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Article

Research on Artificial Intelligence-driven Resident Demand Forecasting Model for Digital Community Governance

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Abstract: This study starts from two aspects, data-driven and demand insights, to realize accurate forecasting of residential demand. Firstly, the raw data are sculpted and feature extraction of load fluctuation is performed using mutual information and principal component analysis. And an intelligent prediction model Bi-ITCN-Att, a bidirectional improved temporal convolutional network incorporating a self-attention mechanism, is built.Innovatively, the article introduces the Kano model as a demand decoder to analyze the motivation of residents' electricity consumption behavior from the perspective of humanistic demand. The model performs well in predicting load in a neighborhood, with a root mean square error of 0.027 and a MAPE of only 1.86%, and the prediction accuracy is significantly better than that of the original TCN and Bi-ITCN models. The analysis of 369 valid questionnaires reveals that 54.47% of the residents regard circuit fault warning (ESR1) and other as the bottom line demand M that must be guaranteed, while the laws such as AI energy conservation advice (ECF2) are regarded as glamorous attributes A. The quadrant diagram of the demand strategy drawn through the analysis of Better-Worse coefficients further proclaims that the key to improving the satisfaction lies in the implementation of the electricity price services such as reminders, which has a satisfaction coefficient of 0.549, while the defense of emergency security must be maintained. The study provides a set of decision support system for digital community governance that is not only accurate in data, but also handy in human needs, thus promoting the community energy service from passive response to a new stage of proactive and humanized intelligent governance.

Keywords: community governance; artificial intelligence; demand forecasting; residential electricity demand; Kano modeling

1. Introduction

Looking at the qualitative leap in productivity, human society has experienced four industrial revolutions: the steam age (18th century), the electric age (19th century), the information age (20th century), and the intelligent age (21st century). Science and technology, as the primary driving force leading this development process, This led to corresponding changes in steam technology, electrical technology, information technology and intelligent technology, etc. The essence of the first two was the materialization of physical labor by machines, while the latter two were the replacement of mental labor by artificial intelligence [1]. With the advancement of The Times, the development of information technology, and the application of the Internet, China has now basically achieved all-round wireless communication network coverage. Intelligent technologies are constantly refreshing the production and lifestyle of residents. Big data, the Internet of Things, artificial intelligence and other technologies are gradually penetrating into various service fields of residents' lives, such as transportation, finance, healthcare and education. Promote meticulous, precise and prompt services to meet people's growing needs for a better life [2-4].

Smart community is the transformation of traditional community and the cornerstone of urban construction, and the study of the digital road of community governance can promote the sinking of the center of gravity of social management and services, provide accurate, refined and intelligent services for the public, and fully balance the growing needs of the masses for a better life [5]. In the context of digital community governance, the needs of community residents are no longer single and static, but are diversified, personalized and dynamic. The decision-making process of residents has become more complex and the amount of information involved has increased geometrically [6-8]. The traditional method of analyzing residents' needs has been difficult to adapt to this complex change at present [9]. Therefore, it is necessary to construct a more accurate and efficient resident demand forecasting model with the help of advanced technologies such as artificial intelligence and machine learning algorithms, in order to realize the real-time tracking and accurate forecasting of resident demand.

Digital community governance, as an extension of public governance theory, not only makes up for the loopholes of the new public management theory, but also conforms to the development trend of the artificial intelligence era, and once proposed, it has been widely concerned by scholars and constantly refreshes the connotation of the theory, and the practice of the theory in the areas of policy services, subject participation, and technological change has also achieved fruitful results. In terms of digital community governance, many scholars have explored the role of information technology in promoting community governance based on the current state of information technology. For example, Aziiza and Susanto [10] paid attention to the significance of the construction of smart communities for community governance, and constructed dimensions of digital communities from practice, specifically including six dimensions of governance, technology, resources, services, life and tourism.Saez et al [11] considered digital community governance as a new way of interaction between citizens and the government, and they did so by studying the EU Southern Member States' innovative experiences of digital community governance, they pointed out that digital government can provide government administrative effectiveness, strengthen democracy and openness, but it cannot improve the quality and efficiency of public services. In terms of case studies, Purwanto [12] explored digital city governance in Indonesia, discussing the role of digital cities in improving the effectiveness of community governance, pointing out that digital cities should target two main areas of strength, namely governance and public services. The governance of digital cities and the implementation of e-government should not be limited to improving the efficiency of the bureaucracy, but should also aim to innovate community governance, to drive community governance with digital cities, and to improve the efficiency of community governance as a whole.

