ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Nonlinear influence mechanism and threshold effect of abnormal temperature fluctuation on regional electricity sales - Empirical analysis based on panel smooth transformation model

Jiakui Zhao[1], *Shichong Chen*[1,*], *Xiaoteng Ma*[1], *Yushu Zhang*[1], *Xishuang Hu*[1] *and Wenli Liu*[1]

[1] State Grid Information & Telecommunication Center (Big Data Center) Beijing150001, China

SUMMARY: *The combination of increasing extreme weather and climate warming makes the disturbance of abnormal temperature fluctuations on regional electricity sales increasingly stronger. Based on the panel data constructed by regional electricity sales, temperature, humidity and economic variables, this paper uses abnormal temperature identification, temperature shock quantification, threshold effect test and panel smooth transformation model to empirically analyze the nonlinear response mechanism of electricity sales. The results show that there is a significant U-shaped relationship between regional electricity sales and temperature. The V-shaped single threshold is 18.8℃, the comfort zone identified by the U-shaped nonlinear model is 13.5 -- 21.7℃, and its RMSE is 10.270, which is better than the V-shaped nonlinear and U-shaped linear models. In the model comparison, the RMSE, MAE and R² of the PSTR model reach 9.986, 7.516 and 0.796, respectively, and the comprehensive performance is the best. The increase of humidity reduced the threshold of high temperature side by about 2.2℃, and the width of comfort zone narrowed from 9.4℃ to 8.0℃ at different time periods. The research can provide more targeted quantitative basis for regional electricity sales forecasting, load scheduling and extreme weather response.*

KEYWORDS: *Abnormal temperature fluctuation; Regional electricity sales; Nonlinear influence; Panel smooth transition model*

1 Introduction

Regional electricity sales forecasting is an important basis for safe dispatching, capacity planning, load management and market operation of power system, in which temperature change has the most direct disturbance to electricity demand. Whether it is the rapid rise of cooling load in summer or the centralized release of heating demand in winter, temperature will change the power consumption intensity through multiple paths such as residential life, commercial activities and industrial operation, so it is always in the position of the core explanatory variable in the analysis of electricity sales. Previous studies have shown that the relationship between electricity sales and temperature is not simple linear, but has obvious segmentation, asymmetry and threshold characteristics, and there are significant differences in response slopes at different stages. Early studies summarized the relationship between them as a "V" shape structure, that is, low temperature and high temperature would push up electricity consumption, and there was a single inflection point in the middle. With the development of

*shichong_chen@163.com
https://doi.org/10.65102/is2026703 Published: 30 April, 2026

high-frequency samples and refined identification methods, it is further found that there is often a comfort zone between the heating zone and the cooling zone that is not sensitive to the change of power demand, and the overall relationship is closer to the "U" -shaped structure. At the same time, the threshold temperature is not constant in different cities, years and climates, and its upper and lower boundaries can even shift by several degrees Celsius.

From the existing research, although the relevant results provide useful reference for electricity sales forecasting, there are still some shortcomings. On the one hand, many researches are still only oriented to prediction accuracy, accustomed to follow a single model or directly apply the existing threshold, and lack of re-identification and calibration for local samples. On the other hand, the lack of consideration of the linkage influence of relative humidity, time migration, behavior change and other factors can easily lead to the deviation of critical temperature identification, which will weaken the explanatory power and prediction robustness of the model. The original results you provided also show that there are obvious differences in the threshold interval under different structures. For example, the critical points of the "V" model and the "U" model are not consistent, and the increase in humidity will obviously lower the boundary temperature between the comfort zone and the cooling zone, and there is a right shift of the threshold under different samples at different periods. This indicates that the response of electricity sales to abnormal temperature fluctuations has prominent nonlinear and dynamic migration characteristics.

Based on this, this paper focuses on the influence mechanism of abnormal temperature fluctuations on regional electricity sales. On the basis of inherits the idea of threshold regression and smooth conversion regression analysis, the panel smooth conversion model is introduced to describe the change law of regional electricity sales under different temperature intervals, focusing on identifying the nonlinear conversion path and threshold effect under abnormal high temperature and abnormal low temperature impact. Combined with regional electricity sales, temperature, humidity and related time series samples, this study will systematically test the benchmark relationship, temperature and humidity coupling effect and threshold drift under different periods, in order to provide more targeted empirical basis for regional electricity sales forecasting, grid elastic scheduling and power demand response management under the background of extreme weather.

2 Literature Review

The existing research on the relationship between temperature change and power consumption response has formed a rich result. Pablo Romero et al. analyzed the joint impact of economic growth and global warming on electricity consumption from the sector level in Spain, and pointed out that temperature change would significantly change the electricity elasticity of different sectors [1]. Roman-Collado et al. further verified that temperature change is an important driving factor for regional sector electricity consumption differences [2]. In the research on residential energy consumption, scholars have introduced nonlinear temperature effects into the quantile regression framework, revealing the heterogeneity of energy demand response under different temperature intervals [3]. For urban samples in China, relevant studies show that climate change will affect urban electricity consumption through seasonal and regional differences, and household monthly electricity consumption is obviously sensitive to temperature shocks [4, 5]. In addition, Kostakis et al. used pseudo-panel data to study residential electricity demand, which also showed that temperature change was not linear transmission, but was jointly regulated by household behavior and structural factors [6].

In terms of load forecasting and model construction, existing studies pay more attention to the improvement of algorithm accuracy. Hybrid integrated model, artificial neural network, fuzzy optimal combination model and multi-step prediction meta-model are widely used in power load forecasting [7-10], and environmental variables and economic variables are gradually introduced to carry out feature enhancement [11]. Meanwhile, the epidemic shock, income difference and energy use behavior are also included in the demand analysis framework, which enriches the explanatory dimension of power consumption fluctuations [12]. Under the influence of extreme temperature, power grid fault reliability analysis has also attracted attention [13]. From the perspective of method evolution, methods such as adaptive back propagation, SHAP feature interpretation, bidirectional GRU, fuzzy weighted LSTM, K-means and SVM are continuously used for short-term load forecasting optimization [14-18]. The research on micro-grid scenario, ARIMA-ANN fusion, parallel ConvLSTM, multi-convolutional and recurrent network, CNN-LSTM fusion model, spatio-temporal meteorological information fusion and probabilistic forecasting model further promote the development of power load forecasting to depth and refinement [19-26].

In general, the existing literature has fully discussed the impact of temperature change on power consumption and the improvement of load prediction methods, but it still focuses on the improvement of prediction performance, and insufficient attention is paid to the nonlinear influence mechanism of electricity sales under abnormal temperature fluctuations, the threshold conversion characteristics, and the dynamic boundary identification under temperature and humidity coupling. Especially in the research of regional electricity sales, how to simultaneously describe the smooth conversion process of abnormal high temperature, abnormal low temperature and comfortable interval from the perspective of panel still has large space for expansion. Therefore, on the basis of absorbing the aforementioned research results, this paper introduces the panel smooth transformation model to empirically analyze the nonlinear mechanism and threshold effect of abnormal temperature fluctuations affecting regional electricity sales.

3 Calculation and analysis framework and model construction of nonlinear influence of abnormal temperature fluctuation on regional electricity sales

3.1 Mechanism representation and variable setting of the influence of abnormal temperature fluctuation on regional electricity sales

Abnormal temperature fluctuation does not have a uniform and linear impact on regional electricity sales, but forms a segmented response under the combined action of thermal comfort deviation, equipment start and stop intensification and load structure reorganization. For regional electricity consumption, when the temperature is in a relatively comfortable range, the operation intensity of temperature control equipment in residential life, commercial operation and general production activities is low, and the electricity sales mainly show basic and stable fluctuations. When the temperature continues to be higher than the comfort limit, the refrigeration equipment starts centrally, the residential air conditioning load, commercial refrigeration load and office service electricity consumption rise synchronously, and the regional electricity sales increase rapidly. When the temperature is significantly lower than the comfort lower limit, the demand for heating, insulation and auxiliary heating is gradually released, and the electricity sales will also increase, but the growth slope is usually weaker than that of the high temperature scenario. This shows that although the influence direction of abnormal high temperature and abnormal low temperature on electricity sales is consistent, that is, they both promote the increase of electricity consumption, the influence intensity is not symmetrical, and the relationship between regional electricity sales and temperature is closer to the nonlinear relationship with threshold boundary.

Furthermore, the effect of abnormal temperature fluctuation on regional electricity sales is also regulated by humidity conditions, time evolution and regional energy consumption structure differences. The rise of humidity will strengthen the stuffiness of the human body, making the refrigeration equipment start in advance at low temperatures, resulting in the high temperature side threshold moving to the low temperature end. On the contrary, in a dry environment, the somatosensory load corresponding to the same temperature is relatively weak, and the refrigeration response will lag. At the same time, under the background of climate warming, residents' requirements for indoor comfort continue to increase, the increase of air conditioning ownership, the extension of commercial service time and the enhancement of electric energy substitution will also promote the migration of temperature threshold in the time dimension. Therefore, it is often difficult to accurately identify the true boundary of abnormal temperature shock if only a single daily average temperature is used to explain the change of electricity sales. It is necessary to incorporate the degree of temperature deviation, humidity correction and time period difference into the variable setting.

