling	20.9%	61.2	48.5	3.6%	56.7	467
Linear interpolation	14.7%	49.6	40.0	2.7%	43.0	36.5
Spine interpolation	21.0%	53.4	45.0	4.0%	63.3	50.9
Transformer	8.9%	27.6	23.0	2.0%	34.0	27.3

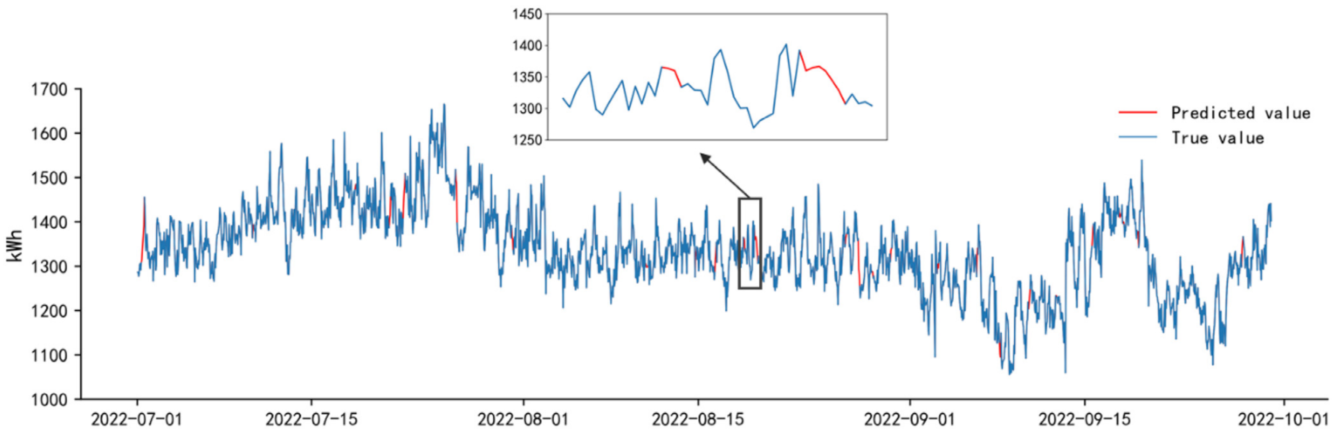


Fig. 4. Energy consumption data with filled-in values of Building B.

Table 3
Descriptive statistics of two industrial buildings.

Parameters	Descriptions	Building A	Building B
Time	Range	2022.06.06–2022.10.15	2022.07.01–2022.09.29
Area (m^2)	Floor area	24,000	60,000
Energy consumption (kWh)	Min	0	1055.8
	Max	533.6	1665.6
	Avg	262.2	1337.7
	Std	97.4	94.1
Temperature (°C)	Min	17.2	23.0
	Max	37.2	35.4
	Avg	28.6	28.5
	Std	3.0	2.2
Dew point temperature (°C)	Min	4.4	15.3
	Max	27.9	27.0
	Avg	24.3	23.9
	Std	3.3	2.2

The median values of multiple random selections for these assessments are presented in Table 2. In both cases, the transformer-based imputation model outperforms other methods in reconstructing missing building energy data, achieving lower prediction errors. The MAPE for two cases is reduced by 5.8% to 12.1% and by 0.7 to 2.0% respectively. The larger decrease observed in the case of Building A suggests that the missing data may not occur randomly, making it difficult for simple imputation methods to provide accurate predictions. Fig. 4 shows the pre-processed data for Building B with fill-in values highlighted in red. Table 3 presents the descriptive statistics of the final data. It can be seen that Building B has a higher level of energy consumption, averaging 1337.7 kWh per hour, compared to approximately 262.2 kWh per hour for Building A. Both industrial buildings experience similar outdoor meteorological conditions, with average temperatures and dew points at around 28.5 °C and 24 °C, respectively. The range of these parameters is somewhat wider for Building A compared to Building B.

4.2. Preliminary analysis

In this part, the distribution and trend of energy time series data is explored. Fig. 5 and Fig. 6 present the cooling energy consumption patterns over the study period for the two buildings. Points below the lower bound or above the upper bound are not shown in the figures. Throughout the day, the energy consumption patterns of the two buildings exhibited similarities. They operated almost continuously, except for intermittent periods in Building A. Generally, energy consumption began to rise around 6 a.m. and declined around 3 p.m. Building A reached its peak energy consumption at 9 a.m. and maintained a prolonged peak plateau with a significant peak-to-trough difference. Building B exhibited a shorter peak period and a smaller peak-to-trough difference, with a relatively flat trend of change. On a per-week basis, Building A tended to consume more energy on weekdays compared to weekends. Although the energy consumption of Building B fluctuated, as seen on the weekly scale, it did not demonstrate a distinct pattern of change.

Seasonal and trend decomposition using loess (STL) is a useful technique for analyzing time series data by decomposing energy consumption into distinct components, specifically trend, seasonality, and remainder [50]. The decomposition results are displayed in Fig. 7 and Fig. 8. The trend component represents the long-term progression of the data, capturing gradual changes over time. For Building A, energy consumption shows a noticeable decrease during weekends on a weekly basis. Additionally, in September and October, there were instances where

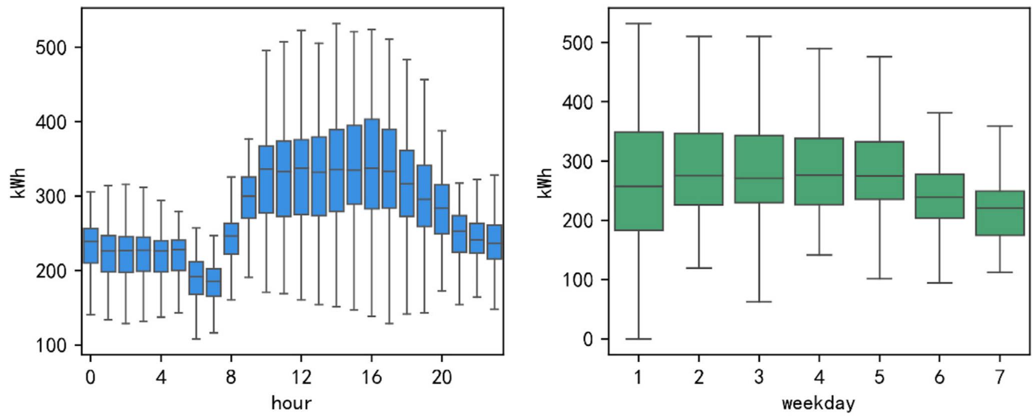


Fig. 5. Daily and weekly energy consumption of Building A.