Academics have also explored the problems faced by digital community governance in a multidimensional way. Yigitcanlar et al [13] pointed out that the current lack of synergistic mechanisms between the elements of technology, policy and residents in digital community governance is very obvious, and it can be improved and optimized from a number of perspectives and aspects. Young [14] pointed out that digital technologies are able to optimize the effectiveness of governance in local governments, improve government transparency and citizen participation, and reduce management costs, but the effectiveness of governance in practice is also affected by factors such as the management system and public demand. Atkočiūnienė et al [15] pointed out that the combination of traditional governance and emerging technologies facilitates a strategic breakthrough in community governance in response to the general context of urban-rural integration, and also pointed out that the main constraints limiting the development of communities into digital communities lie in the following lack of technology, talent and efficiency in the community. Goodman et al [16] found that there is a strong correlation between the good and bad development of digital communities and the enthusiasm of each subject, the degree of government attention and investment, and the participation of ordinary residents all have an impact, and the lack of public participation constrains the development of digital communities. From the perspective of good governance, Asriadi et al [17] revealed the problems in the process of digital community governance, pointing out that the elements of digital community governance include community participation, legal rules, transparency, stakeholders, etc., and should be oriented to reach a consensus on governance. Delgado et al [18] pointed out that the key to improving the effectiveness of government governance lies in the synergistic change of technological innovation and governance thinking, emphasizing that Advanced technology should be deeply integrated into the whole process link of policy making, social service provision and government affairs. The arrival of artificial intelligence technology has revolutionized the government's management and service model, and the government can use information technology to connect multiple subjects, expand the government's behavior from the original sectional organization to the whole society, and then enhance the response to differentiated needs, which is also known as digital community governance.

In concert with emerging technologies such as artificial intelligence, machine learning, and the Internet of Things, scholars have conducted research on demand forecasting for residents in the areas of infrastructure services, travel services, consumer services, and energy services [19]. In the area of public infrastructure service demand of community residents, Husin et al [20] argued that the demand for infrastructure services of residents was predicted and simulated using a system dynamics model, which enabled the provision of reliable estimates and the generation of scenarios to compare the financial viability of projects before and after the functional innovations involved. In terms of water demand of community residents, Preciado et al [21] constructed a method for forecasting residential water demand based on pattern recognition and pattern similarity techniques fused with machine learning algorithms. In terms of community residents' travel service demand, Chu et al [22] developed a novel deep learning model called Multi-scale Convolutional Long Short-Term Memory Network (MultiConv-LSTM) for predicting future residents' travel demand, which reduces the waiting time by taking into account temporal correlation and spatial correlation. Mi et al [23] addressed the insufficient supply of public transportation in Beijing, the unable to meet residents' transportation demand, proposed a residential travel prediction model (SRBM) based on Softmax regression machine learning algorithm. In terms of consumer service demand, Smith [24] reviewed the impact of digital transformation on residents' consumption behavior and deeply analyzed the changing trends of urban and rural residents' consumption demand in the context of digitalization. It is pointed out that the popularity and development of digital technology has made consumers' demand for products and services more diversified and personalized, which poses new challenges and opportunities for enterprises and governments. In terms of energy service demand, Rodrigues et al [25] systematically reviewed the residential short-term load-based electricity demand forecasting (STLF) model, and explored the evolution of the performance of artificial intelligence (AI) in short-term load forecasting and its impact.

