Received 2 February 2024, accepted 8 March 2024, date of publication 13 March 2024, date of current version 5 April 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3376737

RESEARCH ARTICLE

Assessing the Impact of the COVID-19 Pandemic on Electricity Consumption: A Machine Learning Approach

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ABSTRACT This study aims to quantitatively assess the impact of the COVID-19 pandemic on societal electricity consumption behavior, particularly considering the interference of special events. Currently, there is insufficient quantitative analysis of the extent to which the COVID-19 pandemic affects electricity consumption behavior. Therefore, we endeavor to introduce new theories and methods to comprehensively understand the potential impact of the pandemic on electricity usage in this field. Our proposed machine learning methods demonstrate significant results and advantages in two key aspects. Firstly, we innovatively introduce an abnormality detection algorithm based on the lunar calendar, thereby establishing a detection system capable of accurately identifying abnormal fluctuations in electricity consumption, to precisely determine the onset of the pandemic. Secondly, we design an evaluation system that integrates CNN-LSTM predictive models and controlled variable strategies, enabling us to reconstruct electricity usage patterns less affected by the pandemic. By comparing actual electricity consumption with reconstructed patterns, we deeply evaluate the impact of the pandemic on different regions and industries and introduce the pandemic impact percentage as a quantification method to precisely assess the extent of the impact. The findings indicate a significant impact of the COVID-19 pandemic on commercial and industrial electricity consumption. Furthermore, our methods are not limited to pandemic research but can also be applied to investigate the effects of other events such as holidays, typhoons, and special production schedules on electricity consumption. In summary, by delving into the complex associations underlying electricity consumption, this study provides a solid theoretical and methodological foundation for future similar research and offers crucial decision support for the electricity industry and emergency management.

INDEX TERMS COVID-19 pandemic, electricity consumption, lunar calendar alignment, abnormality detection, time series prediction.

I. INTRODUCTION

The global outbreak of the COVID-19 pandemic has raised urgent concerns worldwide, exerting unprecedented and far-reaching effects on various domains of human society. Apart from posing a direct challenge to public health systems, it has also given rise to extensive and complex social and economic ripple effects. The impact of the pandemic's spread extends beyond the realm of human health [1], profoundly affecting aspects such as social structures [2], [3], economic systems [4], [5] [6], educational systems [7], [8] [9], and ecological environments [10]. In response to this situation, scientific communities have actively conducted in-depth research in an attempt to fully understand the impact of the epidemic.

In addition to the enormous loss of life, the pandemic has presented significant challenges to the energy system [11]. This is because governments worldwide have implemented

The associate editor coordinating the review of this manuscript and approving it for publication was Ravindra Singh.

stringent containment measures such as lockdowns and social distancing to mitigate the spread and minimize the impact of the pandemic [12]. These measures have had a substantial negative impact on both the demand and supply sides of the energy industry, particularly in the early stages of the pandemic. Energy consumption, as a fundamental pillar of contemporary society, directly reflects the dynamism and complexity of human societal operations. Accurate prediction of electricity demand holds paramount significance for maintaining the smooth operation and cost control of power systems. In recent years, the electricity market has been gradually moving towards marketization, highlighting the critical role of precise electricity demand forecasting in guiding decisions regarding power system planning, resource allocation, and facilitating the integration of renewable energy sources. However, the outbreak of the COVID-19 pandemic in recent years has triggered widespread societal operational changes, consequently affecting electricity consumption patterns and presenting new challenges for power system management and planning. In this context, this study will focus on exploring the pandemic's impact on the power system, with special attention to its influence on user electricity consumption. The research aims to provide specific data support and decision-making basis for the operation and emergency response of power systems through empirical analysis.

A. EXISTING RESEARCH ON THE IMPACT OF COVID-19 ON POWER SYSTEMS

In power systems, time series analysis has long been regarded as a crucial method for studying electricity consumption. In recent years, numerous research efforts have focused on understanding the impact of COVID-19 on power systems. In the early stages of the pandemic, many studies initially discussed the influence of the pandemic on power systems from a qualitative perspective. This qualitative analysis often employed methods comparing the periods before and after the pandemic (2019 and 2020) [13], [14], [15], or before and after lockdowns [16], to assess the effects brought about by the pandemic. As time progressed, the accessibility of pandemic data and electricity supply data continued to improve, leading to an increasing incorporation of quantitative analyses. For instance, Norouzi et al. [17] applied autoregressive elasticity and neural network-based sensitivity analysis, proposing a method combining both models for constructing and analyzing, to explore the impact of COVID-19 on petroleum and power demand in China. Eryilmaz et al. [18] utilized linear regression analysis to empirically examine the impact of stay-at-home advisories on various fuel-based power generation. Based on an optimized electricity price model, Costa et al. [19] analyzed the impact of COVID-19 on the distribution market and found that producers and consumers were affected. Li et al. [20] introduced an LSTM-ADRL method, aiming to estimate the effect of the pandemic on electricity consumption and apply it to emergencies in different regions. Wang et al. [21] employed the ARIMAR-BP simulation method to conduct a comparative analysis between the actual energy consumption in 2020 and a pandemic-free scenario, aiming to investigate the impact of the pandemic on energy consumption. These quantitative studies have increased, providing more precise data support for a deeper understanding of the pandemic's impact on power systems. Through these explorations, we have distinctly observed that the sudden outbreak of the pandemic has profoundly affected power systems. However, currently, no scholars have proposed a comprehensive analytical framework for perceiving significant events, such as COVID-19, from the perspective of electricity consumption. Furthermore, by comparing simulated non-pandemic electricity consumption with actual electricity consumption, the aim is to assess the significance of its impact. Therefore, our goal is to establish a comprehensive analytical methodology to analyze the impact of the pandemic on power systems, enhance the accuracy of electricity consumption predictions, and provide a solid foundation for flexible and effective decision-making in the power industry.

B. METHODOLOGY OF THIS STUDY

It is important to note that there may be potential biases if data from 2020 is directly compared with that of 2019, as the initial outbreak of the pandemic coincided with the Chinese New Year period. This holiday has a significant impact on power systems, but its effects have not been fully accounted for. Moreover, existing studies have predominantly focused on specific regions or industries, without conducting quantitative analyses on how special time periods perceive the pandemic through electricity consumption and the extent of its impact on power systems. Therefore, we propose to delve deeper into the impact of the pandemic on electricity consumption using machine learning methods, aiming to elucidate its perception across different regions and types of electricity usage, and assess the trends in electricity consumption changes influenced by the pandemic. Our research methodology can be divided into two primary components. Firstly, we introduce a detection system employing an abnormality detection algorithm rooted in the lunar calendar to assess the impact of the pandemic on electricity consumption. The outbreak of the pandemic coincided with the Chinese Lunar New Year, a period significantly influencing electricity usage. However, distinguishing the pandemic's effect on electricity consumption from the inherent fluctuations during festivities is necessary. Given the discrepancy between the lunar and Gregorian calendars, our method aligns time series data using the Dynamic Time Warping (DTW) algorithm [22] to effectively address this challenge. Subsequently, we apply the Anomaly Transformer algorithm [23] for outlier detection. By analyzing anomalies in time series data and comparing them with the actual outbreak time of the pandemic, we aim to investigate the perception of the pandemic's impact on electricity consumption. Secondly, we establish an evaluation system utilizing the CNN-LSTM model for predicting electricity consumption assuming no pandemic impact. Subsequently, we compute the discrepancy between actual and predicted electricity consumption to quantify pandemic-induced fluctuations and analyze their significance. Leveraging a machine learning framework, our study successfully evaluates the impact of COVID-19 on six major electricity consumption categories across nine cities in a certain province in southern China.

Finally, it is worth emphasizing that the objective of this study is to establish a comprehensive analytical methodology for systematically evaluating the significant impact of pandemics on electricity consumption. Moreover, this approach exhibits a degree of generality, applicable to the analysis of the significance of other specific events on electricity consumption. Through in-depth data analysis and the establishment of an event database, it aims to provide a convenient avenue for the swift implementation of electricity responses to future unforeseen events. The goals of this research extend beyond a deepened understanding of the diverse effects of different event types on the power system. The study also aspires to enhance the accuracy of electricity consumption predictions, laying a solid foundation for flexible and effective decision-making in the power industry.

II. METHOD

We establish an assessment framework for scrutinizing the pandemic's impact on electricity consumption through a machine-learning approach. Our proposed method comprises two core components(as shown in Fig.1(a)): we introduce a detection system utilizing an abnormality detection algorithm rooted in lunar calendar alignment, capable of identifying unusual fluctuations in electricity consumption, thus enabling the precise identification of the pandemic's inception. Secondly, we propose an assessment system that integrates a CNN-LSTM predictive model and a controlled variable strategy to reconstruct electricity consumption patterns unaffected by the pandemic, thereby analyzing the extent of the impact of the epidemic on electricity consumption behavior. Simultaneously, we also present the flowchart of our proposed method, as illustrated in Fig.1(b). It is crucial to emphasize that the timing of the initial outbreak of the epidemic coincides with the Chinese New Year. The primary challenge lies in eliminating the influence of significant holidays on electricity usage, separating it from the impact introduced by the epidemic. The first step of our method, based on lunar calendar alignment, successfully addresses this issue.

Based on the above analysis framework, we conducted a comprehensive analysis of the electricity consumption data of six types of electricity consumption in nine cities of a certain province in southern China before and after the epidemic. In this section, we briefly expound on the principles of these three algorithms and their application in this study. The detailed algorithms are presented in Algorithm 1 and Algorithm 2.

Algorithm 1 Lunar-Based Time Alignment Algorithm

Input: Time series X
Output: Aligned time series $\tilde{\mathcal{X}}$
function AlignTwoYear(s, t)
$path \leftarrow \mathrm{DTW}(s, t)$
$t\_aligned, s\_aligned \leftarrow$ empty lists
for i, p **in enumerate**(path) **do**
  if $p[0] > p[1]$ **then**
    $t\_aligned$.append(expand($t[: p[1]]$, diff(p)))
    $s\_aligned$.append($s[: p[0]]$)
  else
    $s\_aligned$.append(expand($s[: p[1]]$, diff(p)))
    $t\_aligned$.append($t[: p[0]]$)
  end if
end for
return $s\_aligned, t\_aligned$
function AlignTimeSeries(X)
$\tilde{\mathcal{X}} \leftarrow [x_1]$
for $iin2ton$ **do**
  $\tilde{\mathcal{X}}$.append(AlignTwoYear(x_1, x_i))
end for
return $\tilde{\mathcal{X}}$

Algorithm 2 Assessing the Impact of COVID-19 on Electricity Consumption

Input: Time series data $\tilde{\mathcal{X}}$ and the temporal window associated with the anomaly values $\hat{\mathcal{Z}}$.
Output: Percentage of Pandemic Impact ($\mathcal{S}$) and Significance.
Train the CNN-LSTM model using the dataset $\tilde{\mathcal{X}}$.
Feed $\hat{\mathcal{Z}}$ into the trained CNN-LSTM algorithm to obtain the electricity consumption assuming no pandemic impact, denoted as the restored electricity consumption $\mathcal{Y}$.
Compare the electricity consumption at corresponding times between $\tilde{\mathcal{X}}$ and $\mathcal{Y}$ using $\mathcal{S} = \frac{\tilde{\mathcal{X}} - \mathcal{Y}}{\tilde{\mathcal{X}}}$.
if $|\mathcal{S}| \geq 0.05$ **then**
  The pandemic impact is significant.
  Return Significance: Significant, Percentage of Pandemic Impact : $\mathcal{S}$.
else
  There is no significant impact.
  Return Significance: Not Significant, Percentage of Pandemic Impact : $\mathcal{S}$.
end if

A. OUTLIER PERCEPTION ALGORITHM BASED ON LUNAR ALIGNMENT METHOD

In this section, we introduce a Lunar Calendar Aligned Anomaly Detection Algorithm, which primarily consists of two steps: Firstly, we utilize the Dynamic Time Warping (DTW) algorithm to align the time series data based on the Lunar New Year. Next, on the foundation of the aligned data, we use the Anomaly Transformer algorithm for outlier

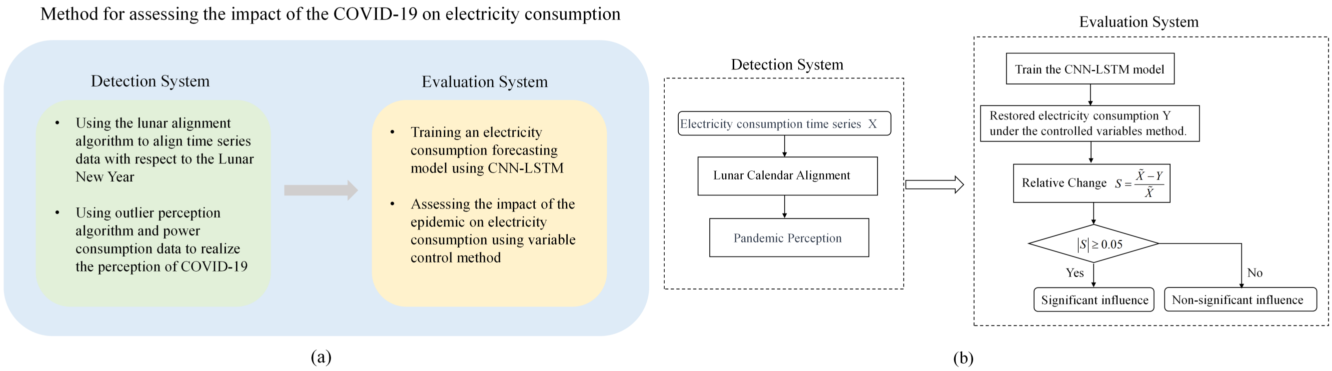

FIGURE 1. Overview of our method.