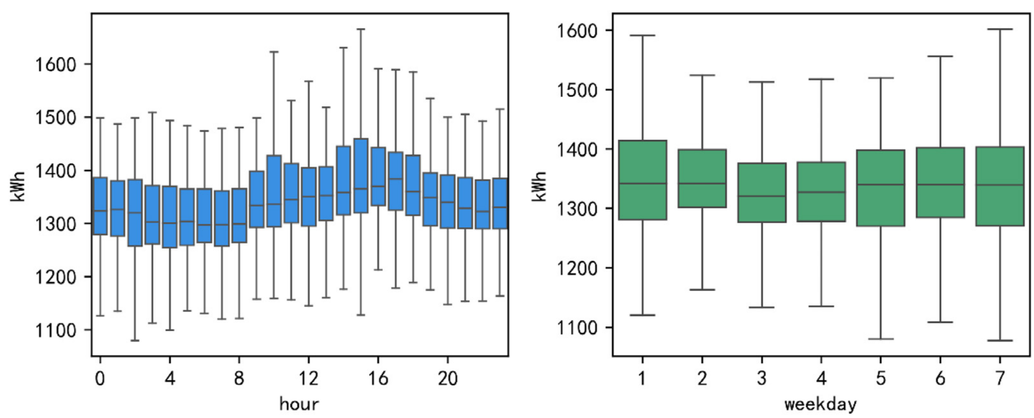


Fig. 6. Daily and weekly energy consumption of Building B.

energy consumption abruptly dropped to zero. For Building B, the overall energy consumption increased towards the end of July, then declined to a certain level and remained steady until September, during which the fluctuations in energy consumption were more significant. The seasonal component accounts for systematic and calendar-related movements, showing clear daily patterns. The remainder, or residual, includes irregular fluctuations that cannot be attributed to the seasonal or trend components, effectively isolating the noise and unexpected deviations in the data.

4.3. Subsequence anomaly detection

This part applies unsupervised learning methods for anomaly detection on the cleaned and complete dataset. The proposed approach automatically identifies abnormal energy consumption periods, assisting building managers in mitigating potential risks. For Building A, the anomaly detection results of the three algorithms are shown in Fig. 9(a)–9(c). The detection ratio of each algorithm was set at 10%. Based on the majority voting, the final result of ensemble methods excluding subsequences of only 1 hour was about 9.5%, as shown in Fig. 9(d). 10 abnormal subsequences were detected, and the average duration was 30 h. It can be observed that the abnormal data segments identified by the three algorithms had high consistency. This finding demonstrates the effectiveness of these algorithms in detecting abnormal power consumption based on the characteristics of the dataset.

In terms of DTW-LOF, six abnormal subsequences were identified, with durations from 1 day to 5 days with an average of 52 h. DIF identified 16 subsequences as abnormal, ranging from 1 hour to over 4 days and span 20 h on average. AT detected 26 subsequences, each lasting between 1 and nearly 2 days with an average duration of 12 h. The variations in the number of identified subsequences and their durations can be attributed to the underlying principles of the algorithms. DTW-LOF transformed the problem into point anomaly detection by partitioning the data into equal-length intervals. This method determined the degree of anomalies based on the density of the neighborhood around each interval, placing greater emphasis on detecting anomalies within smaller, local regions of the data. DIF utilized a deep neural network to extract data features autonomously and focus on the high-dimensional feature distribution of the data. It isolated anomalies by analyzing the hierarchical structures within the data and excels at detecting anomalies that manifest as deviations from the typical distribution of learned features. AT measured the difference in association patterns between normal and abnormal time points. This allows for a nuanced detection of anomalies that are subtle and not just based on feature-level anomalies or local density changes, but are also contextually unusual in the time series. As a result, it is capable of capturing a wider range of subtle and context-dependent deviations. Each of the three algorithms brings a distinct strength to generate a better-rounded response for anomaly detection.

According to Fig. 9(d), the proposed method successfully identified both short and long periods where energy consumption dropped to zero, as well as unusual changes compared to surrounding periods. The reasons for the anomalies can be summarized as follows. First, the cooling system suddenly shuts down, resulting in energy consumption falling from the normal level to a state close to zero. This can be due to system failures or human errors. Second, corporations often operate differently during holidays. For example, in early October 2022, when it was the National Day holiday, the factory stopped production activities; this resulted in a significant decrease in energy demand. The energy consumption stayed close to zero for an extended period, which dif-