Based on this, this paper first expresses the regional electricity sales in logarithmic form to weaken the impact of dimensional differences and heteroscedasticity:

$$\mathrm{y_{it}} = \ln(\mathrm{S_{it}}) \tag{1}$$

where, y_{it} represents the log value of electricity sold in region i in period t, and S_{it} is the actual electricity sold. After logarithmic processing of the explained variables, the model estimation results can more intuitively reflect the relative change effect of abnormal temperature shocks on electricity sales.

In order to describe the abnormal degree of temperature deviation from long-term normal, the regional abnormal temperature index is defined as follows:

$$\mathrm{AT_{it}} = \mathrm{T_{it}} - \overline{\mathrm{T}}_{\mathrm{i,m}} \tag{2}$$

Here, AT_{it} represents the abnormal temperature deviation value of region i in period t, T_{it} is the actual average temperature of the current period, and $\overline{\mathrm{T}}_{\mathrm{i,m}}$ is the multi-year average temperature of the region in the corresponding month m. Considering the correction effect of humidity on body temperature and equipment operation intensity, the comprehensive index of temperature impact is further constructed as follows:

$$\mathrm{TI_{it}} = \mathrm{AT_{it}} + \lambda(\mathrm{RH_{it}} - \mathrm{RH_{i}}) \tag{3}$$

where, TI_{it} is the comprehensive index of temperature shock, RH_{it} is the relative humidity of the current period, RH_{i} is the regional average humidity level, and λ is the humidity correction coefficient. When the TIit value rises, it means that the area is facing stronger heat load pressure. When its value decreases, it indicates that the region is biased towards the cooling load scenario.

In terms of variable setting, this paper takes the logarithmic value of regional electricity sales as the explained variable, takes the comprehensive index of temperature shock as the core explanatory variable, and introduces control variables such as economic activity level, population size, industrial structure, electricity price level and time effect, so as to remove the interference of non-meteorological factors on electricity sales fluctuations as far as possible.

The purpose of this setting is to enable the marginal impact of abnormal temperature shocks to be more accurately identified after controlling for conventional economic and social factors. Since the influence of abnormal temperature on electricity sales has obvious state dependence, the comprehensive index of temperature shock will be used as the conversion variable in the subsequent model to further identify the smooth conversion process among high temperature zone, comfort zone and low temperature zone, and test the change characteristics of electricity sales response coefficient under different states.

The conduction mechanism of abnormal temperature fluctuations affecting regional electricity sales is shown in Figure 1.

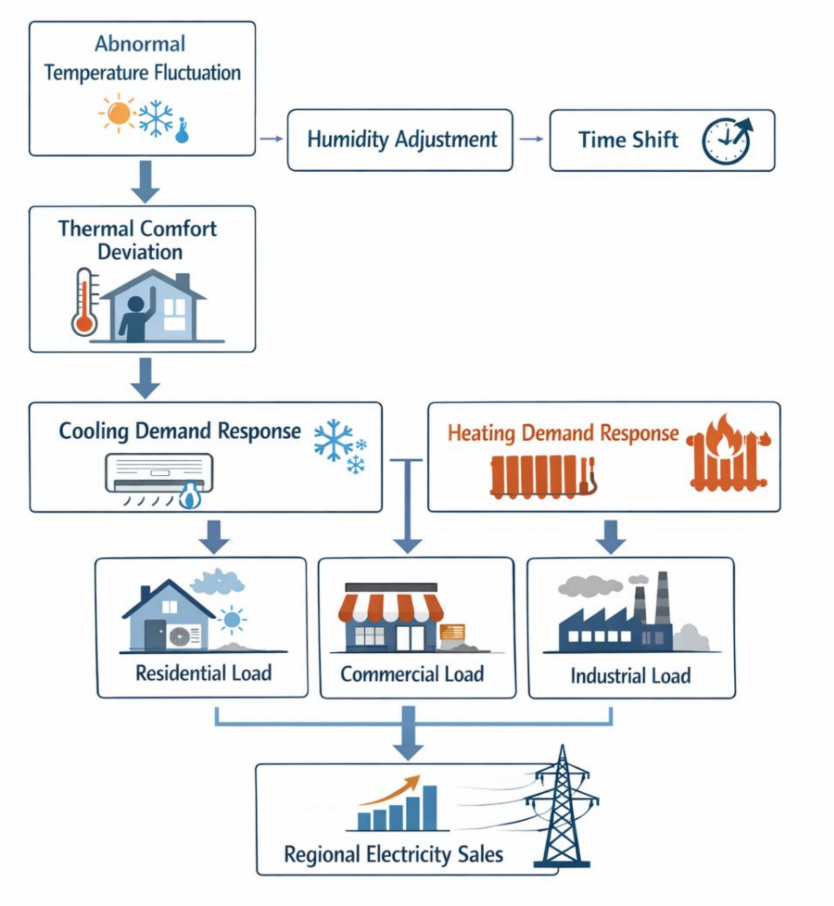

Figure 1: The action mechanism diagram of abnormal temperature fluctuations affecting regional electricity sales

3.2 Multi-source meteorological economy and regional electricity sales panel data acquisition and preprocessing

In order to ensure the stability of abnormal temperature shock identification and threshold estimation, this paper constructs a panel data system of three types of information fusion: regional electricity sales, meteorological conditions-economic environment. In the electricity sales data, the regional daily electricity sales was taken as the core observation variable. In the meteorological data, the daily average temperature, relative humidity and other indicators matched with the regional spatial location were selected, and the long-term average temperature series was added to identify the climate background changes. The samples from 2019 to 2024 are mainly used to estimate the main model, the samples from 2010 to 2013 are used to compare the threshold drift in different periods, and the long-term average temperature series are used to explain the background trend of abnormal temperature fluctuations. Considering that electricity sales is not only driven by weather, but also affected by factors such as regional economic activities, population size, industrial structure and holiday arrangements, this paper further introduces regional economic operation indicators as control variables, and extends low-frequency economic variables to the daily degree panel through time matching, thus forming a comprehensive sample system with both high-frequency meteorological characteristics and medium and low frequency economic characteristics.

In the process of sample stitching, this paper uses "region-date" as a unified index to align multi-source electricity sales, temperature, humidity and economic variables, and defines the original panel set as follows.

$$\mathcal{P} = \{(\mathrm{i}, \mathrm{t}) \mid \mathrm{S_{it}}, \mathrm{T_{it}}, \mathrm{RH_{it}}, \mathrm{E_{it}}\} \tag{4}$$

where, *i* represents the regional unit, *t* represents the observation date, S_{it} is the electricity sold, Tit is the average daily temperature, RH_{it} is the relative humidity, and E_{it} is the set of economic control variables. For missing observations, the meteorological variables are processed by combining the interpolation of adjacent time points and the imputation of the mean value of the same month, and the economic variables are matched to the daily samples after frequency conversion according to the statistical caliber. In order to reduce the interference of outliers on the nonlinear estimation results, continuous variables are tail-reduced at the 1% and 99% quantiles and uniformly converted to a standardized form:

$$\mathrm{X_{it}^{*}} = \frac{\mathrm{X_{it}} - \mu\mathrm{X}}{\sigma_{\mathrm{X}}} \tag{5}$$

where X_{it} is the original variable, μX and σX are the sample mean and standard deviation, respectively, and $\mathrm{X_{it}^{*}}$ is the normalized variable. This process helps to eliminate dimensional differences and improve the comparability of different source variables in the same model framework.

Considering that the daily electricity quantity sequence contains both the weekly cycle and the long-term trend, if the original electricity sales are directly used for estimation, it is easy to amplify the interference of non-meteorological factors on threshold identification. Therefore, this paper conducts pre-purification on the electricity sales sequence. Specifically, the weekly dummy variables and time trend items are removed from electricity sales to obtain a net effect series that better reflects the weather-sensitive part:

$$\tilde{\mathrm{S}}_{\mathrm{it}} = \mathrm{S_{it}} - \sum_{\mathrm{k}=1}^{\mathrm{m}} \delta_{\mathrm{k}}\, \mathrm{D_{k,t}} - \mathrm{g(t)} \tag{6}$$

where, S_{it} is the electricity sold after pretreatment, $D_{k,t}$ is the weekly dummy variable, δ_k is the corresponding coefficient, and g(t) represents the time trend function. After this process, the long-term growth term, intra-week fluctuation term and some institutional disturbances in the sample are effectively stripped, and the remaining series can more accurately reflect the marginal impact of abnormal temperature fluctuations on regional electricity sales. In general, this section completes the unified collection of multi-source data, spatio-temporal alignment, missing repair, outlier control and standardization processing, which provides a reliable data basis for subsequent abnormal temperature identification, panel smooth transformation estimation and threshold effect test.