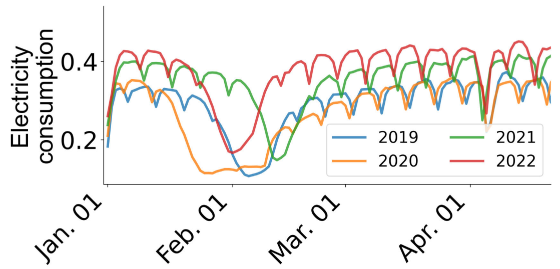

FIGURE 2. Illustration of electricity consumption diagram of industry (City 1).

detection, aiming to study the perception of electricity consumption on COVID-19 (refer to Algorithm 1 for detailed algorithmic specifics). Subsequently, we provide a detailed exposition of the specific implementation details of these two parts.

1) LUNAR CALENDAR ALIGNMENT USING DTW ALGORITHM

The outbreak occurred during the Chinese New Year period in 2020, but we commonly use the Gregorian calendar to record electricity consumption. We plot the industrial electricity consumption curves for the years 2019 to 2022, as depicted in Fig. 2. It can be observed that under normal circumstances, there is a certain similarity in the electricity consumption patterns across different years, notably exhibiting a trough around February. This phenomenon is attributed to the celebration of the Chinese New Year, during which production halts and electricity usage decreases due to holidays. Significant impacts on electricity consumption can be seen during major festivals such as the Spring Festival. However, considering the non-alignment of lunar and Gregorian calendar years, a straightforward comparison using the same periods is inadequate for analyzing the epidemic's impact. To eliminate the influence of major holidays like the Spring Festival, we innovatively apply the Dynamic Time Warping (DTW) algorithm to align electricity consumption data according to the lunar New Year. A brief introduction to this algorithm follows.

The DTW algorithm is a nonlinear sequence alignment method capable of aligning time series of different lengths to minimize the distance between them. It achieves this through Dynamic Programming (DP) and has found wide applications in fields such as speech recognition [24], character recognition [25], and heart rate monitoring [26]. The core concept of the DTW algorithm involves dynamically adjusting to find the optimal mapping between two given time series. It calculates the distance between the optimal mappings, known as DTW distance, to assess the similarity between the two-time series. A smaller distance indicates higher similarity. Unlike traditional Euclidean distance measures, the DTW algorithm does not require strict alignment of the two sequences, overcoming the problem of time warping. For two-time series, denoted as $\mathbf{P} = (p_1, p_2, \ldots, p_N)$ and $\mathbf{Q} = (q_1, q_2, \ldots, q_N)$, with lengths N, a regularized path $\mathbf{W} = (w_1, w_2, \ldots, w_L)$ is defined. Here, the i-th element of $\mathbf{W}$, $w_i = (n_i, m_i)$, satisfies $1 \leq n_i \leq N$, $1 \leq m_i \leq N$, and $1 \leq i \leq L$. The selected path in DTW must satisfy three conditions: (1) Boundary conditions: $w_1 = (1, 1)$ and $w_L = (N, N)$, aligning the initial data of the two sequences with their respective final data. (2) Monotonicity: This ensures that the points on the path change monotonically over time. For adjacent points $w_i = (n_i, m_i)$ and $w_{i+1} = (n_{i+1}, m_{i+1})$ on path $\mathbf{W}$, it should satisfy $n_{i+1} - n_i \geq 0$ and $m_{i+1} - m_i \geq 0$. (3) Continuity: In the regularized path W, points $w_i = (n_i, m_i)$ and $w_{i+1} = (n_{i+1}, m_{i+1})$ should satisfy $n_{i+1} - n_i \leq 1$ and $m_{i+1} - m_i \leq 1$, ensuring that the current point can only be matched with adjacent points.

Multiple regularized paths satisfy these conditions. The objective of DTW is to find the minimum total cost of the regularized path between sequences $\mathbf{P}$ and $\mathbf{Q}$. This is expressed as:

$$DTW(\mathbf{P}, \mathbf{Q}) = \min \sum_{i=1}^{L} d(p_{n_i}, q_{m_i}) \tag{1}$$

where $d(p_{n_i}, q_{m_i}) = |p_{n_i} - q_{m_i}|$, it represents the cost of the regularized path between point p_{n_i} and point q_{m_i}. $DTW(\mathbf{P}, \mathbf{Q})$

denotes the minimum total cost of the regularized path between sequences **P** and **Q**.

By adopting the dynamic programming approach to find the optimal regularized path, we define the cumulative distance d_{DTW}. Matching between sequences **P** and **Q** starts from point (0, 0). At each subsequent point, the distance from the previous point is accumulated. The accumulated distance obtained at the final point (p_n, q_m) represents the total cost of the optimal regularized path. This metric serves as a measure of similarity between time series **P** and **Q**. The expression for calculating the cumulative distance is as follows:

$$d_{DTW}(p_i, q_j) = d(p_i, q_j) + \min\{d_{DTW}(p_{i-1}, q_j), d_{DTW}(p_i, q_{j-1}), d_{DTW}(p_{i-1}, q_{j-1})\} \tag{2}$$

Here, $d_{DTW}(p_i, q_j)$ represents the regularized distance from the starting point to point (p_i, q_j).

Based on the description of the DTW algorithm provided above, this study applies it for a precise analysis of the impact of the COVID-19 pandemic on user electricity consumption. The time series data is aligned according to the Lunar New Year, aiming to eliminate the influence of significant holidays on electricity consumption analysis [27].

The fundamental assumption of this study is that the electricity consumption curves for different years should exhibit similar trends under normal circumstances. However, the presence of factors such as holiday effects may impact electricity consumption [28], introducing interference in the analysis of the pandemic. Holiday effects and similar factors can lead to incomplete synchronization of fluctuations in electricity consumption. Nevertheless, through appropriate time axis shifting, it should be possible to achieve alignment of similar waveforms in electricity consumption curves for different years. Therefore, our research applies the DTW algorithm to align the time series of user electricity consumption, aiming to eliminate the time offset issue caused by the Lunar New Year. Specifically, we categorize the study objects into pandemic outbreak years and non-pandemic years, treating them as the time series to be compared. By calculating the DTW distance, we can find the alignment path that minimizes the distance between the two sequences. This alignment path calculation will adjust the relative positions of electricity consumption data within the Lunar New Year cycle, thereby achieving sequence alignment. In particular, we will focus on the fluctuations in electricity consumption during the pandemic and non-pandemic periods, as well as their comparison during the corresponding initial outbreak of the pandemic (around the Lunar New Year of 2020). Based on the aligned results of the lunar calendar, as shown in Fig.3, we can see that the impact of the epidemic can be analyzed intuitively.

The purpose of this alignment process is to eliminate the influence of time offsets, allowing us to more accurately compare the changes in electricity consumption between different years. Through flexible alignment of the sequences, we hope to uncover the impact of the pandemic on electricity consumption data, as well as the differences between the pandemic period and the non-pandemic period. This research method contributes to a deeper understanding of the temporal characteristics of electricity consumption data and provides a more accurate foundation for prediction and analysis [29].

2) ABNORMAL DETECTION BASED ON LUNAR CALENDAR ALIGNMENT DATA

From Fig.3, we can see that the epidemic has had a significant impact on electricity consumption. A natural idea is whether we can achieve detection of the epidemic by analyzing abnormal electricity consumption, that is, predicting the start time of the epidemic.

In the field of time series anomaly detection, traditional methods (like LOF and OC-SVM) don't adequately consider temporal information. While, methods based on deep learning, such as those utilizing recurrent neural networks, often struggle with insufficient feature representation, making it challenging to effectively distinguish anomalies. To address this, Xu et al. proposed the Anomaly Transformer (AT) algorithm in 2021 [23]. This algorithm relies on a self-attention mechanism and deep learning. It excels at capturing temporal correlations in time series data, allowing for a more effective differentiation between normal and anomalous patterns. Across various datasets in different domains, the AT method has demonstrated outstanding performance in time series anomaly detection, opening up new prospects for developments in this field.

The AT algorithm is based on the Transformer architecture and introduces a novel attention mechanism called Anomaly-Attention. This allows for feature extraction and anomaly detection in sequence data. The core idea revolves around leveraging self-attention to compute importance weights for each element in the sequence, thereby capturing internal correlations and anomalous patterns within the data. Specifically, the Anomaly Transformer is composed of multiple attention heads and layers of stacked transformer blocks. It aims to analyze data features from multiple scales and perspectives, enabling the identification and localization of anomalies. The AT algorithm constructs a correlation weight distribution between each data point and the entire sequence through the self-attention mechanism. This captures both global and local correlation patterns among data points. Employing the minimum-maximum correlation learning strategy emphasizes the correlation differences between anomalous and normal data points. This endows it with better adaptability to the characteristics of time series data, providing more precise capabilities for anomaly detection.

To accurately identify abnormal changes in electricity consumption during the pandemic period, this study utilizes the AT algorithm for anomaly detection in electricity consumption. Specifically, we establish an electricity consumption anomaly detection model based on AT for the collected time series data. Subsequently, we input the time series data into the model and calculate the correlation weights and their differences between each data point and the entire sequence. After computing the correlation differences, we classify the data points into normal or abnormal, thereby achieving time series anomaly detection based on correlation differences. Finally, we output anomaly detection results. By comparing them with the actual outbreak time of the epidemic, we can see that using the AT algorithm for outlier detection can accurately perceive and predict the epidemic, providing important guidance for the stable operation of the power system.

B. EVALUATION SYSTEM USING CNN-LSTM MODEL AND ITS CONTROL VARIABLE METHOD

We are interested in the fluctuation of the impact of the epidemic on electricity consumption and the significance of the impact, in order to provide some guidance for the stability of the power supply system. To achieve this, we employ a controlled variable approach. Under the assumption of no pandemic influence, we predict electricity consumption. Subsequently, we compare the restored electricity consumption with the actual data to determine the statistical significance of the pandemic's impact (For detailed information regarding the specific algorithm, please refer to Algorithm 2). To conduct this analysis, we utilize a hybrid algorithm proposed by Kim and Cho [30] known as the CNN-LSTM model. The CNN layer excels at extracting features that influence energy consumption variables, while the LSTM layer is adept at modeling irregular trends in time series components. This enables us to capture the intricate spatiotemporal characteristics of power consumption data, facilitating accurate predictions of electricity consumption. Below, we will provide a concise introduction to the fundamental structure and functions of each component of this hybrid algorithm.

1) CNN ALGORITHM PRINCIPLE

Convolutional Neural Networks (CNNs) are a variant of artificial neural networks [31]. In addition to possessing the advantages of robustness, strong adaptability, and powerful self-learning capabilities, neural networks also exhibit characteristics such as weight sharing and automatic feature extraction. Weight sharing significantly reduces the network parameters, thereby enhancing classification efficiency. Automatic feature extraction reduces the workload associated with manual feature engineering. The basic structure of a Convolutional Neural Network comprises the input layer, convolutional layer, pooling layer, fully connected layer, and output layer. The function of each component is as follows.