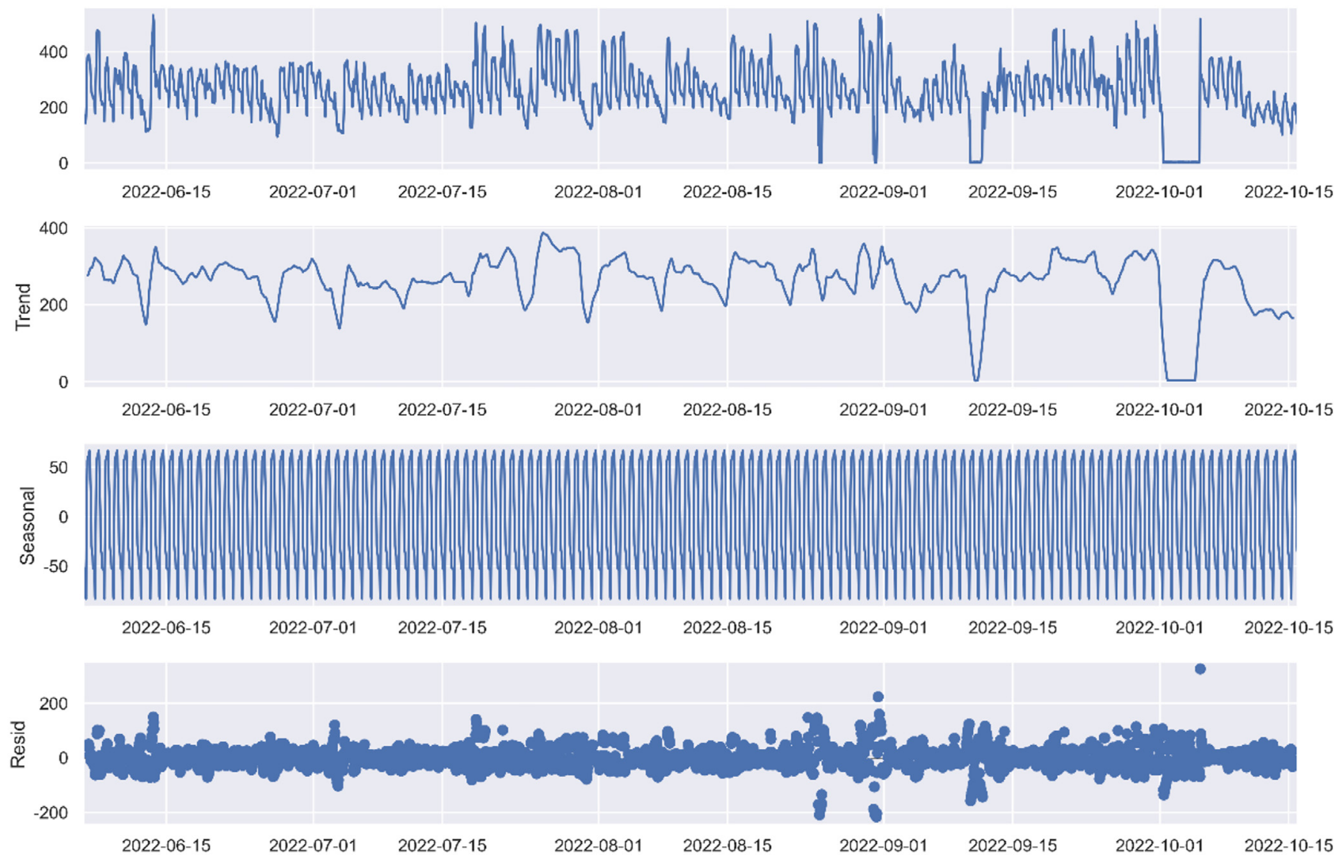


Fig. 7. Energy time series data decomposition of Building A.

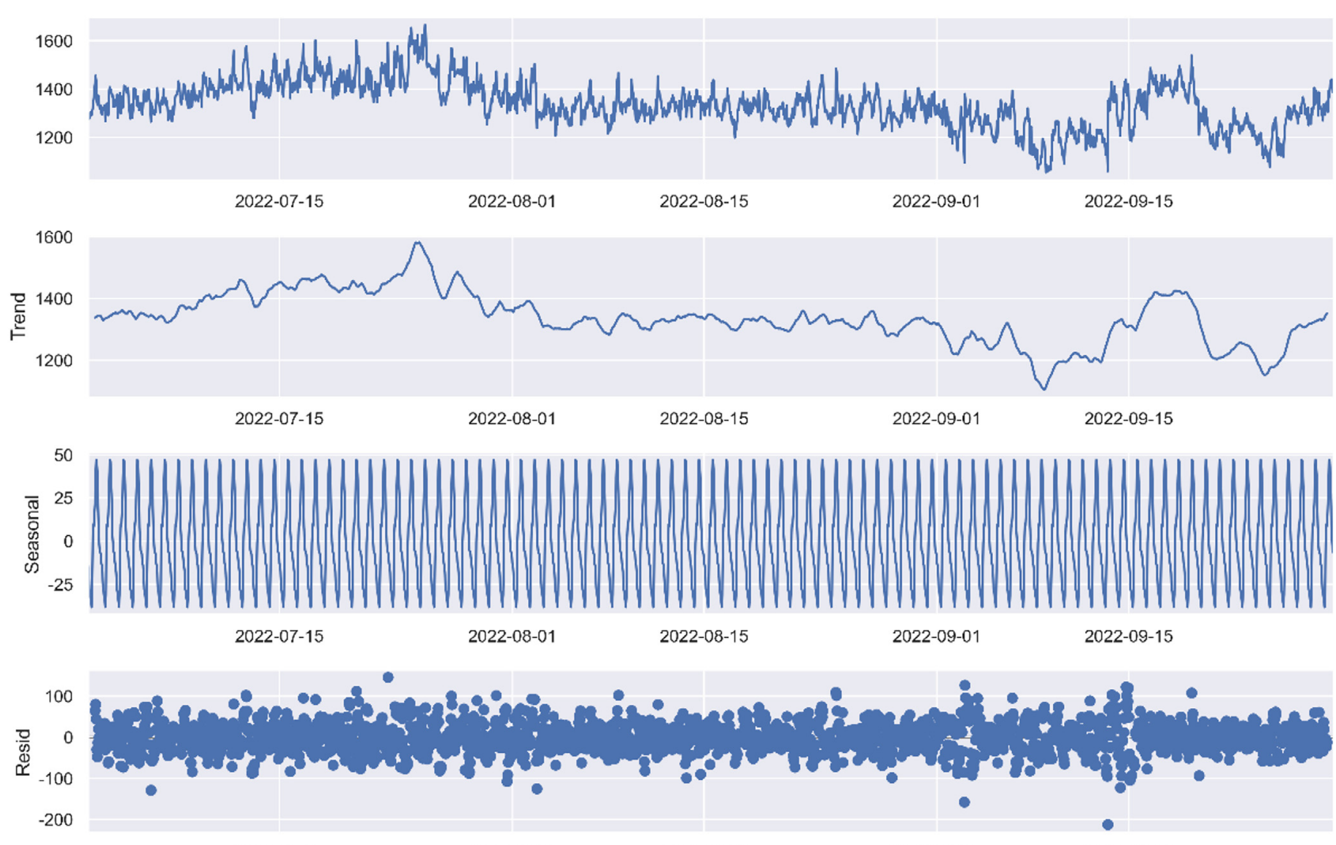
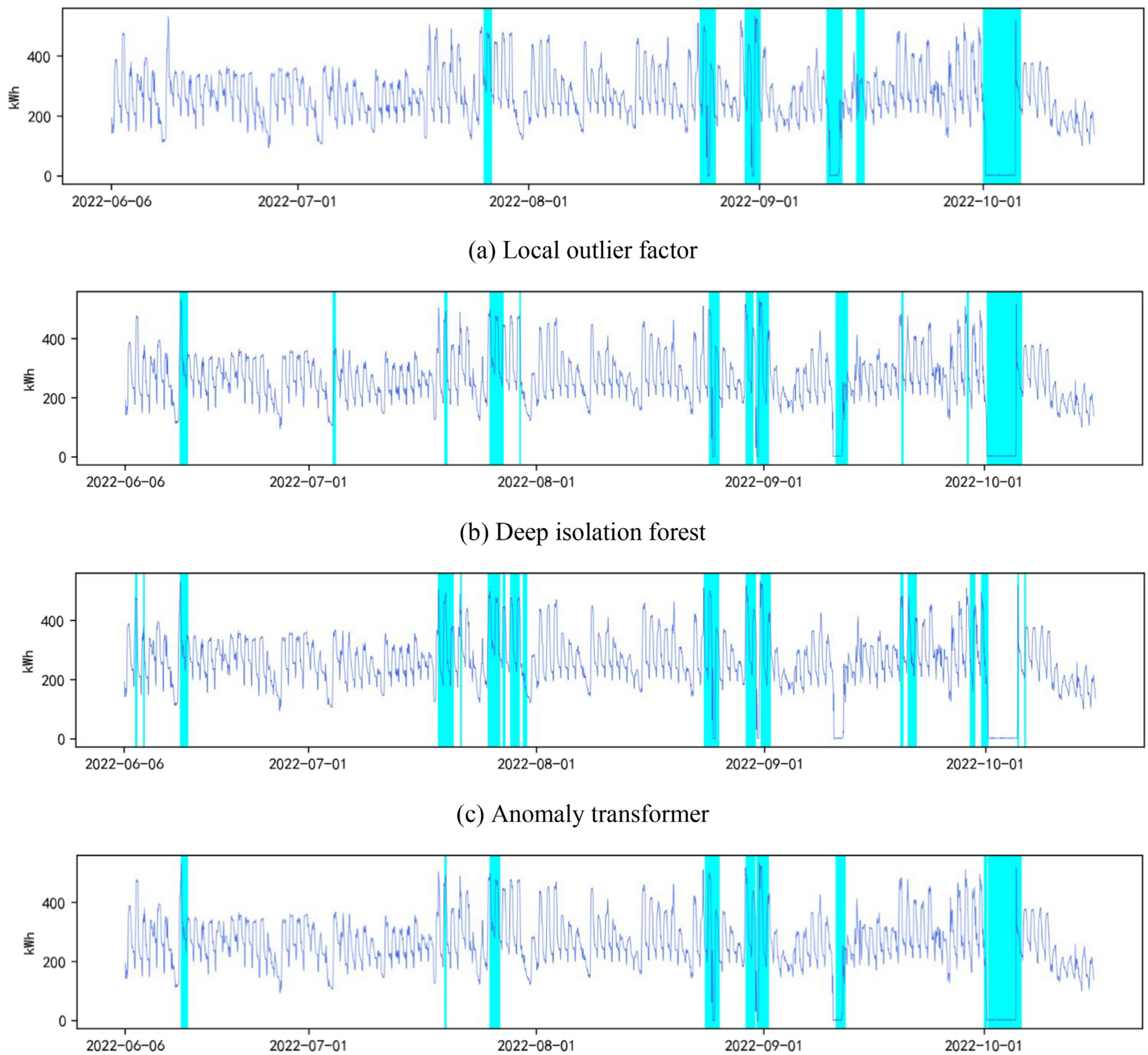