3.3 Abnormal temperature fluctuation identification and temperature shock characteristics quantification method

In order to accurately describe the disturbance intensity of abnormal temperature fluctuation on regional electricity sales, this paper further builds the abnormal temperature identification and temperature shock quantification method after the multi-source panel data cleaning and standardization process is completed. Different from the practice of only using absolute temperature values, this paper pays more attention to the deviation degree of temperature from the regional seasonal norm, because the corresponding somatosensory pressure and electricity response of the same daily average temperature in different months and different regions are not consistent. If the original temperature is directly used in the model, it is easy to misjudge the seasonal normal fluctuation as an abnormal shock, thus weakening the accuracy of threshold identification. Therefore, this paper first identifies the "relatively abnormal" heating and cooling states by referring to the regional monthly historical average temperature, and then further extracts the characteristics of high temperature shock, low temperature shock and persistent shock, which provides the basis of transformation variables for the subsequent panel smooth transformation estimation. The process of abnormal air temperature identification and temperature shock quantification is shown in Figure 2.

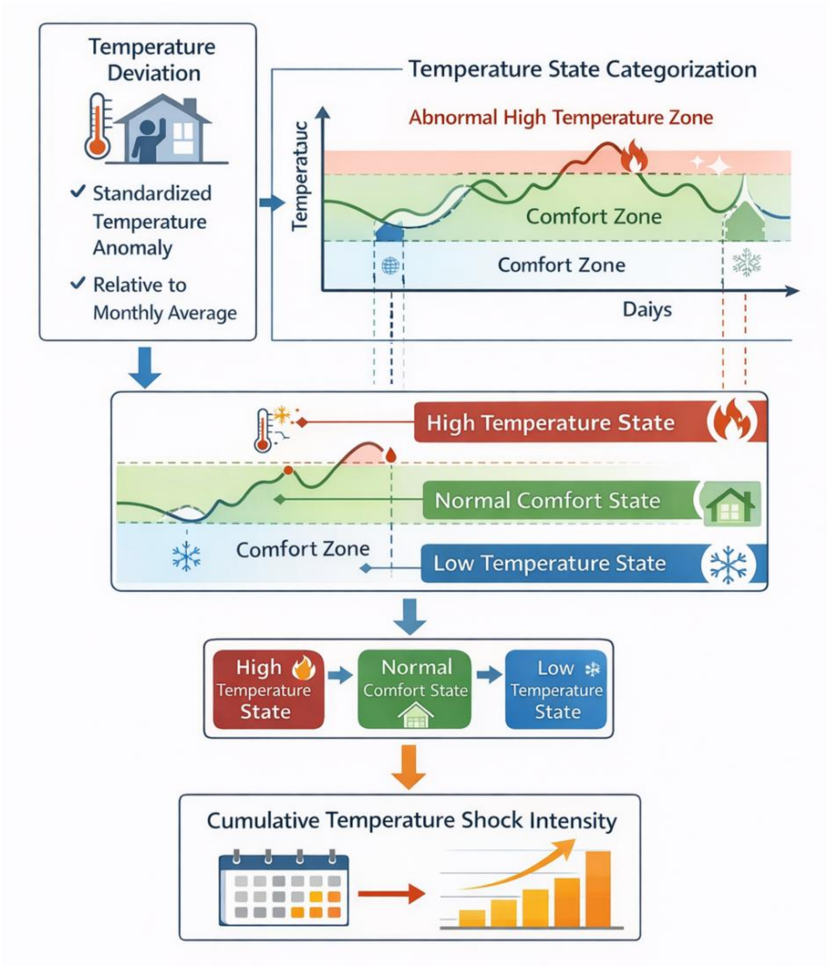

Figure 2: Schematic diagram of abnormal air temperature identification and temperature shock quantification

Firstly, the regional temperature anomaly deviation index is defined as follows:

$$A_{it} = \frac{T_{it} - \bar{T}_{i,m}}{\sigma_{i,m}} \tag{7}$$

where, A_{it} represents the standardized temperature outlier of region i in period t, T_{it} is the actual observed temperature, $\bar{T}_{i,m}$ and $\sigma_{i,m}$ represent the multi-year average temperature and standard deviation of the region under month m, respectively. When $A_{it}>0$, it means that the temperature of the current period is higher than the seasonal normal. When $A_{it}<0$, it indicates that the region is in a state of relative low temperature deviation.

On this basis, according to the upper and lower boundaries of the comfort zone, the temperature state is divided into three categories: low temperature shock, comfort fluctuation and high temperature shock.

$$R_{it} = \begin{cases} -1, & T_{it}^{*} < \theta_l \\ 0, & \theta_l \leq T_{it}^{*} \leq \theta_u \\ 1, & T_{it}^{*} > \theta_u \end{cases} \tag{8}$$

Here, R_{it} is the temperature state recognition result, T_{it}^{*} is the effective temperature after considering the humidity correction, θ_l and θ_u represent the lower and upper thresholds of the comfort zone, respectively. When the effective temperature falls inside the comfort zone, the electricity sales mainly maintains the conventional fluctuation. Once the upper threshold is crossed, the cooling load will increase rapidly. If it is lower than the lower threshold, the heating and insulation electricity is gradually released. After setting this way, the model can not only identify whether the abnormal temperature occurs, but also distinguish the abnormal direction, which is convenient to explain the realistic characteristics of asymmetric influence intensity of high temperature and low temperature on electricity sales.

Considering that the impact of abnormal temperature on electricity sales is often cumulative, this paper further constructs the temperature impact strength index:

$$I_{it} = \sum_{j=0}^{q} \rho^{j} \left[\max(T_{i,t-j} - \theta_u, 0) + \max(\theta_l - T_{i,t-j}, 0)\right] \tag{9}$$

where, I_{it} represents the integrated temperature impact intensity in period t, q is the backtracking order, and ρ is the attenuation coefficient. The index takes into account the direction, amplitude and duration of abnormal temperature. If the high or low temperature only fluctuates in a single day, its impact value is limited. If the abnormal temperature appears continuously, the impact will be continuously amplified through the cumulative term, which is more in line with the actual situation that the electricity sales gradually accelerate the response to the continuous heat load or cooling load. In general, through the three levels of standardized anomaly identification, temperature state division and impact strength quantification, this section realizes the computable expression of abnormal temperature fluctuation characteristics, and also lays the variable foundation for subsequent nonlinear transformation feature identification and threshold effect test.

3.4 Nonlinear influence identification method based on panel smooth transformation model

In order to identify the state-dependent characteristics of abnormal temperature fluctuations on regional electricity sales, this paper introduces the panel smooth transformation model under the panel data framework. The model can describe the continuous change process of electricity sales response coefficient when the temperature shock smoothly transitions from low intensity state to high intensity state on the basis of retaining regional heterogeneity and time effect. Compared with the traditional piecewise regression method that divides the sample into several discrete intervals, the panel smooth transformation model is more suitable for dealing with the realistic process of gradual migration from comfort zone to cooling zone and from comfort zone to heating zone under abnormal temperature shock, and it is more conducive to revealing the asymmetric response relationship of electricity sales to high temperature shock and low temperature shock.

Let the log value of electricity sold in region i in period t be yit, the core explanatory variable vector is Xit, which contains the temperature shock index, humidity variable and economic control variable, and the transformation variable is the temperature shock comprehensive index qit constructed in the previous section. Then the panel smooth transition model can be written as follows：

$$y_{it} = \mu_i + \tau_t + \beta' X_{it} + \delta' X_{it}\, G(q_{it}; \gamma, c) + \varepsilon_{it} \tag{10}$$

where, μ_i represents the individual fixed effect, which is used to control the long-term invariant characteristics between regions. τ_t denotes the time effect, which is used to absorb macro environment and common shocks. β is the benchmark influence coefficient in the low state; δ is the additional coefficient after smooth transformation; Let ε_{it} be the random disturbance term. Equation (10) shows that the influence of abnormal temperature fluctuation on electricity sales is not fixed, but shows continuous adjustment under different temperature states with the change of conversion function value.

The transformation function takes the form of Logistic:

$$G(q_{it}; \gamma, c) = [1 + \exp(-\gamma(q_{it} - c))]^{-1}, \quad \gamma > 0 \tag{11}$$

where c is the position parameter, which is used to describe the central position where the smooth transition occurs. γ is a smoothing parameter, which is used to reflect the state switching speed. When q_{it} is much lower than c, the value of the conversion function tends to 0, and the model mainly shows a linear structure in the state of low impact. When q_{it} is much higher than c, the transformation function gradually approaches 1, and the model turns into a nonlinear structure under high impact state. When the q_{it} is near the critical interval, the electricity sales response coefficient is continuously adjusted with the change of temperature shock, which can better reflect the dynamic characteristics of the equipment start and stop and energy consumption behavior gradually strengthened in reality.

On this basis, the state-dependent marginal effect of abnormal temperature shocks on electricity sales can be further expressed as follows:

$$\frac{\partial y_{it}}{\partial X_{it}} = \beta + \delta G(q_{it}; \gamma, c) \tag{12}$$

It can be seen from Equation (12) that when the value of conversion function is small, the influence of abnormal temperature on electricity sales is close to the benchmark coefficient. As the temperature shock continues to strengthen, the additional coefficient is gradually released, and the sensitivity of electricity sales to meteorological variables increases synchronously. If the conversion function rises rapidly under high temperature conditions, it means that the regional electricity sales has a stronger amplification effect on abnormal high temperature. If the conversion speed is relatively slow under low temperature conditions, it indicates that the heating load release has a certain lag. Therefore, the panel smooth transition model can simultaneously identify the temperature impact strength, state transition speed and asymmetric influence direction, which provides a more explanatory recognition framework for the analysis of the threshold effect of abnormal temperature fluctuations.