The input Layer serves as the entry point for data and can receive raw data stored in matrix form. The convolutional Layer of the CNN conducts convolution operations with convolutional kernels, enabling the extraction of feature maps from the input data. Each convolutional kernel produces a different feature map. Therefore, the more convolutional kernels there are, the richer the types of feature maps that the CNN can extract. The pooling Layer of the CNN samples the features obtained by each convolutional kernel. It captures the essential features of each kernel and reduces computational complexity to improve efficiency, thereby accelerating the training speed of the CNN. The fully connected layer of the CNN connects each neuron with every neuron in the previous layer (which can be a convolutional or pooling layer) using certain weightings. Neurons within the fully connected layer are not interconnected. This process transforms the data from the previous layer's feature maps into vector data, facilitating classification by subsequent classifiers. The output layer of the CNN is typically a classifier that performs further classification based on the effective features extracted by the preceding layers.

2) LSTM ALGORITHM PRINCIPLE

The Long Short-Term Memory (LSTM) network was initially proposed by Hochreiter and Schmidhuber based on Recurrent Neural Network (RNN) architecture [32]. Traditional RNNs often encounter the issues of gradient ''explosion'' or ''vanishing'' when dealing with data with a large number of time steps [33], leading to weight oscillation or excessively prolonged training times [34]. To overcome this problem, LSTM networks were designed to address long-term dependency issues [35]. Within the LSTM network unit, three specifically designed gate mechanisms are employed to effectively regulate the updating and forgetting of internal states. Next, we will elucidate the structure of LSTM and delineate its fundamental parameters.

(1) LSTM Units: The LSTM network layer differs from traditional neural units in that it incorporates specially designed memory units. This enables LSTM to retain memory of past information when processing input sequences. Each memory unit is equipped with three state management gates: the forget gate f_t, the input gate i_t, and the output gate o_t. When processing input sequences, these gates are activated through the sigmoid activation function σ to determine whether to initiate, thereby achieving state updates and information transmission into the unit under specific conditions. The activation function σ, also known as the sigmoid function, is defined as follows:

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{3}$$

(2) f_t: Forget Gate. Let x_t be the current input vector and h_{t-1} be the output vector from the previous time step. When the input flows through the LSTM network layer, it first passes through the forget gate and conditionally decides to discard some irrelevant information from the unit state, i.e.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{4}$$

where, W_f denotes the weight matrix associated with the forget gate, while b_f represents its corresponding bias term. (3) i_t: Input Gate. It determines which information to add to the memory cell. It computes a value between 0 and 1, representing the extent to which the memory cell will be updated. If $\widetilde{C}_t$ is the current candidate value, C_{t-1} is the previous time step's cell state, and C_t is the current cell state, then after the cell state is forgotten by the forget gate, the input gate selectively decides, conditionally, which values from the current input to add to the current cell state:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t \quad (5)$$

(4) o_t: Output Gate. Let h_t be the current output vector. After the state update, the output gate conditionally decides which information to output:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \cdot tanh(C_t) \quad (6)$$

In the field of energy, LSTM has become a crucial tool for energy supply and consumption forecasting [33]. For instance, LSTM has been applied in natural gas supply forecasting [36], [37], wind power generation prediction [21], [38], and electricity load forecasting [39], [40]. In these studies, LSTM networks, by capturing complex patterns in time series data, have provided accurate energy predictions, offering robust support for energy management and planning.

3) CNN-LSTM ALGORITHM

The CNN-LSTM algorithm seamlessly integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to achieve spatio-temporal forecasting of electricity consumption. Specifically, CNN is employed to extract spatio-temporal features from the electricity consumption time series, while LSTM is responsible for the temporal modeling of the extracted features. This fusion allows for an effective capture of both local and global characteristics within the electricity consumption data, thereby enhancing the prediction accuracy (Please refer to Appendix C for the validation of the accuracy of this method).

In this study, we applied the CNN-LSTM algorithm in conjunction with its controlled variable approach to predict electricity consumption under the assumption of no pandemic influence. Subsequently, we compared these predictions with the actual electricity consumption data, enabling us to assess the impact of the pandemic and evaluate the significance of its effect on electricity consumption as a specific event. An overview of data preprocessing and parameter configuration is provided below.

4) DATA SOURCE

The data is calculated based on the power consumption collection system of State Grid Fujian Electric Power Company Limited. The power consumption collection system includes collection terminals (electric energy meters) for 20 million users across the entire province and a collection platform. The system freezes the meter readings at 24:00 of the previous day, differentiates them from the frozen readings of the preceding day, and, following a specified computational logic involving current transformer (CT) and potential transformer (PT) ratios, main meter deduction relationships, etc., obtains daily electricity consumption data for each household. Additionally, the system matches the data with user profile information in the Oracle database, classifies and summarizes the daily electricity consumption data based on region and electricity usage category, and arranges the data into a time series in chronological order. Our dataset comprises electricity consumption data from nine cities in a southern province of China. For each city, the data spans from January 1, 2019, to January 29, 2023, encompassing daily electricity consumption information across six categories (industry, residential, agricultural, non-residential lighting, non-ordinary industry, commercial).

5) DATA PREPROCESSING

Firstly, non-numeric data was encoded to convert it into numerical values. One-hot encoding was applied to the "weekday" data. For the "holiday" and "festival" data, a 0-1 encoding was used where holidays were encoded as 1, workdays as 0, festivals as 1, and others as 0. Next, the data was standardized. Data standardization involves scaling the data proportionally to fit into a small specific range. Its purpose is to remove unit limitations from the data, transforming it into dimensionless pure numerical values, making it easier to compare and weigh indicators with different units or magnitudes. In this study, the min-max normalization method was employed, which scales each column of data to the [0,1] interval before being input into the network for training. Finally, the predicted results were subjected to reverse normalization:

$$x^* = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (7)$$

6) PARAMETER SETTING

For the CNN part, there are 2 convolutional layers (Conv2D) with 32 and 64 filters respectively. The kernel size for the convolutional layers is set to 3×3. In the pooling layers (MaxPooling2D), a pool size of 2×2 is used. After two consecutive operations of convolution and max-pooling, a flattening operation is performed to transform the multi-dimensional array into a one-dimensional vector array, which serves as global feature extraction. Since we aim to predict the values for the next n days at once, a repeat vector operation (RepeatVector) is applied with the repetition number being the predicted number of days, n. We used a single-layer LSTM network with 128 neurons. Therefore, a single LSTM layer with 128 neurons is used. To prevent overfitting, a dropout regularization technique is applied with a rate of 0.2. Finally, a dense layer (Dense) is used to output vectors in the specified format.

7) IMPLEMENTATION CODE OF THE ADOPTED ALGORITHM

The source code associated with this paper can be found on GitHub at [https://github.com/HuangYH0921/fjdw].

III. RESULTS

A. EPIDEMIC PERCEPTION AND IDENTIFICATION OF DIFFERENT TYPES OF ELECTRICITY CONSUMPTION

In this section, we utilize an alignment algorithm based on the lunar calendar in conjunction with an anomaly detection method to predict the outbreak time of the pandemic. Firstly, the alignment algorithm based on the lunar calendar uses the Chinese New Year as a temporal reference point and employs Dynamic Time Warping (DTW) to align the time series data. Its primary objective is to alleviate the influence of significant events like the Chinese New Year on electricity consumption analysis, providing an intuitive analysis of the pandemic's impact based on the aligned data. Subsequently, we apply an anomaly detection algorithm to identify outliers in the time series data. Through analyzing these anomalies and comparing them with the actual outbreak time of the pandemic, our goal is to achieve a prediction of the pandemic outbreak time.

1) THE ELECTRICITY CONSUMPTION TRENDS IN DIFFERENT CITIES

It's worth noting that the data recorded by the power department is typically in chronological order according to the Gregorian calendar. However, considering the initial outbreak of the pandemic during the Chinese Lunar New Year period in 2020, and recognizing that the Spring Festival is a significant holiday that often impacts electricity consumption patterns, it's not appropriate to simply use a year-over-year comparison method to assess the differences in electricity consumption during the pandemic and non-pandemic periods. In order to minimize this interference as much as possible, we employ the Dynamic Time Warping (DTW) algorithm. This algorithm aligns the data based on the lunar calendar, allowing for a thorough investigation of changes in electricity consumption trends in different cities and the extent to which they were affected by the pandemic.

Taking City1 as a case study, we examined the variations in electricity consumption for six different types of electricity usage from the outbreak to the control stage of the pandemic. The orange line in Fig. 3 represents the changes in electricity consumption during the initial outbreak of the pandemic in 2020, while the other colors correspond to the fluctuation in electricity consumption for other years. By examining the electricity consumption curves in the graph, we can observe that the impact of the pandemic varies for different types of electricity usage.

By examining the aligned fluctuation curves of electricity consumption shown in the Fig.3, we can conduct an intuitive analysis. In non-pandemic years, the electricity consumption for various categories typically gradually returns to pre-holiday levels after the Spring Festival. However, in 2020, three types of electricity usage industrial, non-general industrial, and commercial were notably affected by the pandemic, characterized by a slower recovery of electricity consumption after the outbreak. This may be attributed to factors such as reduced commercial activities, business closures, and market uncertainty. Other types of electricity usage, including residential, general industrial, and agricultural, also experienced some fluctuations during the pandemic period following the Spring Festival. These fluctuations had relatively small amplitudes, and their electricity consumption recovery rates were relatively fast, exhibiting no significant differences compared to other non-pandemic years.

We also conducted a similar analysis on eight other cities in the Province. While different types of electricity consumption exhibited unique trends in each city, it is noteworthy that industrial, non-general industrial, and commercial electricity consumption were significantly affected by this epidemic. Overall, they demonstrated a pattern of change similar to that of City1 (refer to Appendix A for details).

2) ABNORMAL PATTERNS OF DIFFERENT TYPES OF ELECTRICITY CONSUMPTION

In Section III-A1, we provide visual representations of the sudden outbreak of the pandemic's impact on various major electricity consumption types. A natural question arises: can we utilize anomalies in electricity consumption to perceive the occurrence of this specific event, with the aim of predicting the outbreak time of the pandemic? To achieve this goal, we introduce the Anomaly Transformer algorithm and conduct an in-depth investigation into the distinct anomaly patterns of different types of electricity consumption, thereby validating the capacity of electricity consumption as a means for infectious disease perception and identification. Essentially, our objective is to explore the sensitivity of power consumption to the outbreak of a pandemic and subsequently employ it for outbreak prediction. We collected time-series data from the early stages of the pandemic in nine prefecture-level cities in a certain province in southern China in 2020, encompassing six different types of electricity consumption in these regions. To detect electricity consumption anomalies, we conducted a comprehensive analysis using the Anomaly Transformer algorithm. Taking one city as an example, we expound upon the analytical methodology and results.