Fig. 8. Energy time series data decomposition of Building B.



(a) Local outlier factor

(b) Deep isolation forest

(c) Anomaly transformer

(d) Ensemble method

Fig. 9. Anomaly detection results of Building A (blue intervals: anomalous subsequences).

fered from normal operation status. Thus, the corresponding time series subsequence is rendered as abnormal by the detection method. Third, changes in meteorological conditions can influence cooling energy demand. For example, on June 13, 2022, the outdoor temperature initially rose to a high level and led to a relatively steep increase in energy consumption over a short period. Subsequently, as temperature dropped, energy consumption also declined. Such changes differed from the surrounding days, where changes were more gradual.

Similarly, Fig. 10 shows the anomaly detection results for Building B. A total of 7 subsequences accounted for approximately 5.8% of the total data detected as abnormal. The average duration was about 18 h. DTW-LOF identifies 11 subsequences, ranging from 12 h to 48 h, with an average of 20 h. For DIF, 8 subsequences were identified, with durations from 1 hour to 3 days and an average of 27 h. AT detects 21 subsequences, each lasting between 1 and nearly 2 days with an average duration of 10 h. Compared to Building A, the final anomaly detection ratio of ensemble methods is reduced, which deems a relatively lower consistency among the three selected algorithms. This outcome relates to the energy usage behaviors and data characteristics of different buildings. As previously noted, the peak-shaped curve of Building A exhibited a noticeable periodicity throughout the day. In contrast, the energy consumption curve in the jagged shape of building B showed irregular variations, making anomaly detection more challenging—particularly for AT, which is sensitive to neighborhood variations. This finding further demonstrates the need of using ensemble methods to improve the accuracy of anomaly detection, as the applicability of algorithms is affected by the acquired data.

Fig. 10(d) shows the results by integrating the detected anomalies of three algorithms. The anomalies mostly came from subsequences that significantly altered the trend of the power consumption, as well as sudden increases or decreases of data points in the dataset. Such anomalies are potentially caused by uncommon increases or decreases in system