This study is dedicated to designing an intelligent system that not only accurately predicts but also understands the real needs of residents to better govern and serve digital communities. The study chooses to take electricity demand, which is closely related to residents' lives, as the entry point, and first focuses on the extraction of external input features affecting residents' electricity behavior, based on mutual information and principal component analysis, and profiling of meteorological factors and day types. Then we turn to how to accurately predict electricity load, for which we construct a Bi-ITCN-Att intelligent prediction model that possesses both super memory and knows how to grasp the key points. The model reads historical electricity consumption data from front to back and back to front, the bi-directional memory module captures the information of the preceding and following texts, and the self-attention mechanism automatically determines which historical moments are the most critical for predicting future electricity consumption, thus realizing the high-precision capture of complex electricity consumption patterns. Immediately afterward, the study digs deeper into the demand of residents behind load fluctuations. Introducing the classic Kano model in management, a detailed questionnaire is designed and distributed to categorize residents' preferences for community electricity services.

2. Data processing and Bi-ITCN-Att model construction for electricity demand forecasting

2.1. Extraction of External Input Features Influencing Electricity Consumption Behavior

Date-type factors and meteorological factors have a significant impact on residential loads and are usually entered into load forecasting models as external influences. Since date types can be simply classified and marked as "working days", "weekends" and "holidays", there is no need to analyze and simplify the date type factor data. However, there are many dimensions of meteorological factors, and the meteorological data obtained in this paper includes a total of 12 dimensions of data, such as hourly temperature, humidity, wind speed, etc. In order to avoid the interference of irrelevant data and the redundancy of coupled data, it is crucial to select the important features and to reduce the dimensionality of the meteorological factors according to the correlation between the meteorological factors and the user load.

2.1.1. Mutual information-based feature selection for meteorological factors

Considering that the traditional Pearson's correlation coefficient cannot measure the nonlinear relationship between two variables, this paper adopts the mutual information (MI) to measure the interdependence between user load and meteorological factors.MI can be regarded as the amount of information contained in one random variable about another random variable, i.e., the degree of information sharing between the two random variables, and the larger the value of MI is the higher the degree of information sharing and the stronger the correlation between two The larger the MI value the higher the degree of information sharing and the stronger the correlation between the two random variables.

Assume that user load and specific meteorological factors are random variables X and Y, respectively. Since user load and weather factor are discrete random variables, their MI can be defined as:

$$I(X;Y) = \sum_{y\in Y}\sum_{x\in X} p(x,y)\log\left(\frac{p(x,y)}{p(x)p(y)}\right) \tag{1}$$

where $I(X;Y)$ is the mutual information of the random variables X and Y; $p(x,y)$ is the joint probability density distribution function of X and Y; and $p(x)$ and $p(y)$ are the marginal probability density distribution functions of X and Y respectively.

Before comparing the MI values of different pairs of random variables, it is necessary to normalize them so that they take a uniform range of values. According to the Wayne diagram shown in Fig. 1, the expression for the normalized mutual information (NMI) values of random variables X and Y can be defined as:

$$NMI(X;Y) = \frac{I(X;Y)}{\sqrt{H(X)\cdot H(Y)}} \tag{2}$$

where $H(X)$ and $H(Y)$ are the informativeness of the random variables X and Y, which can be defined as:

$$\begin{aligned} H(X) &= \sum_{x\in X} p(x)\log\left(\frac{1}{p(x)}\right) \\ H(Y) &= \sum_{y\in Y} p(y)\log\left(\frac{1}{p(y)}\right) \end{aligned} \tag{3}$$