Fig.4 illustrates anomalies in six different types of electricity consumption during the initial phase of the COVID-19 pandemic in early 2020. In the figure, the red dots represent the actual outbreak time of the pandemic, while the orange dots represent the time points corresponding to the abnormal values predicted by the anomaly transformer algorithm. It can be observed from the figure that in industries such as industrial, non-general industrial, and commercial sectors, the algorithm's predicted abnormal values align well with the actual situation. However, for the other three types of electricity consumption residential, agricultural, and non-residential lighting there is a certain degree of deviation in the predicted abnormal values. This phenomenon aligns with the intuitive observations from the earlier images, indicating that for industries significantly affected by the pandemic, we can use them to accurately predict the outbreak

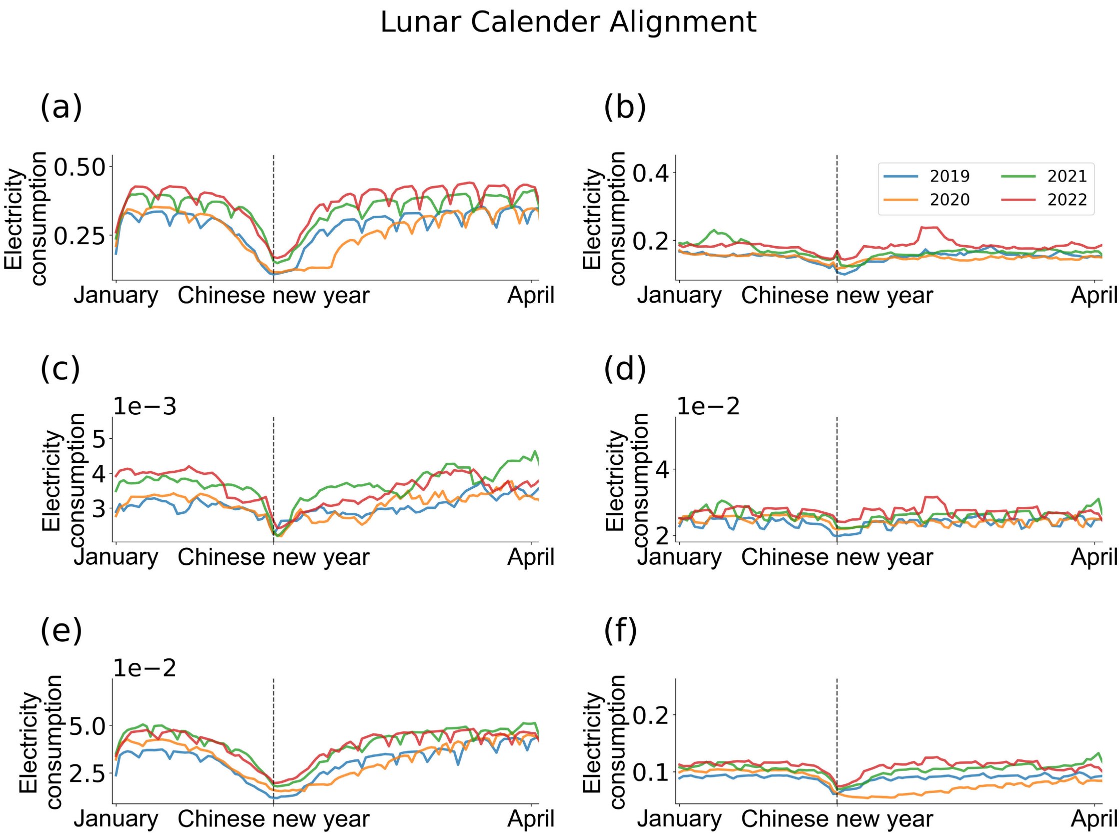

FIGURE 3. Electricity consumption diagram of 6 types of electricity consumption in City1 based on Lunar Calendar Alignment.The orange line in the graph represents the trend of electricity consumption during the initial outbreak of the epidemic in 2020, while the other three sets of lines respectively portray the electricity consumption situations in 2019, 2021, and 2022. The panels (a)-(f) denote the following: (a) industrial, (b) residential living, (c) agricultural, (d) non-residential lighting, (e) non-general industrial, and (f) commercial, illustrating the electricity consumption for these six major usage types in different years.

of the pandemic. Additionally, we conducted a similar analysis on eight other cities in the Province, and the results were consistent with those of City1 (for detailed information, refer to Appendix B).

This section focuses on examining the impact of the pandemic on different types of electricity consumption and the ability to perceive the outbreak time of the pandemic through electricity consumption. Since the initial outbreak of the pandemic coincided with the Chinese New Year in 2020, to eliminate the interference of major holidays on the analysis of the pandemic's impact, we employed the DTW algorithm to precisely align the time series data based on the Lunar New Year, rather than directly using a periodic comparison method. Through a visual observation of the aligned electricity consumption fluctuations, it can be observed that the pandemic had a significant impact on industries such as industrial, non-general industrial, and commercial sectors. This aligned data serves as the basis for further analysis. Furthermore, we aimed to predict the outbreak of the pandemic based on the abnormality of electricity consumption. To achieve this, we introduced the anomaly transformer algorithm for anomaly detection. The results aligned with visual observations. For types of electricity consumption significantly affected by infectious diseases, this method accurately predicts the outbreak time of the disease. Thus, we can utilize the electricity consumption information from these industries to forecast the outbreak of the pandemic. This study comprehensively illustrates the trends in the impact of electricity consumption across different cities and types. Through a comprehensive qualitative and quantitative analysis, it provides reliable foundations for decision-making in the field of electricity. This enables better management of the energy demand changes induced by pandemics.

B. ANALYSIS OF THE IMPACT OF THE COVID-19 ON DIFFERENT TYPES OF ELECTRICITY CONSUMPTION

In this section, we aim to assess the impact and significance of the pandemic on electricity consumption. To achieve this, we employ a comprehensive algorithm, CNN-LSTM, along with its controlled variable approach. In our analysis, we introduce "the pandemic" as a covariate to predict electricity consumption unaffected by the pandemic. By forecasting a baseline electricity consumption without the pandemic, the difference between actual and baseline consumption is considered as the impact on electricity

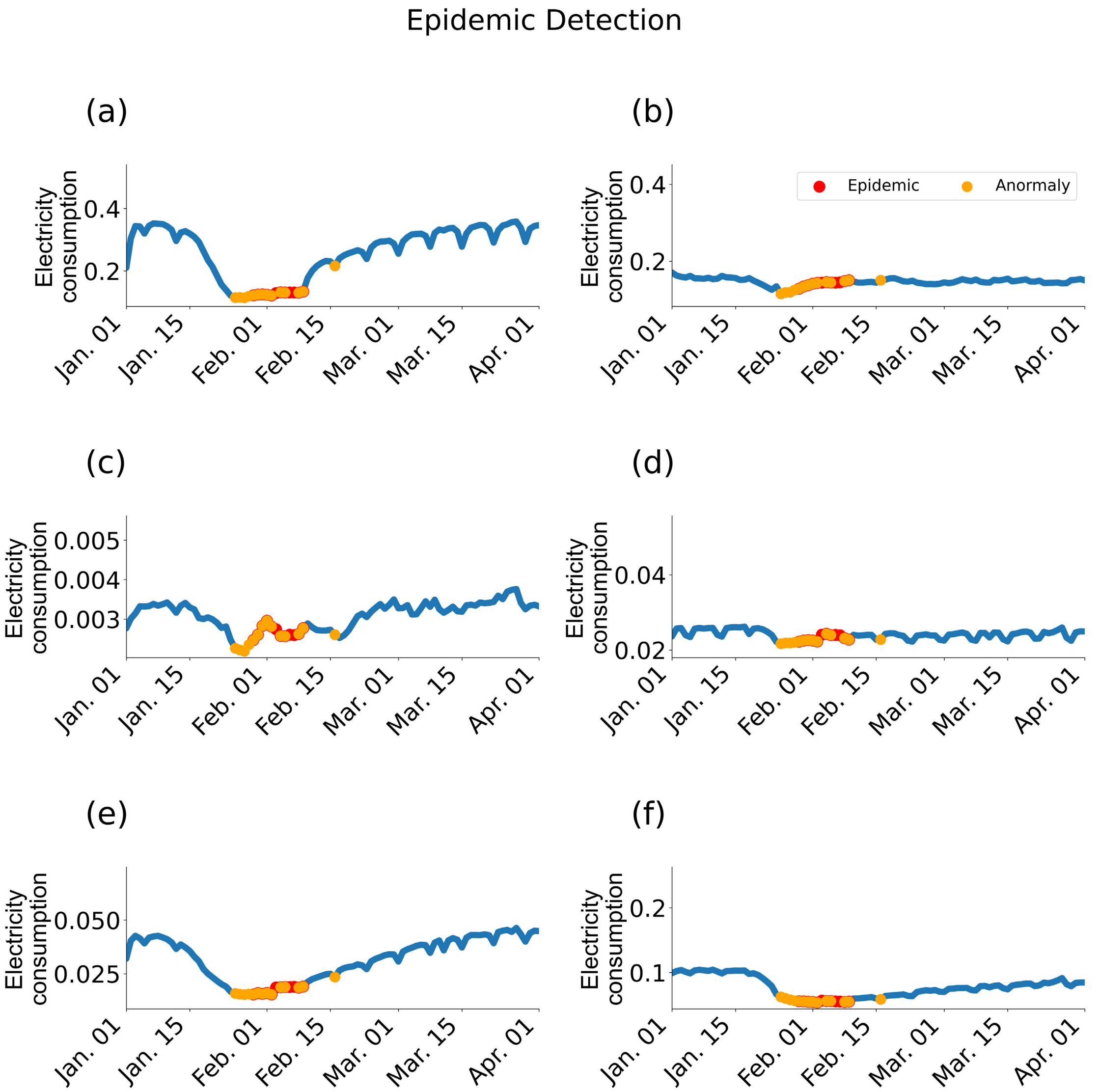

FIGURE 4. Abnormal value test of 6 types of electricity use in City1. The panels (a)-(f) represent the results of the abnormal value tests for the six major electricity usage types: (a) industrial, (b) residential living, (c) agricultural, (d) non-residential lighting, (e) non-general industrial, and (f) commercial. The blue undulating line in the graph represents the actual electricity consumption. Red dots denote the actual outbreak time of the epidemic, while orange dots signify the potential occurrence of the epidemic as predicted by the Anomaly Transformer algorithm.

TABLE 1. Impact of COVID-19 on 6 Types of Electricity Usage in 9 Cities in a certain province in southern China.

Percentage / City / EC	City1	City2	City3	City4	City5	City6	City7	City8	City9
Industry	**-0.223**	**-0.053**	**-0.212**	**-0.062**	**-0.073**	**-0.117**	**-0.178**	**-0.102**	**-0.262**
Non-general Industry	-0.035	**-0.156**	**-0.120**	**0.117**	**-0.103**	0.005	-0.023	**0.228**	-0.002
Residential living	-0.030	0.020	0.010	**-0.056**	-0.033	-0.043	-0.046	0.004	-0.004
Non-residential lighting	0.017	-0.048	**-0.071**	-0.029	-0.028	0.011	-0.023	**0.080**	-0.010
Commercial electricity	**-0.226**	**-0.403**	**-0.289**	**-0.310**	**-0.305**	**-0.326**	**-0.371**	**-0.412**	**-0.386**
Agricultural electricity	**-0.114**	0.005	-0.038	**0.092**	0.047	0.008	**0.062**	**-0.053**	**-0.078**

consumption. This allows us to delve into the extent of the pandemic's influence on electricity consumption.

Furthermore, in the absence of standardization, we introduce the pandemic impact percentage, defined as the ratio of affected electricity consumption to actual consumption, to quantify the degree to which electricity consumption is affected by the pandemic. It's crucial to emphasize that when the absolute value of the pandemic impact percentage exceeds 0.05, we consider it to have a significant impact. Conversely, if it is less than or equal to 0.05, we consider it not to have a significant impact. Through this analytical approach, we can evaluate whether the pandemic has a substantial effect on electricity consumption and determine if it is necessary to develop emergency plans for such special events to better address the impact of sudden public health emergencies on energy demand.

To thoroughly validate the significance of the pandemic's impact on different types of electricity consumption in the nine cities of the Province, we have implemented a series of rigorous validation measures. We are committed to ensuring the credibility and robustness of our research findings through systematic analysis. Table. 1 provides a comprehensive overview of the results of our validation efforts, aiming to clearly demonstrate the importance of the pandemic's impact on various forms of electricity consumption.

In the presented chart, the horizontal axis represents the nine prefecture-level cities in the Province, while the vertical axis represents the six major electricity consumption types. The values depicted in the chart represent the ratio between the impact on electricity consumption and actual electricity consumption. We consider cases where the absolute value of this ratio exceeds 0.05 as significantly influenced by the epidemic, and we highlight them in bold in the chart. Through a meticulous examination of the percentage impact of the pandemic, we have accurately captured the significant extent to which different cities are affected by the pandemic. Evidently, concerning both industrial and commercial domains, the degree of impact in each city surpasses the threshold of 0.05, signifying a substantial influence of the pandemic on these two categories of electricity consumption. This phenomenon is mainly attributed to changes in multiple dimensions such as industrial production, commercial activities, and energy consumption. Firstly, the epidemic has caused serious disruptions to industrial production. Many industrial enterprises have faced challenges such as supply chain disruptions, employee absenteeism, and a sharp drop in production demand, resulting in the inability to carry out production activities normally or a reduction in efficiency. This has led to a certain degree of reduction in industrial electricity consumption. Secondly, the epidemic has had a huge impact on commercial activities. People's travel and gatherings have been reduced, leading to many commercial establishments such as restaurants, entertainment venues, and tourism temporarily closing or having reduced operating hours. This change has led to a decrease in commercial electricity demand. In addition, the reduction in energy consumption during the epidemic is also an important factor. Numerous corporate entities advocate for remote work among their employees, a measure that concurrently exerts an indirect mitigating effect on energy consumption. Simultaneously, we observe that, with regard to residential electricity consumption, only the fourth city exhibits a marginally higher degree of impact exceeding 0.05, thereby indicating a non-significant influence of the pandemic on this particular category of electricity consumption. This observation may be attributed to the inherent stability of fundamental needs in residential life, where activities such as remote work and online learning have maintained a relatively consistent pattern of household electricity usage.