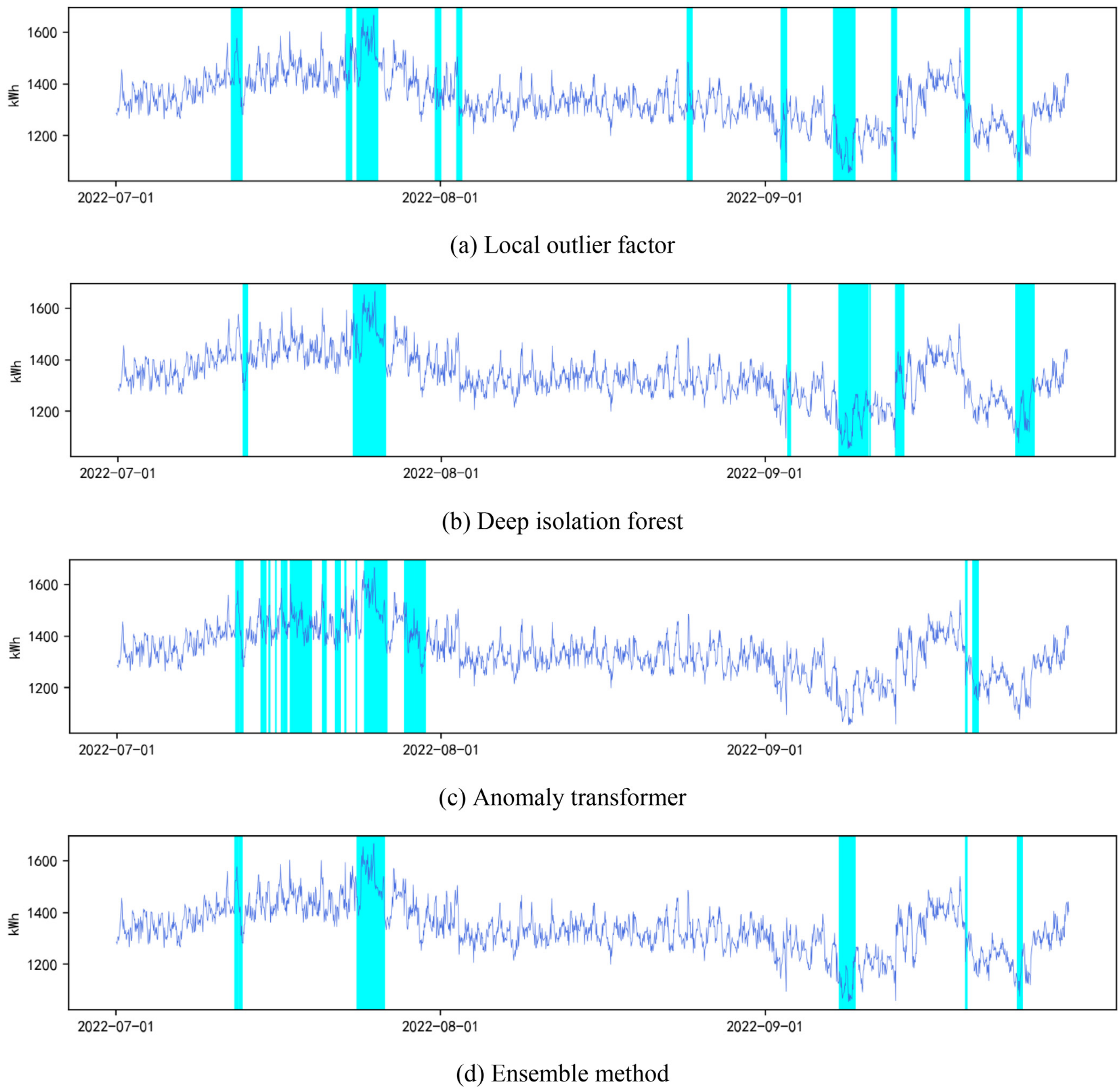


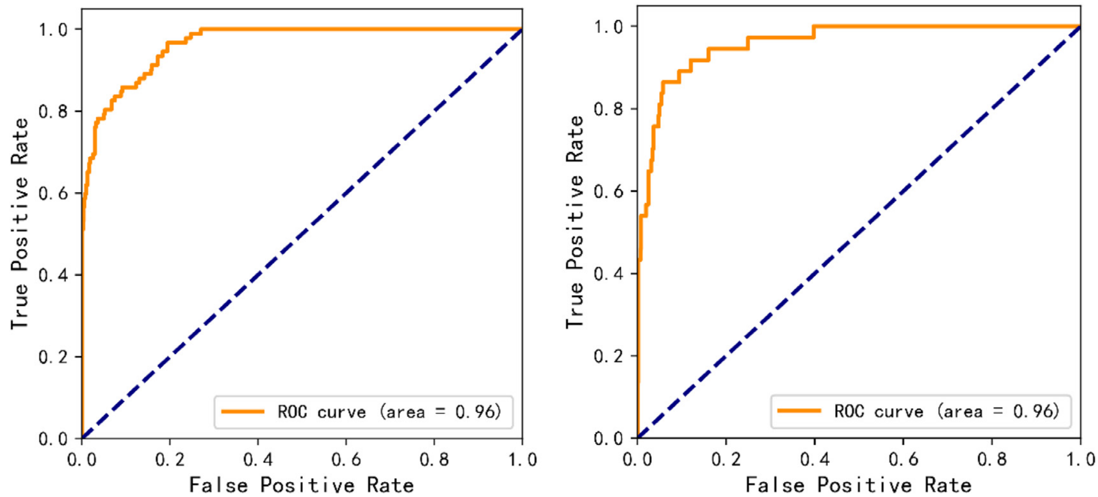
Fig. 10. Anomaly detection results of Building B (blue intervals: anomalous subsequences).

output during those periods. For example, the operating frequency of the freezing pump remained at 50 Hertz for most of the day from July 24 to 27, but on adjacent days, it was typically lower at night. Consequently, this resulted in an overall higher level of energy consumption during this period. Another cause lies in the changes in meteorological conditions, such as the lower dew point temperatures on September 8 and 9, 2022 than on adjacent days. When temperatures are similar, a lower dew point temperature is likely to result in reduced humidity and less demand for cooling energy [51].

4.4. Interpretation of anomalous subsequences

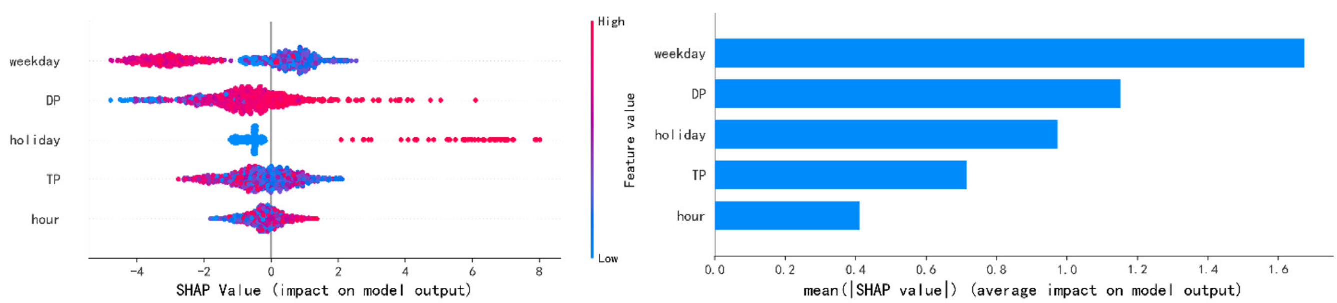
After detecting anomalous subsequences of energy consumption with unsupervised learning, explicit analysis becomes crucial for understanding the underlying reasons and their implications. Hence, this section employed the XGBoost model to provide clear insights into the factors contributing to the occurrence of these anomalies. The dataset is divided into a training set and a test set with a 7:3 ratio. The input variables consisted of (1) weather parameters: temperature and dew point temperature; (2) time parameters: day of the week, hour of the day, and holiday. By designating the label as the one predicted most frequently, the output variable for each timestamp is marked as either 0 (normal) or 1 (abnormal). This study relies on the grid search method to obtain optimal parameters and enhance prediction accuracy. Considering the importance and time complexity of each parameter, the ranges and corresponding optimal values are presented in Table 4.