Based on the above model Settings, the regional electricity sales no longer shows a sudden jump between the low temperature zone, the comfort zone and the high temperature zone, but changes along a continuous evolution trajectory from low state to high state. The model can not only use the advantages of panel data to describe regional differences, but also show the dynamic evolution process of abnormal temperature shocks through smooth transformation functions. Figure 3 shows the basic structure of the panel smooth conversion model: after the temperature shock index enters the conversion module, it determines the change path of the electricity sales response coefficient in different states together with the explanatory variables, and finally forms the identification result of the nonlinear influence on the regional electricity sales. This model structure also provides a clear analytical basis for threshold effect test and parameter estimation in the next section.

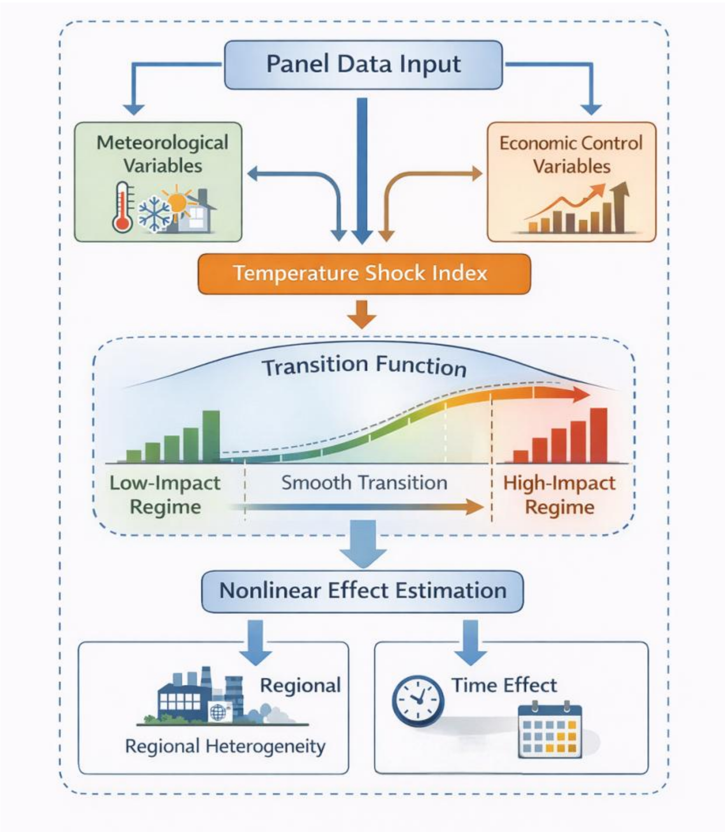

Figure 3: Schematic diagram of the panel smooth transition model structure

3.5 Threshold effect test and smooth transformation parameter estimation method

After completing the construction of abnormal temperature shock variables and the setting of panel smooth transition model, it is necessary to further test whether there is a significant threshold effect in the influence of regional electricity sales on temperature shock, and estimate the transition position and smoothness degree. Since the core of the panel smooth transformation model is to identify the continuous changes of coefficients under different temperature states, the parameter estimation cannot only stop at the linear regression level, but should be gradually carried out around the logic of "whether there is nonlinearity - whether there is still nonlinearity - where is the threshold - how fast is the transformation".

In order to avoid the problem that the smoothing parameters cannot be identified under the null hypothesis, the auxiliary regression model is constructed by using the Taylor expansion of the transformation function near the critical point:

$$y_{it} = \mu_t + \tau_t + \alpha' X_{it} + \phi_1' X_{it} q_{it} + \phi_2' X_{it} q_{it}^2 + \phi_3' X_{it} q_{it}^3 + u_{it} \tag{13}$$

Here, $\phi_1, \phi_2, \phi 3$ are the high-order expansion coefficients. The null hypothesis is set as follows:

$$H_0: \phi_1 = \phi_2 = \phi_3 = 0 \tag{14}$$

If the null hypothesis is rejected, it means that there is a significant nonlinear relationship between abnormal temperature fluctuations and regional electricity sales, and the panel smooth transformation model is better than the ordinary linear panel model.

After the null hypothesis of linearity is rejected, the "no residual nonlinear test" is further used to determine whether a single conversion function is sufficient to describe the electricity selling response process. If the remaining nonlinearity is still significant, it indicates that the effect of temperature shock on electricity sales may include multiple transition stages, and it is necessary to continue to expand the model hierarchy. If the test is not significant, the single-transition structure is retained. In terms of parameter estimation, this paper uses the combination of "grid search + nonlinear least squares" to identify the position parameters and smoothing parameters, and its objective function can be expressed as follows:

$$\widehat{\Theta} = \arg\min_{\Theta} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \varepsilon_{it}^2 (\Theta) \tag{15}$$

Here, Θ is the set of parameters to be estimated, including the base coefficient, the transformation additional coefficient, the location parameter, and the smoothing parameter. By traversing the candidate threshold interval, the initial point that minimizes the sum of squared residuals is obtained, and then the final estimate is obtained by using the nonlinear optimization algorithm.

In order to improve the reliability of threshold identification, the likelihood ratio statistics of location parameters are further constructed as follows:

$$LR(c) = \frac{NT[S(c) - S(\hat{c})]}{S(\hat{c})} \tag{16}$$

Here, $S(c)$ represents the sum of squared residuals at a given candidate threshold, and $S(\hat{c}$ represents the sum of squared residuals corresponding to the optimal threshold. When LR(c) is less than the given critical value, the corresponding interval can be regarded as the effective threshold confidence interval. If the estimation results show that the location parameter is stable, the smoothing parameter is significant and the residual nonlinearity no longer exists, it can be determined that the abnormal temperature fluctuation has a clear threshold effect on the regional electricity sales, and the dynamic transition between the low impact state and the high impact state can be realized through the smooth conversion method. Thus, this section completes the threshold effect test, conversion times determination and key parameter estimation, which provides a methodological basis for subsequent empirical results analysis.

The table of threshold test and parameter estimation items is shown in Table 1.

Table 1: Threshold test and parameter estimation item table

Item Category	Specific Content	Statistic or Method	Null Hypothesis or Evaluation Objective	Decision Criterion	Output Result
Linearity Test	Test whether the relationship between electricity sales and temperature shock can be characterized by a linear model	Auxiliary LM, LMF, and LRT tests	No smooth transition nonlinearity exists	Reject the null hypothesis when $p < 0.05$	Whether to adopt the PSTR model
Remaining Nonlinearity Test	Determine whether additional nonlinearity still exists after introducing a single transition function	Remaining LM test	A single-transition structure is sufficient	$p < 0.05$ indicates that further extension is needed	Number of transition functions
Threshold Location Search	Identify the central location where the temperature shock state switches	Grid search	Minimize the residual sum of squares	Select the point with the minimum SSR	Optimal location parameter
Smoothing Parameter Estimation	Identify the switching speed and smoothness of transition between states	Nonlinear least squares estimation	The degree of smoothness can be stably identified	Parameters are significant and convergent	Optimal smoothing parameter
Joint Parameter Estimation	Simultaneously estimate the baseline coefficients and transition-added coefficients	Iterative NLS optimization	Coefficients achieve the global optimum	Minimize the objective function	Complete parameter vector
Threshold Interval Identification	Determine the stable range of the estimated threshold	Likelihood ratio statistic	Whether the candidate threshold falls within the valid interval	LR value is lower than the critical value	Threshold confidence interval
Model Validity Test	Verify whether the estimated model has explanatory power and stability	Goodness-of-fit and residual tests	The model specification is reasonable	High R^2 and stable residuals	Judgment on model applicability
Robustness Check	Test whether parameter estimates are affected by sample segmentation or indicator replacement	Subsample regression and alternative-variable tests	Parameter results are stable	Consistent direction and limited fluctuation	Robustness conclusion of estimation

3.6 Model calculation process and evaluation index system construction

After completing the variable setting, temperature shock identification and panel smooth transformation model construction, this paper further establishes the model calculation process and evaluation index system to ensure the interpretability, stability and comparability of the abnormal temperature fluctuation nonlinear identification results. The overall calculation process can be summarized as six steps. First, the electricity sales, meteorological and economic data are aligned, cleaned and standardized according to the "region-date" index to form a balanced or approximately balanced panel sample. Secondly, the abnormal high temperature and abnormal low temperature states were identified by combining the historical average temperature, humidity correction and comfort zone boundary, and the temperature impact index was generated. Thirdly, the linear null hypothesis test and the residual nonlinear test were carried out to determine whether the panel smooth transformation model was suitable for use. Fourthly, grid search is used to determine the initial values of the position parameters, and the nonlinear least square method is used to estimate the smoothing parameters and state coefficients. Fifth, the marginal impact of abnormal temperature shock on regional electricity sales under different temperature states is calculated. The sixth is to comprehensively evaluate the effectiveness of the model by combining prediction error, goodness of fit and information criteria.