These findings not only deepen our understanding of the differential impacts of the epidemic on electricity consumption behaviors but also offer us more profound insights, enabling us to respond more effectively to similar unforeseen events. The information extracted from the data allows us to infer the vulnerability of different types of electricity usage and regions, thereby providing more instructive recommendations for emergency response and future planning of the power system. These discoveries will aid in optimizing the allocation of power resources, strengthening the stability of the power system, and addressing potential future changes and challenges with greater precision.

IV. CONCLUSION AND FUTURE DIRECTIONS

A. CONCLUSION

The global outbreak of the COVID-19 pandemic has had significant ramifications across various sectors, posing challenges to the accurate prediction of electricity consumption. Although some studies have recognized that factors such as "holidays" may introduce disturbances to analytical results, a comprehensive investigation has yet to be conducted [28]. Moreover, multiple research findings indicate a declining trend in business electricity consumption and an increasing trend in residential electricity consumption, consistent with our study results [11], [41]. Some studies have employed methods comparing electricity consumption in 2020 under non-pandemic conditions with actual consumption, revealing a significant reduction in electricity consumption due to the pandemic [21]. However, these methods have not proposed relative metrics to assess the pandemic's impact nor formed a comprehensive analytical framework. This study, focusing on the early stages of the 2020 pandemic, utilizes electricity consumption data from six categories in nine prefecture-level cities in a southern province of China. We have developed a deep learning-based approach to analyze the pandemic's impact on electricity consumption, as depicted in Fig. 1. The research methodology primarily comprises two parts: firstly, employing the DTW algorithm and Anomaly Transformer algorithm to perceive the pandemic's impact on different types of electricity usage; secondly, utilizing the CNN-LSTM algorithm to analyze the pandemic's influence on electricity consumption, with specific algorithms is presented in Algorithm 1 and Algorithm 2.

Through anomaly analysis of data arranged based on the lunar calendar, we obtained the pandemic perception results for different types of electricity consumption. In the analysis of the pandemic's impact on electricity consumption, we employed the Dynamic Time Warping (DTW) algorithm to align time series data with the lunar New Year, eliminating the influence of major holidays on electricity consumption. Upon observing the processed data, we found that the pandemic had a significant impact on electricity consumption in the industrial, non-general industrial, and commercial

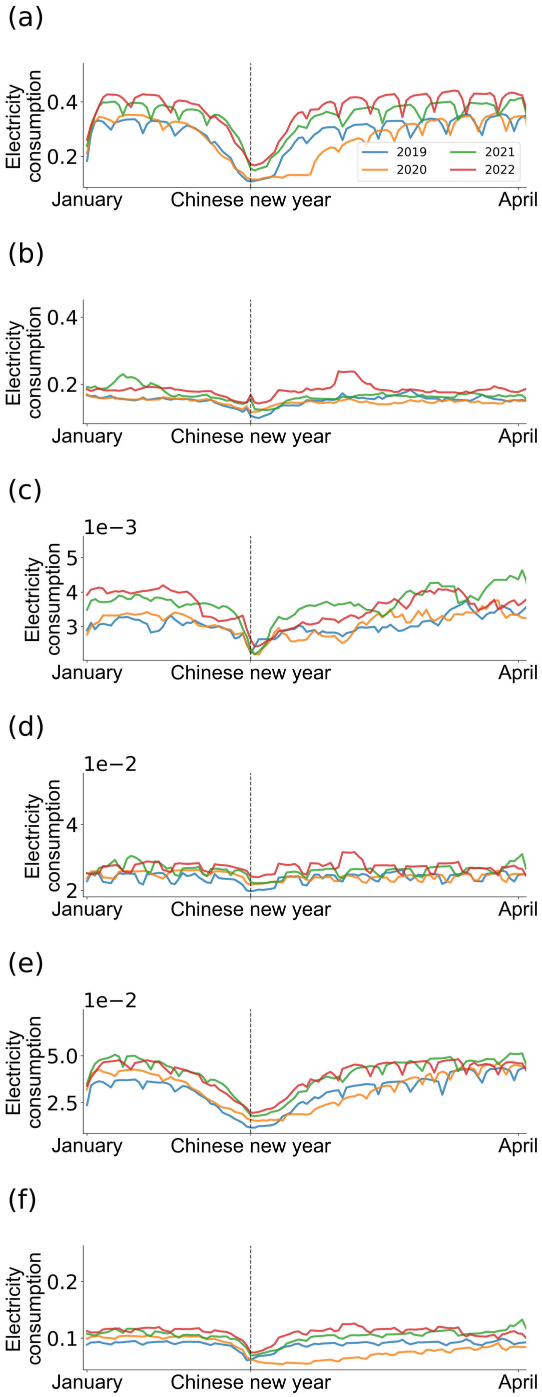

FIGURE 5. Lunar calendar alignment for city2.

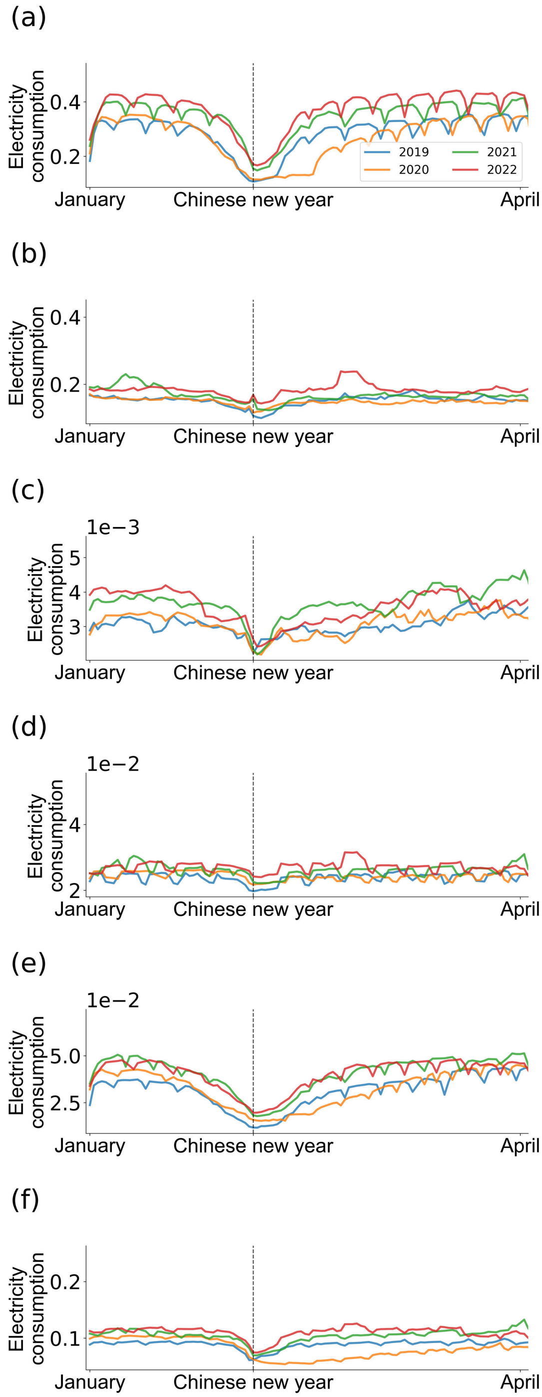

FIGURE 6. Lunar calendar alignment for city3.

sectors, with a slow recovery in electricity consumption. However, other types of electricity consumption exhibited trends similar to non-pandemic years, lacking significant differences. We attempted to predict the outbreak time of the pandemic through electricity consumption analysis, using the Anomaly Transformer algorithm to validate anomalies in electricity consumption and predict the pandemic outbreak time. The results indicate that the algorithm can accurately detect anomalies in industrial, non-general industrial, and commercial electricity consumption. However, its predictive ability for the outbreak of the pandemic based on changes in other types of electricity consumption is limited due to their minor susceptibility to pandemic effects.

Additionally, utilizing the CNN-LSTM model and the controlled variable method, we derived an analysis of the varying degrees of the pandemic's impact on different