After training the model, the classification performance of the XGBoost model was verified on the test set. Considering the imbalance of the dataset due to abnormal samples comprising only a small proportion of the total samples, the study selected AUC as the metric for evaluat-



(a) Building A (b) Building B

Fig. 11. ROC curves and corresponding AUC values.



(a) Individual SHAP values (b) Mean of absolute SHAP values

Fig. 12. Individual SHAP values and average absolute SHAP Values of Building A (DP=dew point temperature; TP=temperature).

Table 4
Grid search range and optimal values in the XGBoost model.

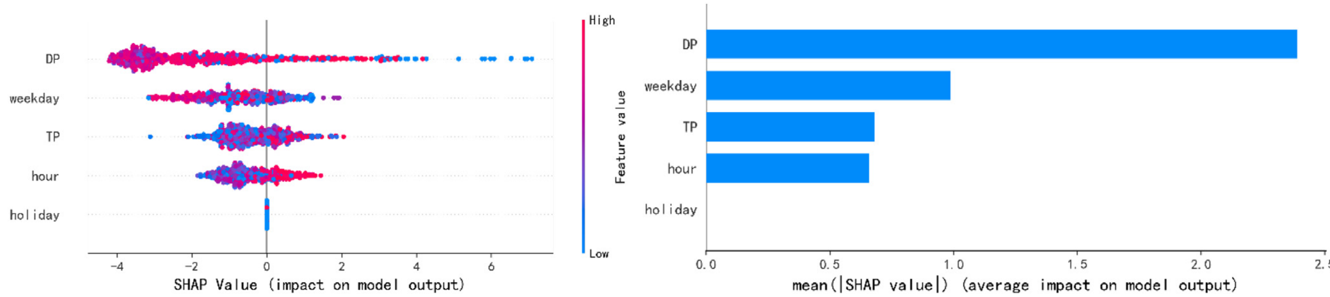
Parameter	Grid search range	Building A	Building B
max_depth	[3, 4, 5]	5	5
learning_rate	[0.01, 0.015, 0.025, 0.05, 0.1]	0.1	0.1
n_estimators	[100, 200, 300, 500]	300	300

ing model performance. Unlike other indicators such as precision and recall, AUC is insensitive to the imbalanced sample distribution and remains unaffected by the classification threshold. As illustrated in Fig. 11, the AUC values are both 0.96, respectively, indicating that the XGBoost model adeptly predicts the classes of hourly energy consumption data for the two industrial buildings.

The contribution of different input features to the model is evaluated by SHAP values. Each point in Fig. 12(a) represents a data point of Building A, where a higher absolute SHAP value suggests a stronger potential association with anomalous behavior. Fig. 12(b) shows the overall impact on model output by calculating the average absolute values for each feature. Similar visualizations are presented in Fig. 13 for Building B. In both industrial buildings, the day of the week and dew point temperature were deemed critical due to their extensive range in SHAP values and their high average impact. Variations in these two features significantly influence the model output and are closely linked to changes in energy consumption in industrial buildings. For Building A, holidays are also important variables since energy use behavior tend to undergo significant changes during these periods. While temperature also influences energy consumption, its impact is comparatively less pronounced. Given the emphasis on anomalous data over a period, the hour variable appears to hold lower importance in both buildings.

This study automates the detection of anomalous cooling electricity usage within energy time series data. The preliminary interpretation of the detection results closely aligns with the quantitative results derived from SHAP values. In summary, the anomalies can be attributed to several factors. First, holidays and other special days lead to changes in enterprise production and operational behaviors, thus deviating from usual patterns. Second, equipment malfunctions or human errors result in abnormal system outputs. Third, sudden changes in external weather conditions lead to sharp increases or decreases in electricity consumption, inconsistent with adjacent periods.

The performance of the unsupervised anomaly detection framework has been validated through case studies on two buildings, which represent different types of industrial settings. However, this study is constrained by the relatively small number of buildings analyzed. The limited dataset may affect the adaptability of the proposed method across various industrial contexts, highlighting the need to include more buildings for better generalizing the results. Furthermore, incorporating on-



(a) Individual SHAP values (b) Mean of absolute SHAP values

Fig. 13. Individual SHAP values and average absolute SHAP Values of Building B (DP=dew point temperature; TP=temperature).

line learning in future research could enhance the timeliness of anomaly detection by enabling real-time data updates.

5. Conclusions

Anomaly detection is critical for industrial building operators, as it helps discover improper operations and improve energy efficiency. This study proposes an unsupervised anomaly detection method tailored for industrial buildings, which is capable of filtering unwanted point anomalies and pinpointing abnormal periods of interest. Three distinct algorithms were used for subsequence anomaly detection and integrated to generate the final predictions. To provide deeper insights into the detection results and investigate the factors driving anomalous electricity consumption, an XGBoost classifier was developed. Overall, the methodology proposed in this study enables building managers to identify key factors influencing energy consumption, provide fault warnings, and implement timely corrective measures. This approach does not require real anomaly labels or complex parameters, making it directly applicable to other buildings with accessible energy consumption data. Through the analysis of cooling energy consumption data from two manufacturing companies, the following conclusions were drawn.

(1) In real-world building energy data, the occurrence of missing values is often not random. The transformer-based imputation method demonstrated superior performance in reconstructing missing building energy data compared to simple methods. The MAPE of the two cases is reduced by an average of 9.9% and 1.3%, respectively.
(2) The proposed method effectively detects abnormal energy consumption and can be incorporated into building management systems to enhance fault detection and diagnosis, energy-efficient operation, and streamlined management. Compared with a single unsupervised algorithm, the ensemble of DTW-LOF, DIF, and AT can increase the effectiveness and accuracy of subsequence anomaly detection.
(3) The anomaly ratios of Building A and Building B are 9.5% and 5.8%, respectively. These anomalies can be attributed to factors including operational changes during holidays, unexpected fluctuations in weather conditions, and equipment malfunctions. These factors lead to distinct gaps in the energy consumption subsequences, which are identified as abnormal patterns.
(4) The XGBoost classifier performs well in prediction tasks, and the AUC of the two buildings both exceeds 0.96. The SHAP analysis of the developed classifier shows that the day of the week and dew point temperatures are major impact factors on the status of energy consumption, while the hour of the day is deemed less critical. This insight directs attention toward features at longer time scales and uncommon meteorological changes for predicting anomalous periods in industrial building energy.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Yi Song: Writing – original draft, Methodology, Formal analysis. **Sennan Kuang:** Visualization, Investigation, Data curation. **Junling Huang:** Resources, Conceptualization. **Da Zhang:** Writing – review & editing, Supervision, Conceptualization.