In the model output stage, set the actual electricity sales log value as yit and the model fitting value as y^it, then the root mean square error is defined as follows.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it} - \hat{y}_{it})^2} \tag{17}$$

This index is used to measure the overall fitting deviation of the model, and the smaller the value is, the more accurate the model is to depict the regional electricity sales fluctuations. To further reflect the mean absolute error level, it is defined as follows.

$$\mathrm{MAE} = \frac{1}{\mathrm{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}|y_{it} - \hat{y}_{it}| \tag{18}$$

Compared with RMSE, MAE is less sensitive to extreme errors and is more suitable for observing the average fitting ability of the model in general sample intervals.

In addition to the error index, this paper also uses the coefficient of determination to evaluate the explanatory ability of the model:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it} - \hat{y}_{it})^2}{\sum_{i=1}^{N}\sum_{t=1}^{T}(y_{it} - \bar{y})^2} \tag{19}$$

where $\bar{y}$ is the sample mean. The higher R^2 is, the more fully the abnormal temperature shock, humidity correction and control variables explain the fluctuation of electricity sales. At the same time, in order to take into account the fitting effect of the model and the complexity of the parameters, the AIC, BIC and the significance results of the parameters will also be combined for auxiliary judgment in the subsequent empirical study. By constructing a closed-loop calculation process of "data preprocessing, anomaly identification, model estimation, threshold test and effect evaluation", this paper can systematically evaluate the nonlinear impact of abnormal temperature fluctuations on regional electricity sales and its threshold conversion characteristics, which provides a unified method support for subsequent empirical analysis.

4 Analysis of empirical results

4.1 Sample area characteristic variable setting and descriptive statistical analysis

Taking the panel data of regional daily degree from 2019 to 2024 as the main sample, this paper constructs an empirical data set around the variables of electricity sales, temperature, humidity and economic activity, and uses the samples in the early period as a comparison reference. It can be seen from Table 2 that there are obvious fluctuations in regional electricity sales, temperature and humidity, especially the high dispersion degree of abnormal temperature impact strength, which indicates that the sample contains a variety of states such as comfort zone, abnormal high temperature zone and abnormal low temperature zone, and provides a good data basis for subsequent identification of nonlinear conversion characteristics and threshold effect. At the same time, the economic activity index and industrial structure variables also show certain differences, indicating that in addition to meteorological factors, the differences in the development level and electricity consumption structure of different regions can not be ignored.

Table 2: Descriptive statistics of the sample variables

Variable Name	Symbol	Sample Size	Mean	Standard Deviation	Minimum	Median	Maximum
Regional Electricity Sales (100 million kWh)	Sales	35136	1.84	0.67	0.52	1.79	4.36
Logarithm of Electricity Sales	lnSales	35136	0.53	0.34	-0.65	0.58	1.47
Daily Average Temperature (℃)	Temp	35136	16.92	10.41	-9.80	17.60	33.70
Relative Humidity (%)	Humidity	35136	58.47	14.26	21.30	59.10	92.40
Abnormal Temperature Index	AbTemp	35136	0.00	1.12	-3.48	-0.03	3.76
Temperature Shock Intensity	Shock	35136	1.27	0.96	0.00	1.05	4.85
Economic Activity Index	Econ	35136	103.84	11.37	78.25	102.96	136.42
Industrial Structure Upgrading Index	Industry	35136	1.46	0.21	1.02	1.44	1.98

4.2 Analysis of benchmark influence results of abnormal temperature fluctuations on regional electricity sales

The benchmark regression and fitting results show that abnormal temperature fluctuation has a significant impact on regional electricity sales, and this effect does not show a symmetrical linear feature, but gradually increases as the temperature deviates from the comfort range. Figure 4 shows the nonlinear fitting relationship between regional electricity sales and temperature.

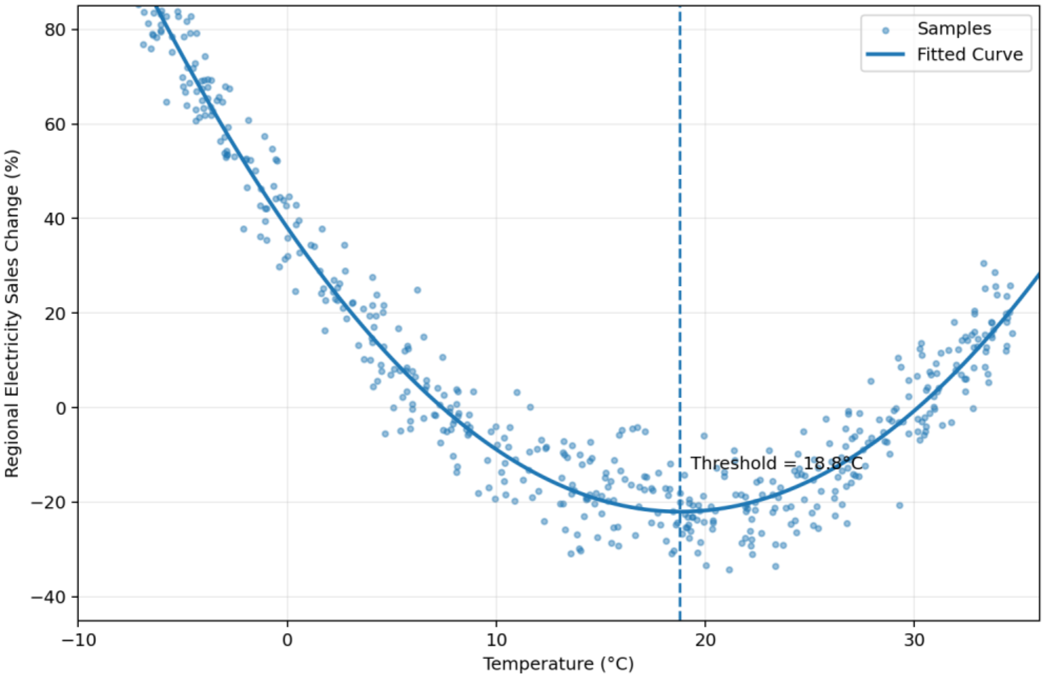

Figure 4: Nonlinear fitting plot of regional electricity sales and temperature

It can be seen from the figure that the sample as a whole shows a relatively obvious U-shaped change trajectory: when the temperature is near the comfort zone, the regional electricity sales fluctuation is small, and the curve is relatively smooth. When the temperature continued to rise and crossed the upper threshold, the electricity sales rose rapidly, indicating that the cooling load began to be released centrally. When the temperature continues to drop and is lower than the lower threshold, the electricity sales also shows an increasing trend, but the increase is significantly weaker than that of the high temperature side, indicating that the heating load expansion under low temperature conditions is relatively gentle. Further comparison shows that the comfort zone is roughly located at 13℃ -22 ℃, and the average electricity sold in this zone is about 180 million kWh. When the temperature rises to about 30℃, the electricity sold increases to 264 million kWh, which is about 46.7% higher than the average value of the comfort zone. When the temperature drops to near 0 ℃, the electricity sold is about 218 million kWh, an increase of about 21.1 percent. This indicates that the pull effect of abnormal high temperature on regional electricity sales is significantly stronger than that of abnormal low temperature, and the response of regional electricity sales has shown a clear nonlinear threshold feature.

4.3 Analysis of nonlinear conversion features and threshold interval recognition results

The threshold temperature and the prediction effect under different response relationships are shown in Table 3. The results show that the response of regional electricity sales to temperature change is not a single inflection point fluctuation, but has obvious segmented conversion characteristics. In the "V" -shaped nonlinear framework, the single threshold is located at 18.8℃. When the model is extended to a "U" shape, the electricity sales response is further decomposed into three stages: heating zone, comfort zone and cooling zone. The comfort zone identified by the linear asymmetric model is 12.3-23.4 ℃, while the nonlinear model shrinkages the interval to 13.5 -- 21.7℃. This indicates that the nonlinear setting can more accurately capture the boundary changes at both ends of the comfort zone and avoid mistakenly incorporating the transition zone into the stability interval.

From the perspective of the prediction effect, the RMSE of the "U" -shaped nonlinear model is 10.270, which is lower than the "V" -shaped nonlinear model's 10.338 and the "U" -shaped linear asymmetric model's 10.387. Its R2 is 0.781, which is also higher than the other two Settings of 0.778 and 0.776. It shows that in the same sample interval, the dual threshold and nonlinear setting can more fully describe the real change trajectory of electricity sales under abnormal temperature shock. In general, the ranking of prediction accuracy shows that the "U" -shaped nonlinear is the best, the "V" -shaped nonlinear is the second, and the "U" -shaped linear asymmetry is relatively weak, indicating that there is not only a threshold effect in the response of electricity sales to temperature, but also an obvious nonlinear conversion process within the threshold interval.