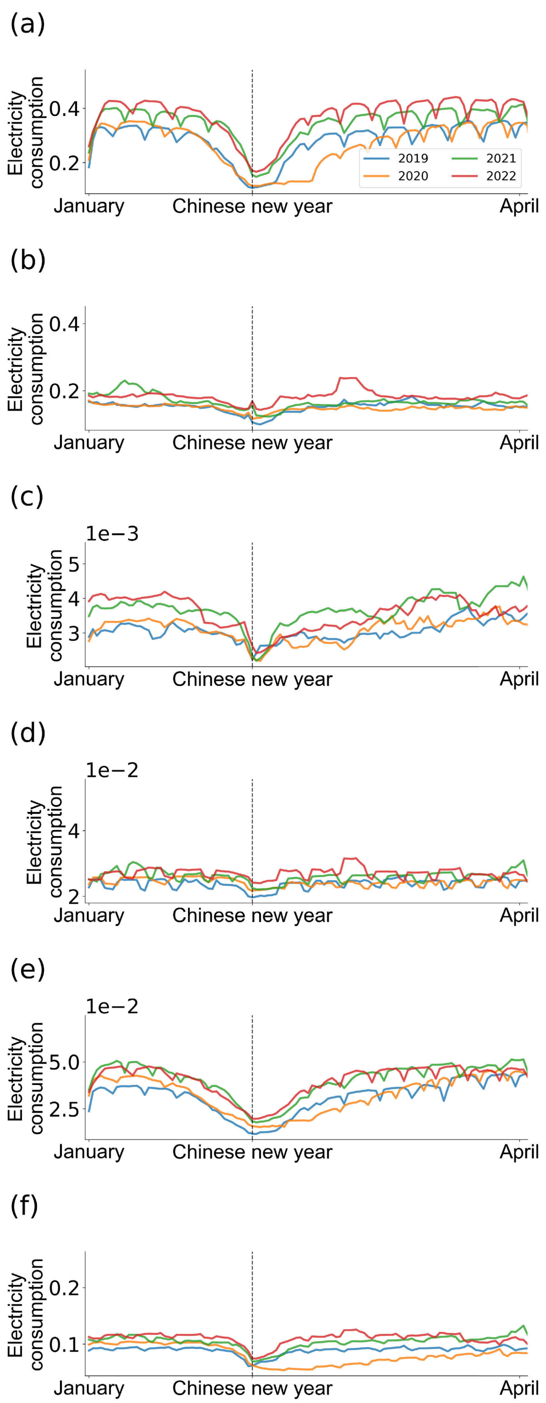

FIGURE 7. **Lunar calendar alignment for city4.**

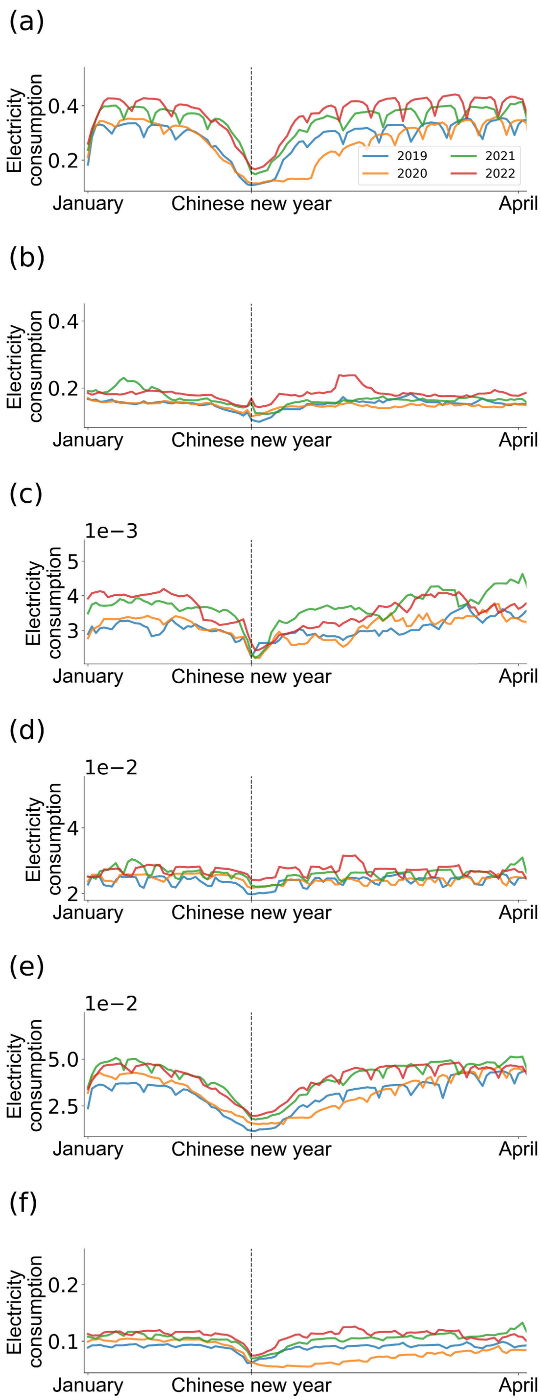

FIGURE 8. **Lunar calendar alignment for city5.**

types of electricity consumption across distinct cities. ''Pandemic'' was introduced as a covariate in the model to predict electricity consumption without the influence of the pandemic, thereby obtaining the baseline electricity consumption. By calculating the difference between the baseline and actual electricity consumption, we determined the impact of the pandemic on electricity consumption. To provide a dimensionless description, we introduced the pandemic impact percentage, which is the ratio of the impact on electricity consumption to actual consumption. Based on the absolute value of this percentage, we assessed the significance of the pandemic's impact.

The analysis results indicate that, for the commercial and industrial electricity consumption types, the impact magnitudes in all cities exceed 0.05. Specifically, the commercial sector experiences the greatest impact, reaching a maximum magnitude of 0.386, while the industrial sector shows the highest impact magnitude at 0.223. In summary, the

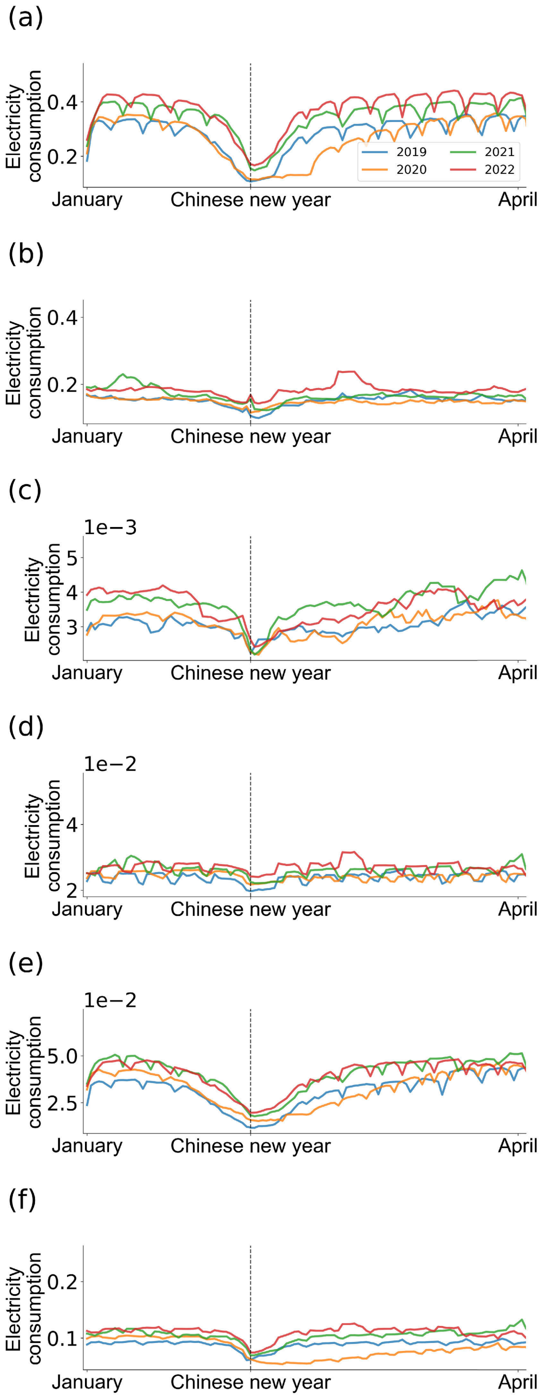

FIGURE 9. Lunar calendar alignment for city6.

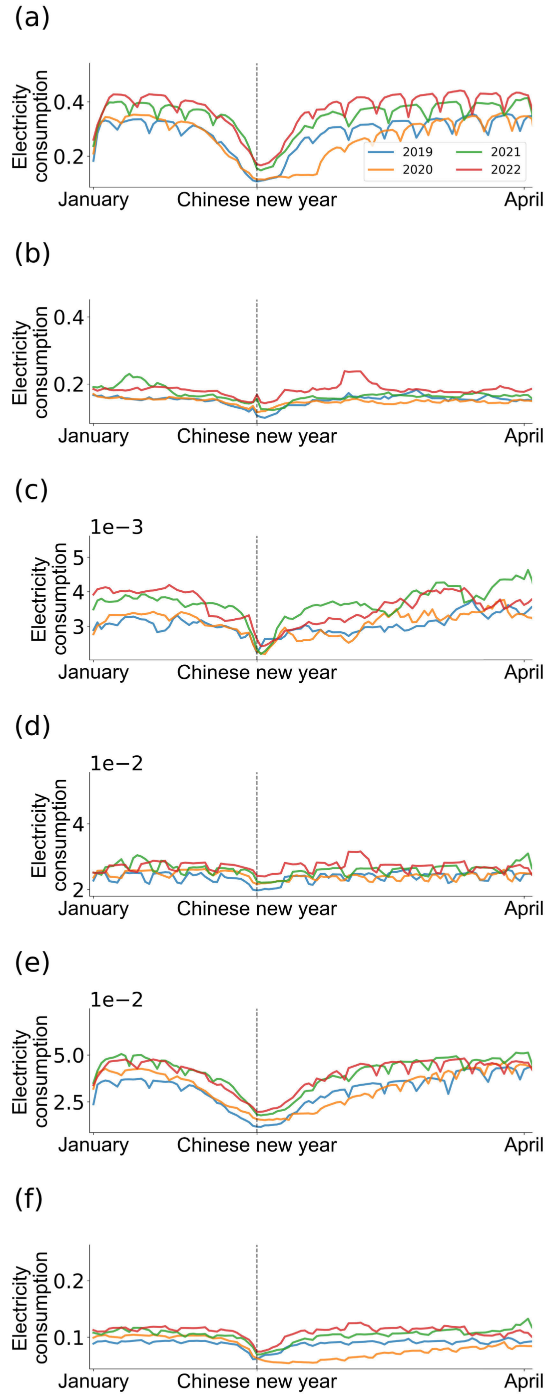

FIGURE 10. Lunar calendar alignment for city7.

influence of the pandemic on both industrial and commercial electricity consumption types is substantial, aligning with the findings from the initial part of this study (see Table 1 for detailed information). The significant impact of the pandemic on industrial and commercial electricity usage primarily manifests across various dimensions, including production interruption, supply chain issues, economic uncertainty, labor force constraints, industry disparities, and fluctuations in energy prices. Stagnation of production lines and labor shortages have resulted in decreased production efficiency, while economic uncertainty has prompted enterprises to exercise caution in investment and expansion. Industry disparities have led to notable variations in electricity demand across different sectors, and fluctuations in energy prices may profoundly affect enterprises' energy costs. In terms of residential electricity consumption, only the impact in the fourth city slightly exceeds 0.05, with the lowest impact level being merely 0.004. This suggests that the pandemic's

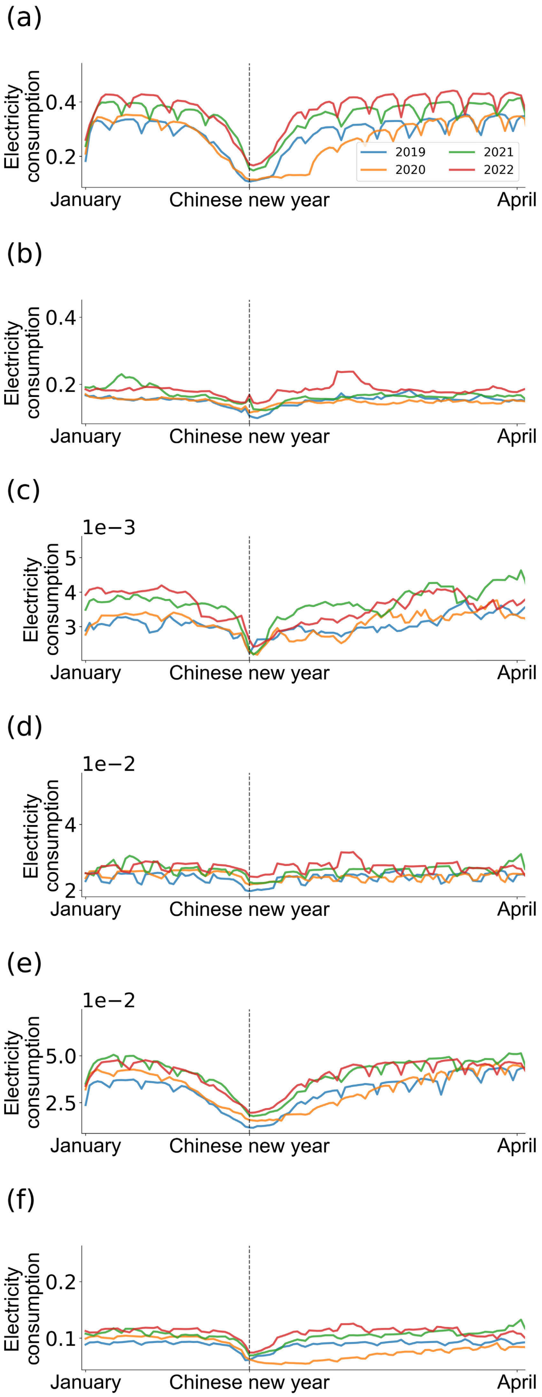

FIGURE 11. Lunar calendar alignment for city8.

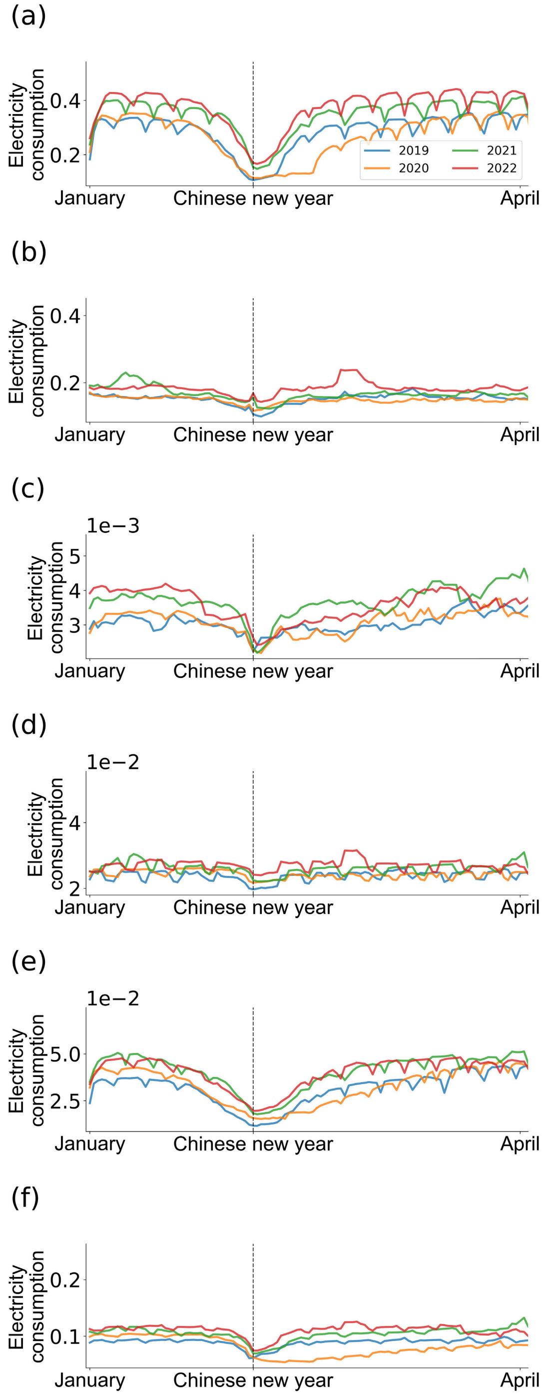

FIGURE 12. Lunar calendar alignment for city9.

influence on this particular electricity consumption category is not significant, likely attributable to the stability of basic life requirements.