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References

[1] International Energy Agency, Buildings - energy system, Accessed: July 11, 2023. Available: http://www.iea.org/energy-system/buildings.
[2] S. Kapp, J.K. Choi, T. Hong, et al., Predicting industrial building energy consumption with statistical and machine-learning models informed by physical system parameters, Renewable Sustainable Energy Rev. 172 (2023), doi:10.1016/j.rser.2022.113045.
[3] C. Kaymakci, S. Wenninger, A. Sauer, et al., Energy anomaly detection in industrial applications with long short-term memory-based autoencoders, in: the 54th CIRP Conference on Manufacturing Systems, 2021, pp. 182–187, doi:10.1016/j.procir.2021.11.031.
[4] J.Y. Park, Z. Nagy, Comprehensive analysis of the relationship between thermal comfort and building control research - a data-driven literature review, Renewable Sustainable Energy Rev. 82 (3) (2018) 2664–2679, doi:10.1016/j.rser.2017.09.102.
[5] R.J. Meyers, E.D. Williams, H.S. Matthews, Scoping the potential of monitoring and control technologies to reduce energy use in homes, Energ. Build. 42 (5) (2010) 563–569, doi:10.1016/j.enbuild.2009.10.026.
[6] C. Fan, F. Xiao, Y. Zhao, et al., Analytical investigation of autoencoder-based methods for unsupervised anomaly detection in building energy data, Appl. Energy 211 (1) (2018) 1123–1135, doi:10.1016/j.apenergy.2017.12.005.
[7] D.M. Hawkins, Monographs on statistics and applied probability, identification of outliers, 1980. Available: https://link.springer.com/book/10.1007/978-94-015-3994-4.
[8] V. Chandola, A. Banerjee, V. Kumar, Anomaly detection: a survey, ACM Comput. Surv. 41 (3) (2009) 1–58, doi:10.1145/1541880.1541882.
[9] A. Blázquez-García, A. Conde, U. Mori, et al., A review on outlier/anomaly detection in time series data, ACM Comput. Surv. 54 (3) (2021) 1–33, doi:10.1145/3444690.
[10] K.H. Lai, D. Zha, J. Xu, et al., Revisiting time series outlier detection: definitions and benchmarks, the 35th Conference on Neural Information Processing Systems, 2021.
[11] A. Alghanmi, A. Yunusa-Kaltugo, A whole-building data-driven fault detection and diagnosis approach for public buildings in hot climate regions, Energy Built Environ. 5 (6) (2024) 911–932, doi:10.1016/j.enbenv.2023.07.005.
[12] M.D. Nadai, M.V. Someren, Short-term anomaly detection in gas consumption through ARIMA and Artificial Neural Network forecast, in: 2015 IEEE Workshop on Environmental, Energy, and Structural Monitoring Systems (EESMS) Proceedings, Trento, Italy, 2015, pp. 250–255, doi:10.1109/EESMS.2015.7175886.