Table 3: Comparison table of threshold temperature and prediction effect under different response relationships from 2019 to 2024

Response Model	Th/℃	Th1/℃	Th2/℃	RMSE	R^2
“V”-shaped Nonlinear	18.8	—	—	10.338	0.778
“U”-shaped Linear Asymmetric	—	12.3	23.4	10.387	0.776
“U”-shaped Nonlinear	—	13.5	21.7	10.270	0.781

4.4 Difference analysis of regional electricity sales response under temperature and humidity coupling conditions

The differences in temperature-electricity sales response under different humidity intervals are shown in Figure 5. The results show that the humidity change does not change the overall pattern of "U" -shaped fluctuation of regional electricity sales with the rise and fall of temperature, but significantly changes the width of the comfort zone and the threshold position of the cooling side. Compared with the low humidity range, the overall curve rises earlier in the high temperature section under the high humidity condition, indicating that the rise of relative humidity will enhance the degree of body sultry, make the refrigeration equipment start in advance at a low temperature, and thus promote the regional electricity sales to enter the growth channel faster. On the contrary, in the low temperature segment, the difference between the two fitted curves is small, which indicates that the effect of humidity on the heating side threshold is relatively limited.

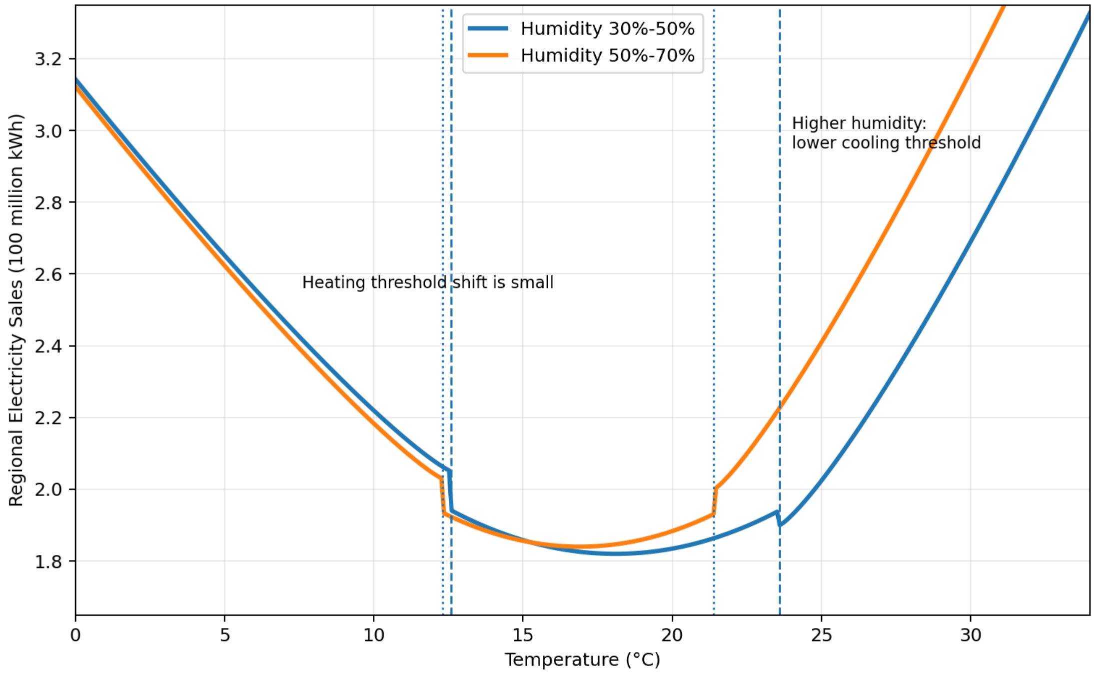

Figure 5: temperature-electricity sales response difference diagram under different humidity intervals

It can be seen from the figure that the comfort zone corresponding to the 30% -50% humidity interval is wider, and the threshold on the high temperature side is about 2.2 ℃ higher than that on the 50% -70% humidity interval, while the threshold on the low temperature side only differs by about 0.3 ℃. When the temperature is in the range of 26℃ to 30℃, the electricity sales corresponding to the high humidity sample is significantly higher than that of the low humidity sample, and the maximum difference is about 18 million kWh. However, in the range of 8℃ to 12℃, the two types of curves almost fit, and the difference is not more than 40 million kWh. Therefore, the coupling effect of temperature and humidity mainly amplifies the high temperature load response by reducing the "comfort-cooling" boundary, and has a weak effect on the "comfort-heating" boundary. On the whole, the increase of humidity will promote the regional electricity sales to enter the dominant stage of cooling demand earlier and faster, and the temperature and humidity coupling effect is mainly reflected in the high temperature end.

4.5 Analysis of threshold drift and heterogeneity effect under samples at different periods

In order to investigate the time differences of electricity sales in regions affected by abnormal temperature fluctuations, this paper further compares the change characteristics of the threshold position under different time samples, and analyzes the formation background of threshold drift combined with the change trend of long-term annual average temperature. Figure 6 shows the comparison of the change of threshold position in different stages.

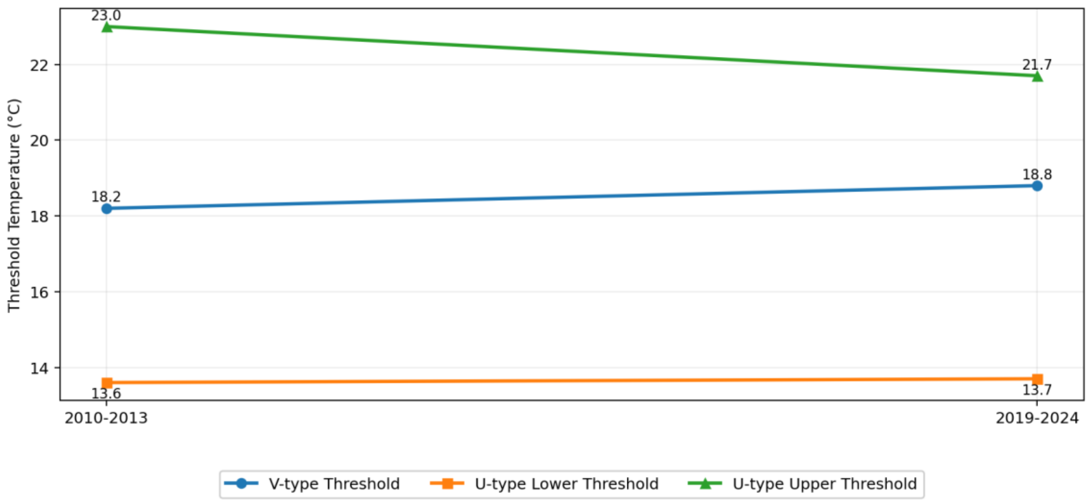

Figure 6: Comparison plot of threshold position changes under samples at different time periods

It can be seen from Figure 6 that the threshold position corresponding to the regional electricity sales under different time period samples has obvious drift characteristics. Among them, the "V" type single threshold was moved up from 18.2℃ to 18.8℃, an increase of 0.6℃. The lower threshold of the U-shaped nonlinear model increased slightly from 13.6℃ to 13.7℃, with a change of only 0.1℃, while the upper threshold decreased from 23.0℃ to 21.7℃, with a decrease of 1.3℃. This shows that the response of regional electricity sales to high temperature shock has been enhanced in advance in recent years, the width of the comfort zone has been narrowed from 9.4℃ to 8.0℃, and the threshold boundary shows strong time heterogeneity and dynamic adjustment characteristics.

The trend of annual average temperature is shown in Figure 7.