B. FUTURE DIRECTIONS

Our analytical framework is not only limited to studying pandemics but can also be applied to investigate the impacts of other special events on electricity consumption. In the future, we plan to utilize this approach to examine the effects of various events such as typhoons, holidays, and special production plans. For example, in the case of a typhoon event, if it coincides with specific significant Chinese holidays, we can first employ the Dynamic Time Warping (DTW) algorithm for temporal alignment (this step can be omitted if there are no significant holiday effects), followed by using the Anomaly Transformer (AT) algorithm to predict the typhoon outbreak time. Subsequently, we will apply the CNN-LSTM method to analyze the typhoon's

TABLE 2. Comparison of electricity consumption prediction across different models.

prediction model	Industry	Non-general industry	Residential living	Commercial electricity	Agricultural electricity	The whole province
ARIMA	-0.8%	-18.95%	-2.53%	2.27%	-2.14%	-2.51%
CNN-LSTM	3.79%	1.54%	-5.5%	-3.8%	-4.58%	0.34%
Prophet	3.42%	13.53%	7.16%	8.95%	-0.44%	5.53%
Prophet+LightGBM	3.15%	7.30%	0.18%	4.71%	-1.94%	2.65%
Sliding window + GBDT	-2.41%	-7.06%	0.59%	-8.89%	-4.37%	-2.8%

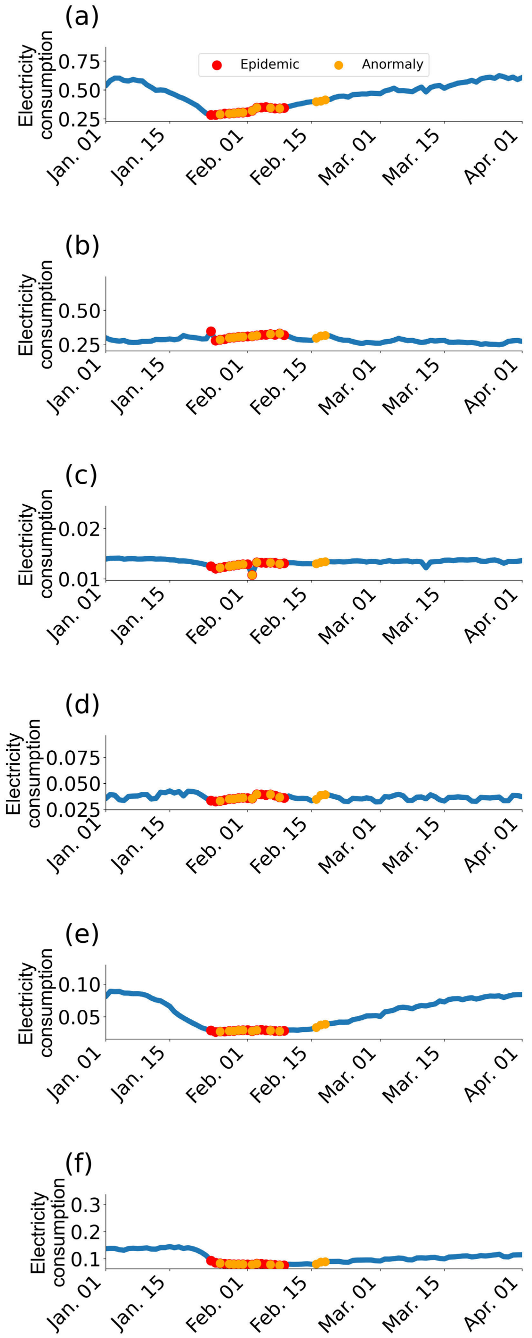

FIGURE 13. Epidemic detection for city2.

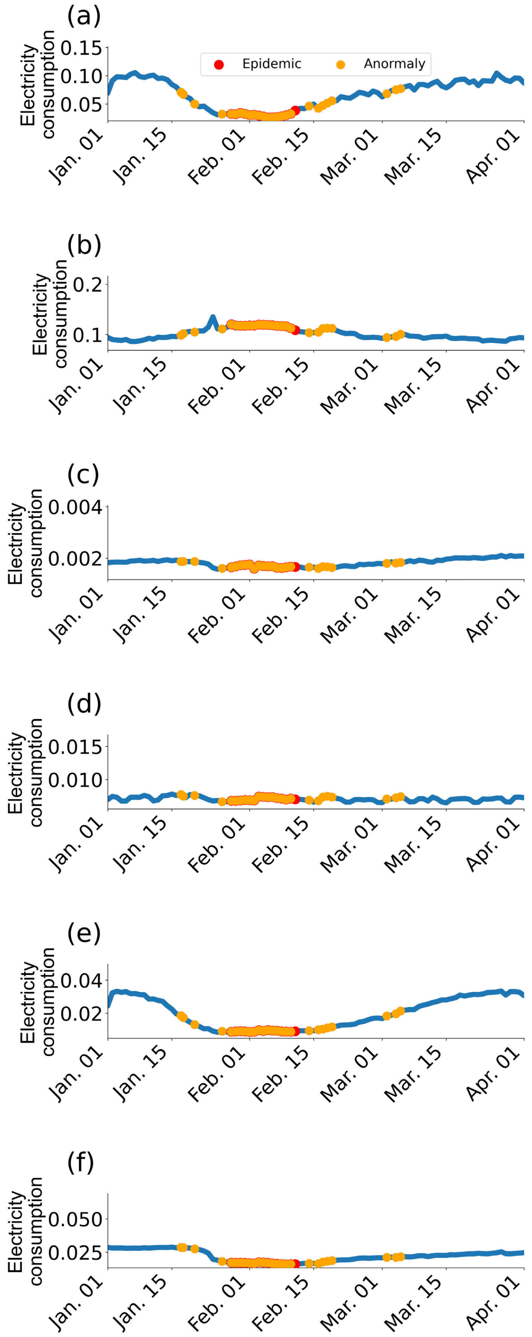

FIGURE 14. Epidemic detection for city3.

impact on electricity consumption across various industries. This proactive approach enables us to make necessary adjustments in electricity supply before the arrival of the next typhoon. Additionally, while our analytical framework is built on data from a specific province, its applicability is not limited to that province. Despite only utilizing data

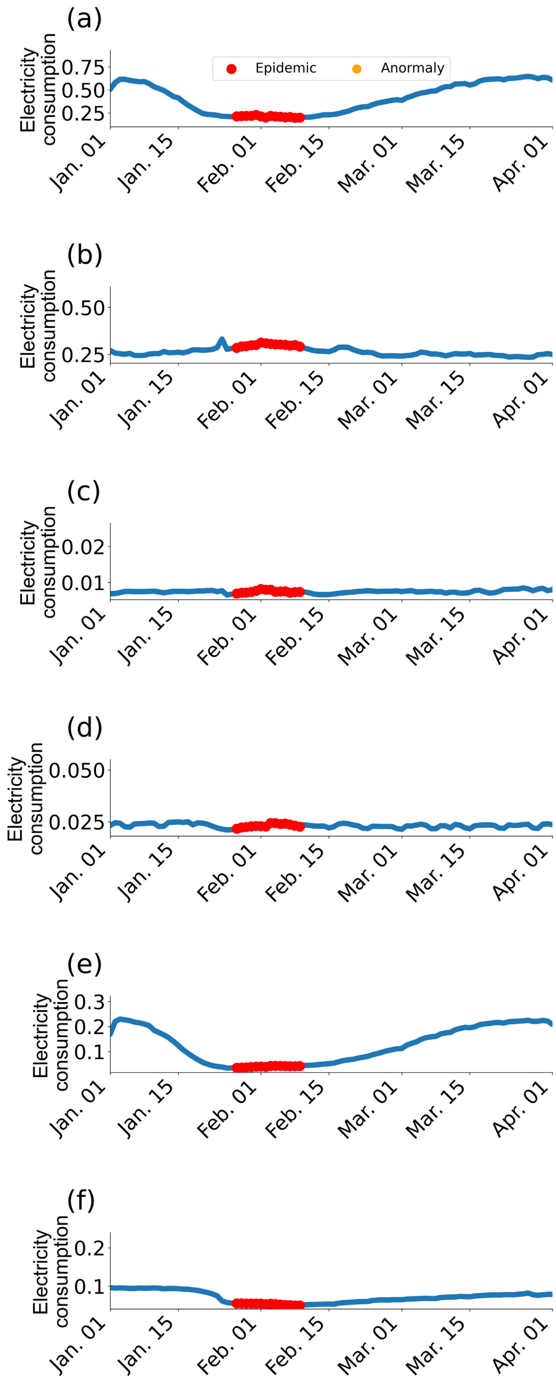

FIGURE 15. Epidemic detection for city4.

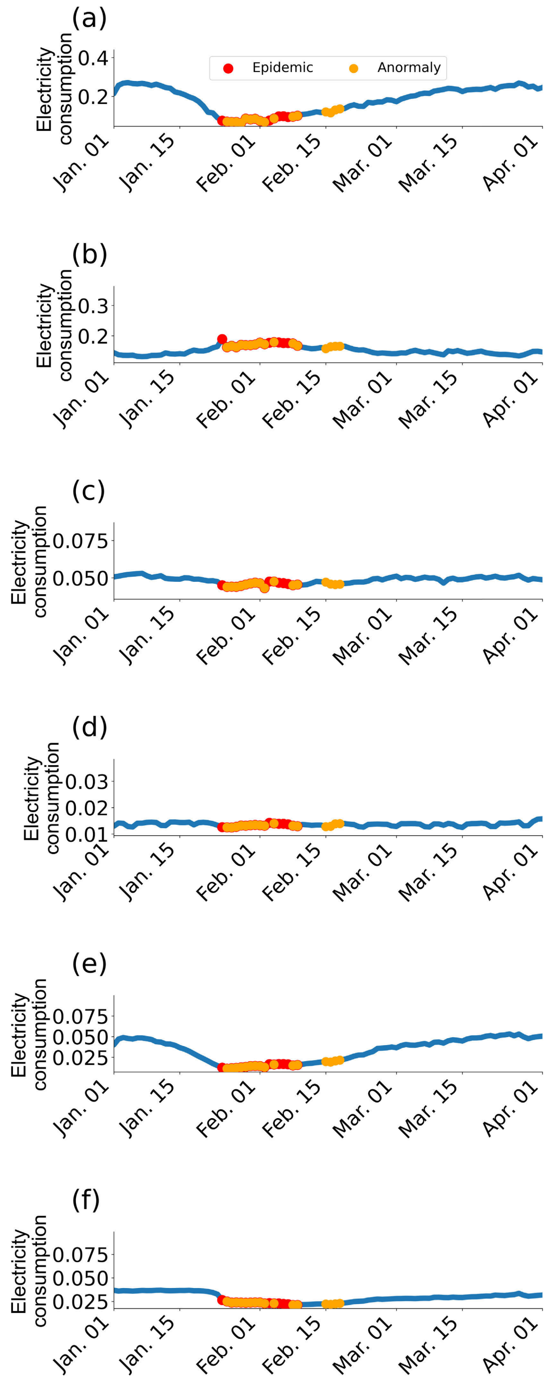

FIGURE 16. Epidemic detection for city5.

from certain southeastern provinces of China, our method has the potential to extend to other regions. On one hand, the evaluation method we have established can be applied to other provinces, with the development of effective methodologies remaining a primary focus of our paper. On the other hand, we speculate that southeastern coastal provinces of China may share highly similar patterns. Thus, expanding the applicability of our method will be a crucial direction for our future work.

