Anomaly Electricity Usage Behavior

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Due to the climate crisis, energy-saving issues and carbon reduction have become the top priority for all countries. Owing to the increasing popularity of advanced metering infrastructure and smart meters, the cost of acquiring data on residential electricity consumption has substantially dropped. This change promotes the analysis of residential electricity consumption, which features both small and complicated consumption behaviors, using machine learning to become an important research topic among various energy saving and carbon reduction measures.

energy saving carbon reduction

1. Introduction

Owing to the depletion of fossil energy and increasingly serious global warming problems, the effective decrease in fossil energy consumption and energy and carbon reduction has become a common concern for governments and enterprises around the world. According to the data from the Bureau of Energy, Ministry of Economic Affairs of Taiwan, sectors that consumed the most energy in Taiwan were the industrial (55.9%), service (17.7%), and residential sectors (17.6%). The data clearly indicated that the electricity consumption of the residential sector was the third highest, only slightly lower than that of the service sector. Therefore, if the electricity consumption of the residential sector can be effectively reduced, considerable energy-saving benefits will be achieved. However, unlike the industrial and service sectors that comprise medium and large users, the residential sector comprises a large number of small users (approximately 13.2 million non-business users and 1.03 million business users of low-voltage meters). In addition, the electricity consumption behaviors of different users vary significantly, complicating the development of a universal energy-saving strategy for residential users. Fortunately, in recent years, information and communication technology has developed rapidly; mobile devices, mobile networks, and Internet of Things (IoT) devices have gained a significant amount of popularity. Furthermore, power companies have actively promoted the advanced metering infrastructure (AMI) and smart meters to replace the existing mechanical meters for understanding the power-load behavior of low-voltage users quickly and efficiently.

The cost of collecting the electricity consumption data of low-voltage users decreases every year, and related energy management systems and devices are gradually implemented. Despite this, residential users lack the motivation to apply energy saving and carbon reduction measures and introduce home energy management systems (HEMS) due to the low electric valance in Taiwan. Therefore, some research [1][2][3][4][5][6][7][8][9][10][11][12][13] has begun using machine learning techniques to collect and analyze the electricity consumption data of residential users and establish artificial intelligence (AI) models to provide appropriate and tailored energy-saving suggestions. Among them, if a mechanism can identify the abnormal electricity consumption behavior of residential users and propose appropriate energy management or saving suggestions, it will be particularly effective in improving user motivation in terms of energy-saving measures. Therefore, various anomaly detection techniques for the energy consumption of residential users and buildings have been proposed and discussed.

At present, the studies predominantly use the low-level feature data (i.e., the row data without being extracted), including electricity consumption data and associated features (temperature and humidity, summer/non-summer months, working/non-working days, etc.) to train machine learning models. However, the significant number of dimensions and a large amount of redundant information of these low-level features can compromise the training performance of subsequent anomaly detection algorithms. Although techniques such as principal component analysis (PCA) and feature selection can be adopted to improve this issue, how to provide a more efficient solution is still an important research topic. Therefore, this entry further discusses this topic. In summary, this entry wants to improve a method to extract the essences of the low-level features by using a deep neural network-autoencoder. That is, this entry wants to use the autoencoder to extract the high-level features (i.e., code in the autoencoder) from the low-level features of the electricity consumption data of residential users. As the high-level features can decode to the original low-level features and the dimensions of the high-level features are less than those of the low-level features, the high-level features are more representative of the power consumption behaviors of users. That is, the high-level features are the essence of the user's power consumption data. This entry uses the actual power consumption data of the five resident users to execute the experiments to verify whether using the high-level features to train the anomaly detection algorithm can benefit performance over using the low-level features. Researchers use an anomaly detection algorithm, one-class SVM, to train the two anomaly detection models with the high-level and low-level features, respectively, and then analyze the performances of the two models to verify the feasibility of the proposed high-level feature extraction method.

2. Anomaly Detection

As early as the 19th century, the statistical community had already started detecting anomalies in data. Anomalies are also referred to as outliers, biases, inconsistencies, and exceptions [14]. Anomalies typically include (1) point, (2) contextual, and (3) collective anomalies. The detection of point anomalies is the most simple and common anomaly detection method and strategy. However, rather than a pattern, point anomalies often represent a noise and consequently possess a low practical value. Alternatively, contextual anomalies are typically analyzed in a specific time sequence and spatial data to determine abnormal behaviors in the specific context, whereas collective anomalies often analyze group data comprising multiple pieces and evaluate whether the resultant model is anomalous. The occurrence of contextual anomalies depends on the availability of contextual attributes in the data. Therefore, when point anomaly detection is supplemented with contextual anomaly detection or part of the group data are categorized as contextual attributes, both point and collective anomalies are considered equivalent to contextual anomalies. Consequently, during anomaly detection, most studies convert anomaly events to contextual anomalies for analysis and processing. Anomaly detection strategies can be divided, according to the inclusion of labels in the analysis datasets, into three types: (1) supervised, (2) unsupervised, and (3) semi-supervised.

The primary techniques adopted by the existing literature to detect abnormal power consumption behaviors include [15] (1) anomaly detection models based on regression models, (2) anomaly detection models based on classifiers, and (3) others.