[13] D.B. Araya, K. Grolinger, H.F. Elyamany, et al., An ensemble learning framework for anomaly detection in building energy consumption, Energy Build. 144 (1) (2017) 191–206, doi:10.1016/j.enbuild.2017.02.058.
[14] T. Pourhabibi, K.L. Ong, B.H. Kam, et al., Fraud detection: a systematic literature review of graph-based anomaly detection approaches, Decis. Support. Syst. 133 (2020), doi:10.1016/j.dss.2020.113303.
[15] C. Fan, Y. Lin, M.S. Piscitelli, et al., Leveraging graph convolutional networks for semi-supervised fault diagnosis of HVAC systems in data-scarce contexts, Build. Simul. 16 (2023) 1499–1517, doi:10.1007/s12273-023-1041-1.
[16] C. Zhang, J. Lu, Y. Zhao, Generative pre-trained transformers (GPT)-based automated data mining for building energy management: advantages, limitations and the future, Energy Built Environ. 5 (1) (2024) 143–169, doi:10.1016/j.enbenv.2023.06.005.
[17] M.S. Piscitelli, S. Brandi, A. Capozzoli, et al., A data analytics-based tool for the detection and diagnosis of anomalous daily energy patterns in buildings, Build. Simul. 14 (2021) 131–147, doi:10.1007/s12273-020-0650-1.
[18] A. Capozzoli, M.S. Piscitelli, S. Brandi, et al., Automated load pattern learning and anomaly detection for enhancing energy management in smart buildings, Energy 157 (2018) 336–352, doi:10.1016/j.energy.2018.05.127.
[19] Z. Qu, H. Liu, Z. Wang, et al., A combined genetic optimization with AdaBoost ensemble model for anomaly detection in buildings electricity consumption, Energy Build. 248 (2021), doi:10.1016/j.enbuild.2021.111193.
[20] L. Lei, B. Wu, X. Fang, et al., A dynamic anomaly detection method of building energy consumption based on data mining technology, Eng 263 (A) (2023), doi:10.1016/j.energy.2022.125575.
[21] W. Lim, K. Yong, B.T. Lau, et al., Future of generative adversarial networks (GAN) for anomaly detection in network security: a review, Comput. Secur. 139 (2024), doi:10.1016/j.cose.2024.103733.
[22] Y. Himeur, K. Ghanem, A. Alsalemi, et al., Artificial intelligence based anomaly detection of energy consumption in buildings: a review, Curr. Trends New Perspect., Appl. Energy 287 (2021), doi:10.1016/j.apenergy.2021.116601.
[23] X. Liu, Y. Ding, H. Tang, et al., A data mining-based framework for the identification of daily electricity usage patterns and anomaly detection in building electricity consumption data, Energy Build. 231 (2021), doi:10.1016/j.enbuild.2020.110601.
[24] J.S. Chou, A.S. Telaga, Real-time detection of anomalous power consumption, Renewable Sustainable Energy Rev. 33 (2014) 400–411, doi:10.1016/j.rser.2014.01.088.
[25] C. Xu, H. Chen, A hybrid data mining approach for anomaly detection and evaluation in residential buildings energy data, Eng. Build. 215 (2020), doi:10.1016/j.enbuild.2020.109864.
[26] Y. Weng, N. Zhang, C. Xia, Multi-agent-based unsupervised detection of energy consumption anomalies on smart campus, IEEE Access. 7 (2019) 2169–2178, doi:10.1109/ACCESS.2018.2886583.
[27] C. Bülte, M. Kleinebrahm, H.Ü. Yilmaz, et al., Multivariate time series imputation for energy data using neural networks, Energy AI 13 (2023), doi:10.1016/j.egyai.2023.100239.
[28] S. Jung, J. Moon, S. Park, et al., Bagging ensemble of multilayer perceptrons for missing electricity consumption data imputation, Sensors 20 (6) (2020) 1772, doi:10.3390/s20061772.
[29] A. Lotfipoor, S. Patidar, D.P. Jenkins, Transformer network for data imputation in electricity demand data, Energy Build. 300 (2023), doi:10.1016/j.enbuild.2023.113675.
[30] Z. Sun, H. Li, W. Wang, J. Liu, et al., DTIN: dual Transformer-based Imputation Nets for multivariate time series emitter missing data, Knowl. Based. Syst. 284 (2024), doi:10.1016/j.knosys.2023.111270.
[31] W. Fu, Y. Fu, B. Li, et al., A compound framework incorporating improved outlier detection and correction, VMD, weight-based stacked generalization with enhanced DESMA for multi-step short-term wind speed forecasting, Appl. Eng. 348 (2023), doi:10.1016/j.apenergy.2023.121587.
[32] D.C. Hoaglin, B. Iglewicz, Fine-tuning some resistant rules for outlier labeling, J. Am. Stat. Assoc. 82 (400) (1987) 1147, doi:10.2307/2289392.
[33] M. Hubert, E. Vandervieren, An adjusted boxplot for skewed distributions, Comput. Stat. Data Anal. 52 (12) (2008) 5186–5201, doi:10.1016/j.csda.2007.11.008.
[34] S. Bhattacharya, F. Kamper, J. Beirlant, Outlier detection based on extreme value theory and applications, Scand. J. Stat. 50 (3) (2023) 1466–1502, doi:10.1111/sjos.12665.
[35] C.H. Sim, F.F. Gan, T.C. Chang, Outlier labeling with boxplot procedures, J. Am. Stat. Assoc. 100 (470) (2005) 642–652, doi:10.1198/016214504000001466.
[36] A. Vaswani, N. Shazeer, N. Parmar, et al., in: Attention is All You Need, Curran Associates Inc., USA, 2017, pp. 600–611, doi:10.48550/ARXIV.1706.03762.
[37] W. Du, D. Côté, Y. Liu, SAITS: self-attention-based imputation for time series, Expert. Syst. Appl. 219 (2023), doi:10.1016/j.eswa.2023.119619.
[38] D. Zou, Y. Xiang, T. Zhou, et al., Outlier detection and data filling based on KNN and LOF for power transformer operation data classification, Energy Rep. 9 (7) (2023) 698–711, doi:10.1016/j.egyr.2023.04.094.
[39] A. Tirulo, S. Chauhan, B. Issac, Ensemble LOF-based detection of false data injection in smart grid demand response system, Comput. Electr. Eng. 116 (2024), doi:10.1016/j.compeleceng.2024.109188.
[40] J. Wang, J. Cao, Z. Liu, Unsupervised machine learning-based multi-attributes fusion dim spot subtle sandstone reservoirs identification utilizing isolation forest, Geoenergy Sci. Eng. 234 (2024), doi:10.1016/j.geoen.2023.212626.
[41] H. Xu, G. Pang, Y. Wang, Deep isolation forest for anomaly detection, IEEE Trans. Knowl. Data Eng. 35 (2023), doi:10.48550/arXiv.2206.06602.
[42] R. Baidya, H. Jeong, Anomaly detection in time series data using reversible instance normalized anomaly transformer, Sensors 23 (22) (2023), doi:10.3390/s23229272.
[43] J. Xu, H. Wu, J. Wang, et al., Anomaly transformer: time series anomaly detection with association discrepancy, Paper presented at the Tenth International Conference on Learning Representations, 2023.
[44] T.B. Chandra, K. Verma, B.K. Singh, et al., Coronavirus disease (COVID-19) detection in Chest X-Ray images using majority voting based classifier ensemble, Expert. Syst. Appl. 165 (2021), doi:10.1016/j.eswa.2020.113909.
[45] C. Wu, H. Pan, Z. Luo, et al., Multi-objective optimization of residential building energy consumption, daylighting, and thermal comfort based on BO-XGBoost-NSGA-II, Build. Environ. 254 (2024), doi:10.1016/j.buildenv.2024.111386.
[46] L. Zhang, D. Jánošíkm, Enhanced short-term load forecasting with hybrid machine learning models: CatBoost and XGBoost approaches, Expert. Syst. Appl. 241 (2024), doi:10.1016/j.eswa.2023.122686.
[47] K. Oksuz, B.C. Cam, S. Kalkan, Akbas, et al., Imbalance problems in object detection: a review, IEEE Trans. Pattern Anal. Mach. Intell. 43 (10) (2021) 3388–3415, doi:10.1109/TPAMI.2020.2981890.
[48] X. Cui, M. Lee, C. Koo, et al., Energy consumption prediction and household feature analysis for different residential building types using machine learning and SHAP: toward energy-efficient buildings, Eng. Builds 309 (2024), doi:10.1016/j.enbuild.2024.113997.
[49] H. Setchell, ECMWF Reanalysis V5, ECMWF, 2020 Accessed: Nov 15, 2024. Available:http://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5.
[50] M. Han, F. Johari, P. Huang, et al., Generating hourly electricity demand data for large-scale single-family buildings by a decomposition-recombination method, Energy Built Environ. 4 (4) (2023) 418–431, doi:10.1016/j.enbenv.2022.02.011.
[51] L. Jia, J. Liu, C. Wang, et al., Study of the thermal performance of a novel dew point evaporative cooler, Appl. Therm. Eng. 160 (2019), doi:10.1016/j.applthermaleng.2019.114069.