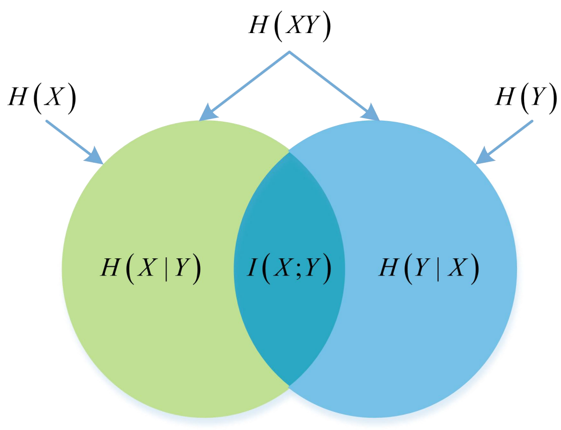

Figure 1. Venn diagram of mutual information and information entropy

2.1.2. Principal component analysis data downscaling for meteorological factors

Since there is still a strong relationship between the meteorological factors (e.g., air temperature and body temperature) after the selection of mutual information, there is still room for further data simplification, so it is necessary to remove the correlation between the meteorological factors by using Principal Component Analysis (PCA) to improve the computing speed, reduce the feature dimensions, and avoid the redundancy of the data.The essence of PCA is to obtain a few variables that are not related to each other by linear combination of vectors to replace a large number of original variables, so as to reduce the dimensionality and avoid the mutual coupling of data. The essence of PCA is to obtain a few unrelated variables by linear combination of vectors to replace a large number of original variables, so as to reduce the dimension of the data and avoid mutual coupling within the data, and its process is shown in Fig. 2.

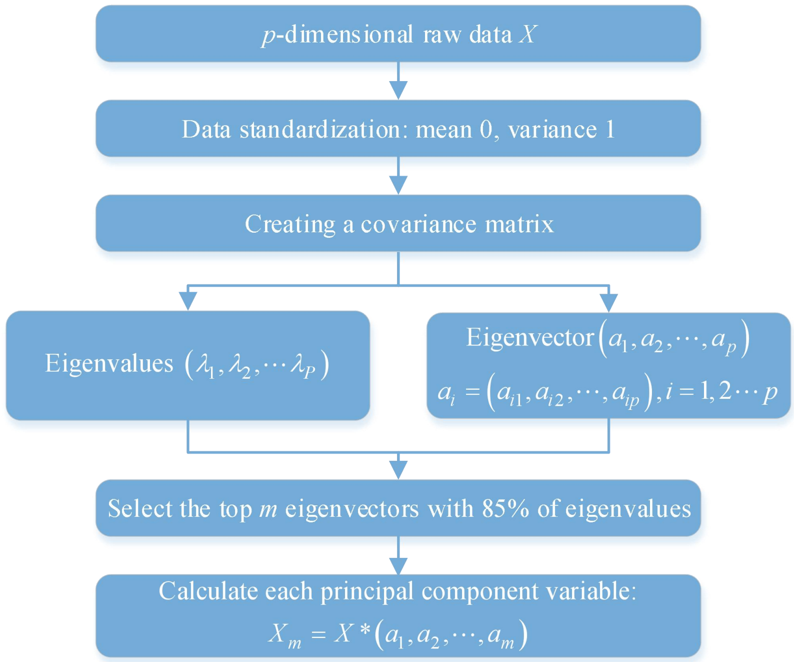

Figure 2. The operational process of principal component analysis method

2.2. Residential load forecasting model based on Bi-ITCN-Att

In order to capture residential electricity loads that are both regular and fluctuating, a prediction model Bi-ITCN-Att incorporating bi-directional memory and self-attention is designed in this section. It automatically determines which historical moments are most critical for electricity consumption forecasting by looking at historical sequences of electricity consumption data from front to back and back to front.

2.2.1. Improved time-convolutional networks in both directions

The study proposes an improved TCN module (ITCN) on TCN based. In this chapter, the convolutional layer in the TCN residual splice is replaced with a causal convolutional layer to maintain the causal relationship between the input and the output, which enables the model to better extract the temporal features of the time series data. In order to improve the training speed and stability of the model, this chapter removes the Dropout layer in the original TCN module and adds a batch normalization layer after expanding the causal convolutional layer. Batch normalization can alleviate gradient vanishing, simplify parameter tuning, and make the network more stable and less prone to overfitting, and thus is an alternative to Dropout to increase the generalization ability of the model.