Anomaly detection models based on regression models first train the regression model using historical power-related data and then use the model to predict future consumption. An anomaly is detected upon a large deviation between the predicted and actual values (for example, the actual value is greater than the predicted threshold). Zhang et al. [16] developed an abnormal electricity load detection model based on a linear regression model and used its predications as the baseline. Power consumption data were considered abnormal when either significantly lower or higher than the threshold. Although the entry provided a load anomaly detection solution that incorporated environmental factors, it could not accurately identify anomalies for residential users owing to their sensitivity to temperature. In addition, as the model was only trained with environmental factors, it might be inapplicable in an environment with a constant annual temperature. Alternatively, Zhou et al. [17] proposed an anomaly detection model based on a hybrid prediction model. The hybrid model integrated the ARIMA model with the ANN model, compensating the prediction error of the former in nonlinear regression and providing the advantages of both linear and nonlinear models. Although this approach improved the prediction accuracy, the anomaly detection strategy used was excessively simple and required further improvement. To eliminate detection errors caused by simple detection methods, Luo et al. [18] proposed an anomaly detection model based on dynamic regression. Instead of a fixed threshold, the model could calculate a dynamic, adaptive threshold for the difference between the predicted and actual loads during anomaly detection. The proposed dynamic-detection rule could improve the accuracy of anomaly detection. However, because the entry used the results of the prediction model as the only reference for anomaly detection, an independent detection mechanism was lacking for anomaly detection, risking a decrease in anomaly detection accuracy when the prediction value was inaccurate. Fenza et al. developed a drift-aware methodology for detecting anomalies in smart grids [19]. Historical data were used to train the long short-term memory (LSTM) and then to determine the anomaly detection thresholds from the prediction error trends obtained by the LSTM over time. As the entry aimed to explore the abnormal load profile of users, the basis of anomaly detection was the error trend rather than the error between the predication and actual result for a specific time. Inayah et al. [20] used SARIMA and ANN models to predicate power consumption of the college buildings, and they adopted the difference between the actual and prediction values to identify the anomaly events. Then, the results of the experiment proved that the ANN model has a better performance than the SARIMA model. Additionally, it is noteworthy that this kind of anomaly detection technology can also be used to protect the cybersecurity issue. For example, Zhang et al. [21] proposed a robustness assessment framework for wind power, and they evaluated the performances of the six forecasting models in terms of protection against the false data injection attack.

Anomaly detection models based on classifiers can be further divided into supervised and unsupervised/semi-supervised models according to the type of classifier. Jokar et al. developed an anomaly detection model for power theft based on supervised learning [22]. During the training process, the k-means cluster analysis algorithm and silhouette coefficient determined the number of patterns in the dataset, and an SVM-based classifier learned the normal and abnormal patterns. Pinceti et al. [23] conducted a model comparison study, during which different supervised learning models detected abnormal load redistribution events. After comparing kNN, SVM, and RNN models, the entry suggested that the performance of the kNN model was superior. Fang et al. [24] adopted the extreme learning machines and the ensemble learning strategy to design a supervised learning anomaly detection system for various users (i.e., the low-voltage non-resident, the low-voltage resident, the high-voltage resident, and the photovoltaic user). Wang et al. [25] proposed a semi-supervised learning anomaly detection model, sample efficient home power anomaly detection (SEPAD), in which the k-means and z-score function [26] were used to point out the suspicious data, and a semi-SVM based pattern matching algorithm was proposed to identify anomaly power consumption events. Hosseini et al. [27] focused on the appliance-level anomaly detection and trained the classification modes by using the operation patterns for the refrigerators depending on the semi-supervised learning strategy. Fan et al. [28] proposed a building electricity anomaly detection model based on unsupervised classification to reduce the training cost lower than that of supervised learning-based models. The entry first determined the primary load frequency of users using spectral density analysis and features affecting the electricity consumption behavior using a decision tree, and then calculated the anomaly score of each event using the autoencoder, which is an unsupervised learning model, and ensemble learning. An event was defined as an anomaly if its anomaly score was higher than the preset threshold. Pereora et al. [29] developed an autoencoder-based unsupervised anomaly detection model for detecting anomalies in solar power generation. They also applied a variational self-attention mechanism to improve the performance of the autoencoder. Although anomaly detection techniques based on unsupervised learning do not require additional training to identify abnormal data, and therefore have a low training cost, evaluating their detection results is difficult due to the lack of reference labels [30]. Additional analysis (such as normal distribution analysis, data visualization analysis, and consulting domain experts) is often required to verify that the specific event is an anomaly.

Others include Janetzko et al. [31], who used the visual analysis to identify the anomaly power consumption events. The study [32] adopted the Hilbert-Huang transform and instantaneous frequency analysis to analyze the hidden anomaly events in commercial buildings. Cabrera et al. [33] adopted an anomaly detection method based on rule-based learning to analyze the waste of electricity in school buildings. They reduced the number of features using data mining methods and introduced various rules to identify wasteful behaviors. Li [34] uses statistical methods and clustering algorithms to identify the anomaly power consumption events in the short-term and long-term time scale data, respectively.

3. Autoencoder

An autoencoder [35][36] is an unsupervised learning algorithm in deep learning. The model is trained by defining the data (X) and output data (Y). According to the neural network architecture, an autoencoder comprises an encoder and decoder, which have neural networks with the same number of neurons. The encoder converts the input data into high-level features (Z) through the hidden layer, and the decoder reconstructs these high-level features into input data through the hidden layer. The autoencoder aims to restore the high-level features of the input data as much as possible using the decoder. Its loss function often uses mean squared error (MSE) or cross-entropy losses. Two common autoencoder structures exist: undercomplete autoencoders whose number of neurons in the hidden layer is smaller than or equal to that in the decoder, and overcomplete autoencoders whose number of neurons in the hidden layer is larger than or equal to that in the decoder. Basic autoencoder structures comprise three fully connected layers: an input, hidden, and output layer. Both the number of hidden layers and its number of neurons can be adjusted to improve the model performance.

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