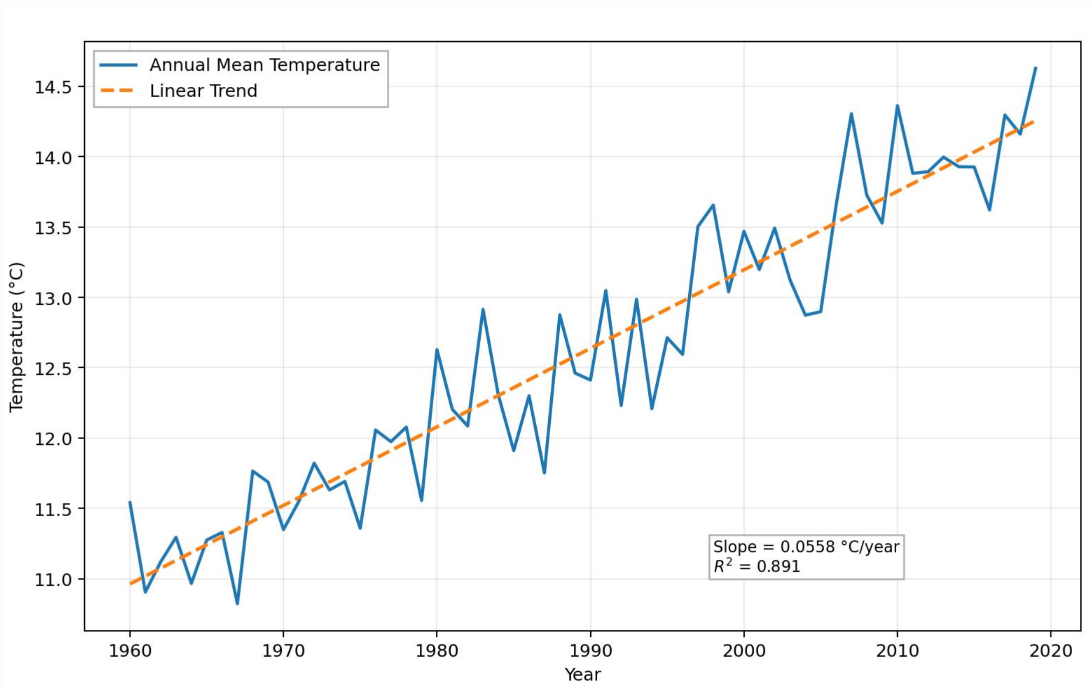

Figure 7: Trend graph of annual mean temperature change

As can be seen from Figure 7, the annual average temperature shows a continuous upward trend, the linear fitting slope is about 0.0550℃/year, and the goodness of fit R2 is 0.924, indicating that the long-term climate warming trend is relatively obvious. As the annual average temperature continues to rise, the requirements of residents and commercial subjects for indoor comfort continue to increase, and the start-up time of refrigeration equipment is correspondingly advanced, thus promoting the migration of the regional electricity sales response threshold to the high temperature side. Figure 7 explains the formation reason of the threshold position drift in Figure 6 from the level of climate background, and also shows that the dynamic influence brought by long-term temperature change should be fully considered when carrying out regional electricity sales prediction.

4.6 Model comparison robustness test and prediction performance evaluation

Table 4 shows the prediction performance of different models.

Table 4: Comparison table of prediction performance of different models

Model	RMSE	MAE	R^2
Linear Panel Model	10.624	8.214	0.751
Threshold Regression Model	10.387	7.963	0.776
Smooth Transition Model	10.270	7.842	0.781
Panel Smooth Transition Model	9.986	7.516	0.796

As can be seen from Table 4, there are obvious differences in the performance of different models in the prediction of regional electricity sales. The RMSE and MAE of the linear panel model are 10.624 and 8.214, respectively, and the prediction error is relatively high, which indicates that it is difficult to fully describe the nonlinear response caused by abnormal temperature fluctuations. After introducing the threshold value, the RMSE of the threshold regression model is reduced to 10.387, the MAE is reduced to 7.963, and the goodness of fit is improved to 0.776. The overall effect is improved. The smooth transition model further compresses RMSE and MAE to 10.270 and 7.842, which indicates that the continuous state transition setting is better than the discrete switching mode. In contrast, the panel smooth transformation model has the best comprehensive performance, the lowest RMSE is only 9.986, the MAE is 7.516, and the R^2 increases to 0.796, which indicates that the recognition and fitting ability of the model for abnormal temperature shocks is further enhanced after considering regional heterogeneity and time effects.

The comparison of prediction errors of different models is shown in Figure 8.

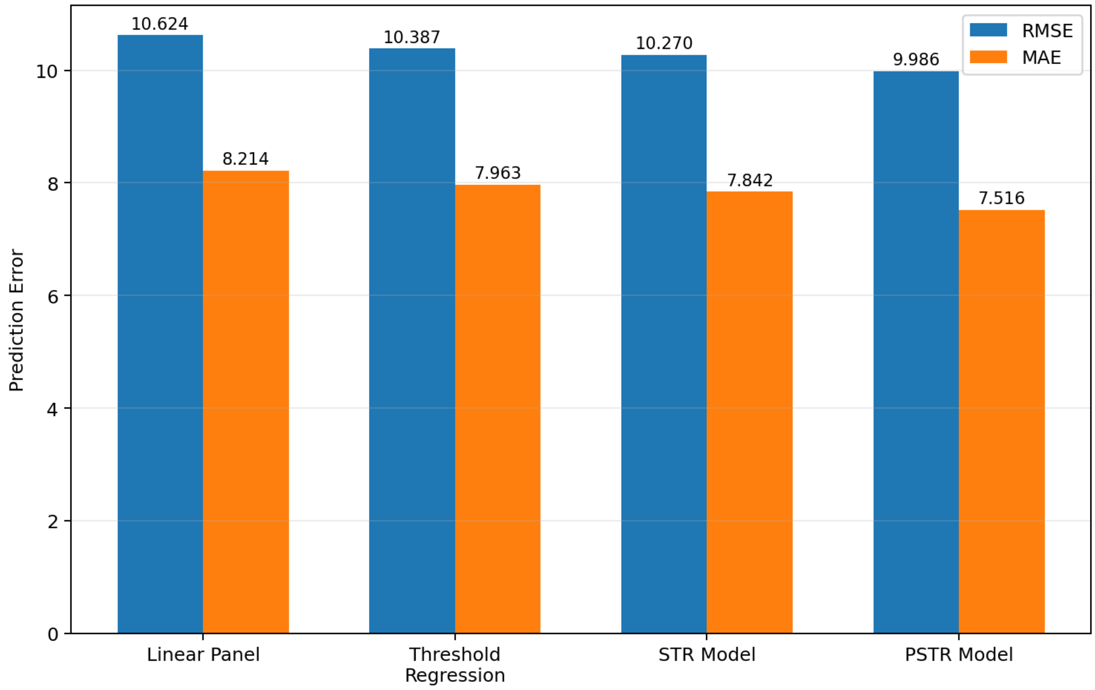

Figure 8: Comparison plot of prediction errors of different models

It can be seen from Figure 8 that the panel smooth transformation model is lower than the other three types of models in the two error indicators of RMSE and MAE, and the advantages are more obvious. Among them, compared with the linear panel model, the RMSE of the PSTR model is decreased by 0.638, the decrease is about 6.0%, and the MAE is decreased by 0.698, the decrease is about 8.5%. Compared with the threshold regression model, RMSE and MAE are decreased by 0.401 and 0.447, respectively. Figure 8 further shows that in the prediction of regional electricity sales, only linear setting or discrete threshold division is difficult to fully reflect the progressive impact of abnormal temperature fluctuations, while the panel smooth transformation model can more accurately capture the continuous response process of electricity sales to high temperature shock, low temperature shock and comfort zone fluctuation, so it has better robustness and prediction performance.

5 Discussion

The results show that the impact of abnormal temperature fluctuation on regional electricity sales is not symmetrical around a single temperature point, but shows obvious segmented response, threshold switching and time-varying migration characteristics. No matter from the baseline fitting or threshold recognition results, the "U" structure is better than the "V" structure, indicating that the regional electricity sales is not only passively rising at both high and low temperature ends, but also there is a relatively stable but dynamically shrinking or moving comfort zone in the middle. Especially in the nonlinear setting, the model depicts the boundary of the comfort zone more precisely, which not only avoids the transition zone being mistakenly incorporated into the stable interval, but also better explains the realistic characteristics of electricity sales accelerating on the high temperature side and slowly increasing on the low temperature side.

The coupling analysis of temperature and humidity further shows that temperature is not the only meteorological factor that determines the change of electricity sales. When the humidity increases, the "comfort-cooling" threshold significantly moves to the low temperature end, while the "comfort-heating" threshold changes slightly, which means that the high humidity environment will significantly amplify the somatosensory pressure at the high temperature end, making the refrigeration equipment enter the high-frequency operation state earlier. As a result, under the same temperature level, samples with high humidity are more likely to fall into the high power consumption range, and regional electricity sales also enter the rising channel faster. This finding suggests that when carrying out regional electricity demand analysis, it is easy to underestimate the increment of electricity consumption under high-humidity environment in summer if only a single temperature variable is used to describe weather shocks.

From the comparison results of time period, the threshold position is not a stable constant, but will migrate with the change of climate background, device penetration rate and user behavior preference. The sample comparison shows that the high temperature threshold in the new period moves forward and the width of the comfort zone Narrows, which is mutually confirmed with the long-term rising trend of annual average temperature. It is not only the change of thermal environment caused by climate warming, but also the improvement of indoor comfort requirements of residents and commercial sectors, and the more active use of air conditioning. Therefore, in the middle and long term analysis or rolling forecast of regional electricity sales, the existing critical temperature cannot be simply used, but the threshold value should be re-estimated according to the sample period, and the parameters of different stages should be dynamically updated.

It should also be noted that although this paper improves the accuracy of abnormal temperature impact identification from three levels of nonlinear response, humidity correction and time drift, the research scope is still mainly based on the single city sample, and the differences in industrial structure, building energy efficiency level and energy substitution mode between regions have not been fully developed. Subsequent studies can construct multi-regional panels on a larger spatial scale, further include wind speed, precipitation, peak and valley electricity prices and electricity sales data by industry, and identify the transmission path of abnormal temperature shocks in a more detailed way, so as to provide a more universal empirical basis for regional power grid dispatch, demand response management and extreme weather warning.