Our further objective is to utilize the systematic analytical approach we have developed to assess the impact of various events on electricity consumption and integrate events with significant effects into an event database to provide more accurate forecasts of electricity consumption, ensuring the stable operation of the power system. However, our research methodology has certain limitations. Firstly, within our detection system, it is necessary to utilize time series data with a longer temporal span to enhance the accuracy of

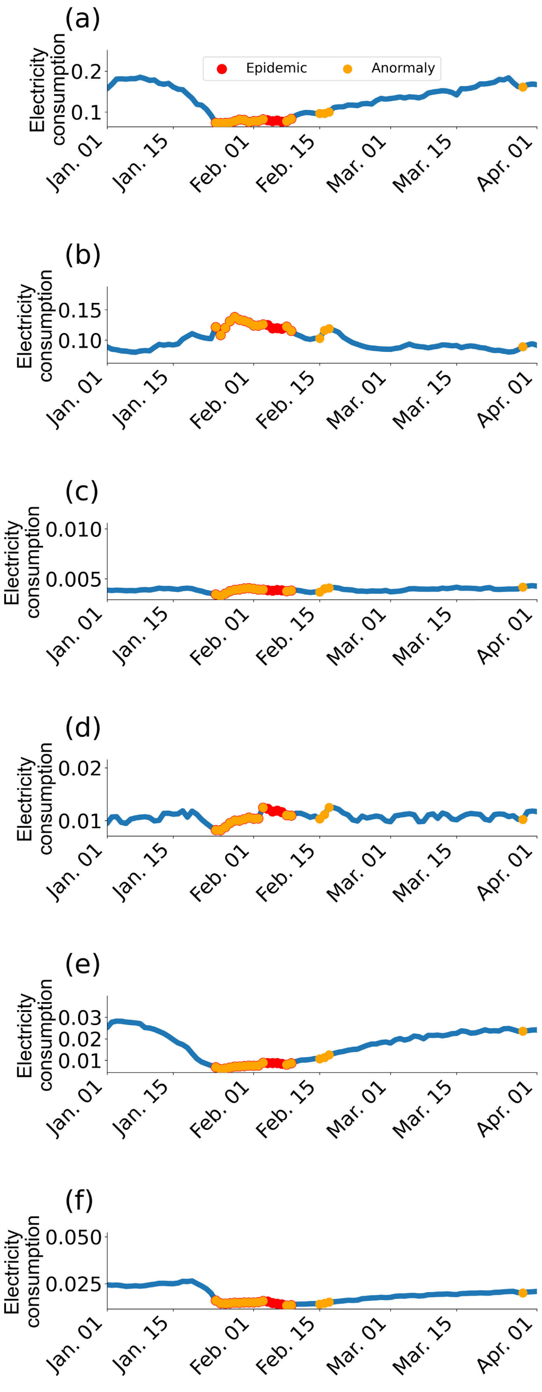

FIGURE 17. Epidemic detection for city6.

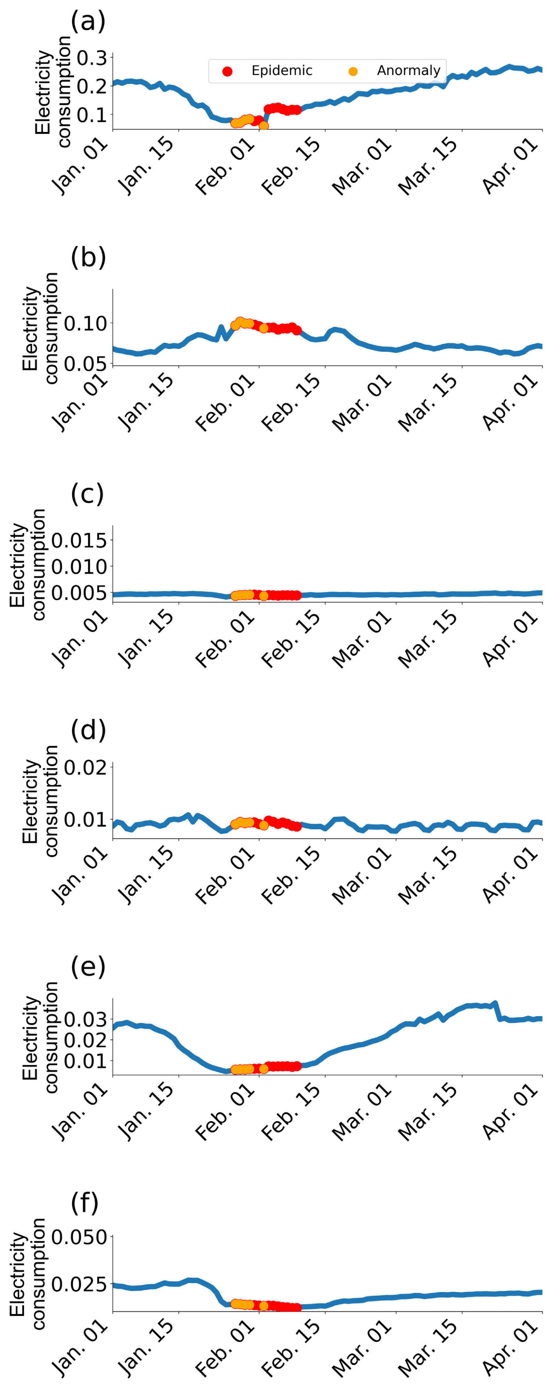

FIGURE 18. Epidemic detection for city7.

pandemic perception and avoid the risk of false positives. Secondly, in evaluating the impact of the pandemic, we rely on the predictive accuracy of CNN-LSTM to determine its significance. Lastly, we have employed a one-hot encoding method to represent pandemic events, which may pose challenges for analysis. Therefore, in future research, we will explore alternative encoding methods to conduct a more comprehensive analysis.

APPENDIX A
RESULTS OF ELECTRICITY CONSUMPTION IN DIFFERENT CITIES AND CITIES

In Section III-A1, we conducted a detailed empirical study using City1, a certain province in southern China as an example. Employing the Time Warping algorithm, we aligned the time series data with the lunar New Year to eliminate the interference of major holidays on the analysis of pandemic

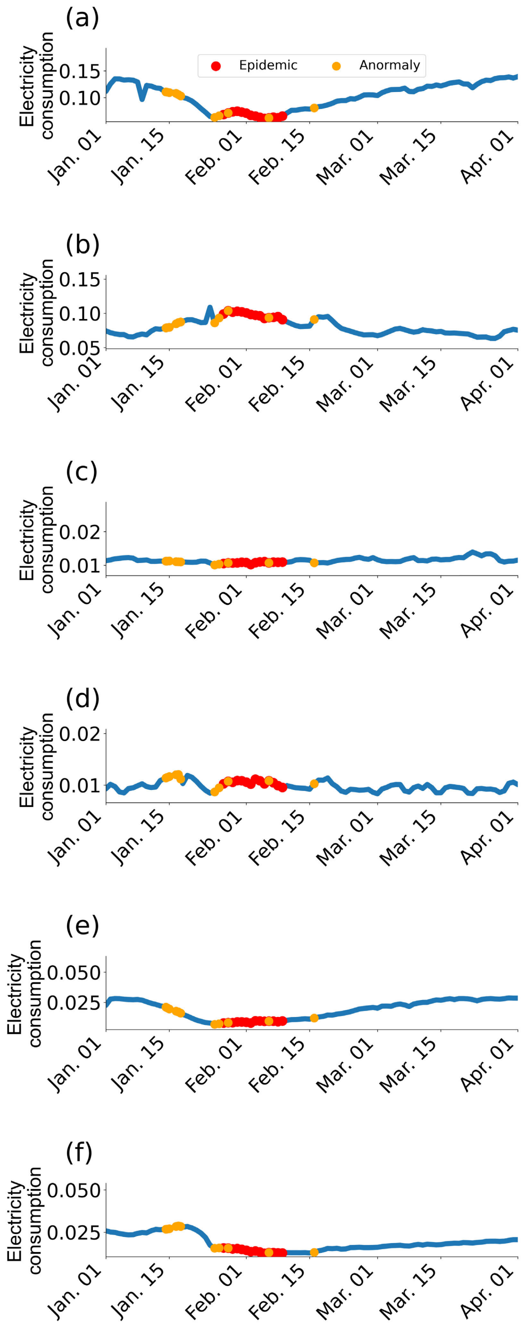

FIGURE 19. Epidemic detection for city8.

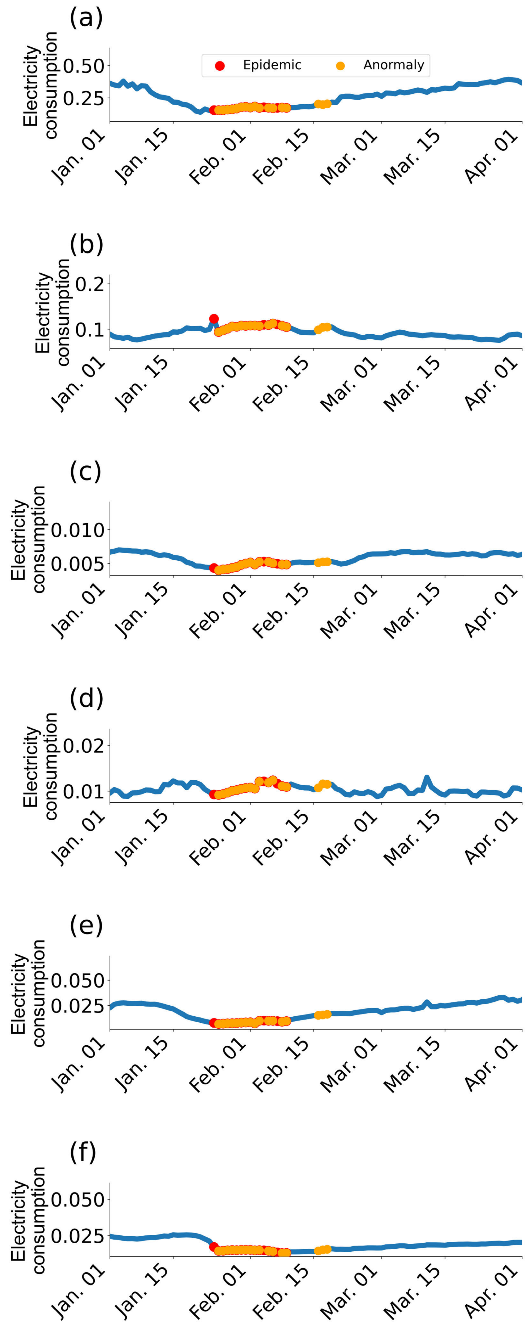

FIGURE 20. Epidemic Detection for City9.

impact. Next, we will present the analysis results for the other eight cities in the Province (Fig.5 to Fig.12).

Based on the data presented in the charts, we observe that after aligning the electricity consumption data for different types in various cities with the lunar new year, the conclusions drawn are consistent with the research findings for City1 as detailed in the main text. Specifically, for industrial, non-general industrial, and commercial electricity usage, there is a noticeably slower recovery in electricity consumption after the outbreak of the epidemic. However, other types of electricity usage, do not exhibit significant differences compared to non-epidemic years. Therefore, we can see that the impact of the epidemic on the first three types of electricity usage is relatively significant.

APPENDIX B
RESULTS OF ABNORMAL DETECTION BASED ON LUNAR CALENDAR ALIGNMENT DATA

Our focus lies in understanding the role of electricity consumption in perceiving the outbreak of a pandemic specifically, utilizing electricity consumption data to forecast the onset of a pandemic. In the main text, we showcased and analyzed City1 as an illustrative example. Similarly, we conducted comprehensive research and validation on various types of electricity consumption in the other eight cities, yielding results akin to those observed in City1. The presentation is outlined as follows (Fig.13 to Fig.20).

APPENDIX C
THE EFFECTIVENESS OF THE CNN-LSTM METHOD

In this section, various methodologies were employed to forecast the electricity consumption across different categories and the entire province. The relative errors of different models (where relative error is calculated as (predicted value - actual value) / actual value)·100% are presented in the table below. The findings indicate that the CNN-LSTM method we implemented exhibits the most stable overall performance.

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