6 Conclusion

Focusing on the influence mechanism of abnormal temperature fluctuation on regional electricity sales, this paper constructs an analysis framework including abnormal temperature index, temperature shock comprehensive index and panel smooth transformation model. It is found that there is a significant threshold effect and asymmetric response of regional electricity sales to temperature change, and the increase of high temperature side is significantly stronger than that of low temperature side. The "U" -shaped nonlinear structure is more accurate to describe the comfort zone boundary and transition zone. The results of temperature and humidity coupling show that humidity mainly depresses the "comfort-cooling" boundary and amplifies the expansion of high temperature load. The comparison results show that the threshold position will continue to drift with climate warming and energy use behavior adjustment. Further robustness tests show that the panel smooth transformation model outperforms the linear panel model, threshold regression model and smooth transformation model in terms of prediction error control and goodness of fit. In general, the impact of abnormal temperature on electricity sales is not a static linear process, but a dynamic nonlinear process affected by threshold switching, humidity correction and time migration. In the future, extended research should be carried out by combining multi-regional samples and more meteorological variables.

Author's Profile

Jiakui Zhao (1979-06), male (Han ethnicity), from Tieling, Liaoning Province, holds a doctorate from Peking University, and is a professor-level senior engineer. His research direction is power big data analysis.

Shichong Chen (1996-11), male (Han ethnicity), from Suihua, Heilongjiang Province, holds a master's degree from Renmin University of China, and is a mid-level engineer. His research direction is energy data analysis.

Xiaoteng Ma (1996-01), male (Han ethnicity), from Langfang, Hebei Province, holds a doctorate from Tsinghua University. His research direction is power big data analysis.

Yushu Zhang (1985-08), female (Han ethnicity), from Jilin Province, holds a doctorate from the University of Strathclyde, UK, and is a senior engineer. Her research direction is power system planning.

Xishuang Hu (1995-06), male, Han ethnicity, from Huanggang City, Hubei Province, holds a master's degree from Peking University, and is a mid-level engineer. His research direction is power big data.

Wenli Liu (1990-06), male (Han ethnicity), from Zhoushan, Zhejiang Province, holds a doctorate from Zhejiang University, and is a senior engineer. His research direction is energy big data.

References

[1] Pablo-Romero M del P, Sánchez-Braza A, González-Jara D. Economic growth and global warming effects on electricity consumption in Spain: a sectoral study[J]. Environmental Science and Pollution Research, 2023, 30: 43096-43112. DOI: 10.1007/s11356-022-22312-5.

[2] Román-Collado R, Colinet-Carmona M J, Fárez-Plasencia M I. Is temperature change a key driver of the regional differences in electricity consumption of the economic sectors in Spain (2000–2016)?[J]. Environmental Science and Pollution Research, 2023, 30: 81131-81150. DOI: 10.1007/s11356-023-27789-2.

[3] Pablo-Romero M del P, Pozo-Barajas R, Molleda-Jimena G. Residential energy environmental Kuznets curve extended with non-linear temperature effects: a quantile regression for Andalusian (Spain) municipalities[J]. Environmental Science and Pollution Research, 2021, 28: 48984-48999. DOI: 10.1007/s11356-021-13608-z.

[4] Wang Y, Hou L, Shi J, et al. How climate change affects electricity consumption in Chinese cities—a differential perspective based on municipal monthly panel data[J]. Environmental Science and Pollution Research, 2023, 30: 68577-68590. DOI: 10.1007/s11356-023-27287-5.

[5] Hou J J, Liu L C, Dong Z Y, et al. Response of China’s electricity consumption to climate change using monthly household data[J]. Environmental Science and Pollution Research, 2022, 29(60): 90272-90289. DOI: 10.1007/s11356-022-21813-7.

[6] Kostakis I, Lolos S. Residential demand for electricity: empirical evidence from Greece using pseudo-panels[J]. Energy, Ecology and Environment, 2022, 7(1): 51-69. DOI: 10.1007/s40974-021-00225-2.

[7] Tsalikidis N, Mystakidis A, Tjortjis C, et al. Energy load forecasting: one-step ahead hybrid model utilizing ensembling[J]. Computing, 2024, 106: 241-273. DOI: 10.1007/s00607-023-01217-2.

[8] Manno M, Intini G, Jabali N, et al. An ensemble of artificial neural network models to forecast hourly energy demand[J]. Optimization and Engineering, 2024, 25: 2315-2343. DOI: 10.1007/s11081-024-09883-7.

[9] Xie Y, Li B, Liu Y, et al. Short-term load forecasting method based on fuzzy optimization combined model of load feature recognition[J]. Electrical Engineering, 2025, 107: 513-526. DOI: 10.1007/s00202-024-02539-w.

[10] Mystakidis A, Ntozi E, Koukaras P, et al. A multi-energy meta-model strategy for multi-step ahead energy load forecasting[J]. Electrical Engineering, 2025, 107: 9675-9699. DOI: 10.1007/s00202-025-02995-y.

[11] Islam M T, Hasan M M, Hasan M K, et al. Enhanced power demand forecasting for Bangladesh: using feature engineering associated with environmental and economic impact[J]. Journal of Data, Information and Management, 2025, 7: 1-19. DOI: 10.1007/s42488-025-00140-9.

[12] Matsumoto S, Hoang V N, Wilson C. Covid-19 lockdown, gender and income dynamics in household energy consumption: evidence from Japan[J]. Empirical Economics, 2024, 67: 1473-1496. DOI: 10.1007/s00181-024-02593-0.

[13] Ocansey S A, Bikdash M. Temperature-Driven Reliability Analysis of Power Grid Failures: A Weibull Distribution Approach To Outage Prediction and Mitigation[J]. Journal of Statistical Theory and Applications, 2025, 24: 233-246. DOI: 10.1007/s44199-025-00109-y.

[14] Mohammed N A, Al Bazi A. An adaptive backpropagation algorithm for long-term electricity load forecasting[J]. Neural Computing and Applications, 2022, 34(1): 477-491. DOI: 10.1007/s00521-021-06384-x.

[15] Lee Y G, Oh J Y, Kim D, et al. SHAP Value-Based Feature Importance Analysis for Short-Term Load Forecasting[J]. Journal of Electrical Engineering & Technology, 2023, 18(1): 579-588. DOI: 10.1007/s42835-022-01161-9.

[16] Eskandari H, Imani M, Parsa Moghaddam M. Best-tree wavelet packet transform bidirectional GRU for short-term load forecasting[J]. The Journal of Supercomputing, 2023, 79: 13545-13577. DOI: 10.1007/s11227-023-05193-4.

[17] Imani M. Fuzzy-based weighting long short-term memory network for demand forecasting[J]. The Journal of Supercomputing, 2023, 79(1): 435-460. DOI: 10.1007/s11227-022-04659-1.

[18] Dong X, Deng S, Wang D. A short-term power load forecasting method based on

k-means and SVM[J]. Journal of Ambient Intelligence and Humanized Computing, 2022, 13(11): 5253-5267. DOI: 10.1007/s12652-021-03444-x.

[19] Muzumdar A A, Modi C N, Madhu G M, et al. Designing a Robust and Accurate Model for Consumer-Centric Short-Term Load Forecasting in Microgrid Environment[J]. IEEE Systems Journal, 2022, 16(2): 2448-2459. DOI: 10.1109/JSYST.2021.3073493.

[20] Tarmanini C, Sarma N, Gezegin C, et al. Short term load forecasting based on ARIMA and ANN approaches[J]. Energy Reports, 2023, 9(3): 550-557. DOI: 10.1016/j.egyr.2023.01.060.

[21] Kshetrimayum N, Singh K R, Hoque N. PConvLSTM: an effective parallel ConvLSTM-based model for short-term electricity load forecasting[J]. International Journal of Data Science and Analytics, 2025, 20: 2493-2510. DOI: 10.1007/s41060-024-00616-8.

[22] Goh H H, He B, Liu H, et al. Multi-Convolution Feature Extraction and Recurrent Neural Network Dependent Model for Short-Term Load Forecasting[J]. IEEE Access, 2021, 9: 118528-118540. DOI: 10.1109/ACCESS.2021.3107954.

[23] Rafi S H, Al-Masood N, Deeba S R, et al. A Short-Term Load Forecasting Method Using Integrated CNN and LSTM Network[J]. IEEE Access, 2021, 9: 32436-32448. DOI: 10.1109/ACCESS.2021.3060654.

[24] Wang L, Zhou X, Xu H, et al. Short-term electrical load forecasting model based on multi-dimensional meteorological information spatio-temporal fusion and optimized variational mode decomposition[J]. IET Generation, Transmission & Distribution, 2023, 17(20): 4647-4663. DOI: 10.1049/gtd2.12992.

[25] Cheng L, Zang H, Xu Y, et al. Probabilistic residential load forecasting based on micrometeorological data and customer consumption pattern[J]. IEEE Transactions on Power Systems, 2021, 36(4): 3762-3775. DOI: 10.1109/TPWRS.2021.3051684.

[26] Ullah K, Ahsan M, Hasanat S M, et al. Short-Term Load Forecasting: A Comprehensive Review and Simulation Study With CNN-LSTM Hybrids Approach[J]. IEEE Access, 2024, 12: 111858-111881. DOI: 10.1109/ACCESS.2024.3440631.