Although TCN has many advantages, due to the nature of causal convolution, it can only extract the positive temporal features in time series data. Bidirectional Long Short-Term Memory Networks (BiLSTM) with Bidirectional Gated Recurrent Units (BiGRU) add a reverse structure to the forward structure to process the reverse time series, which allows the model to not only extract features from past time steps, but also obtain information from future time steps. This is useful for the model to understand the context, predict the future and handle events at different time scales. This chapter adds an inverse ITCN to the ITCN based on this idea to realize the model's bi-directional feature extraction from time series, and names it Bi-directional Improved Temporal Convolutional Network (Bi-ITCN).

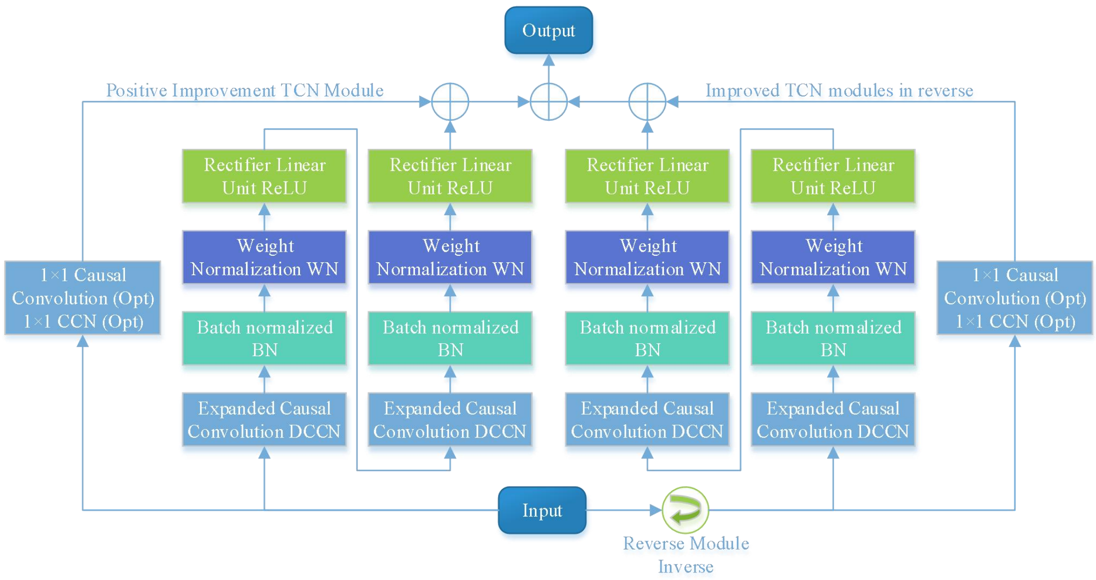

Figure 3. Bidirectional improvement of the structure of the time convolution network

Figure 3 illustrates the structure of the proposed Bi-ITCN. The bi-directional Improved Temporal Convolutional Network contains two improved TCN modules, one belongs to the forward Improved TCN Residuals module for extracting the forward features of the input data, and the other belongs to the reverse Improved TCN Residuals module for extracting the reverse features of the input data. Assuming that the input time series data is $X=[x_1,x_2,\cdots,x_n]$, and the output time series data is $Y=[y_1,y_2,\cdots,\cdots,y_n]$, the positive ITCN is at the t moment the output value y_t is at most only related to $x_1,\cdots,x_{t-1},x_t$, but not to the values after the t moment, and in this way the positive temporal features of the input data are extracted. The reverse ITCN adds a reverse module to the forward ITCN to reverse the input data in the time dimension, at which point the reversed data expression $\tilde{X}$ is:

$$\tilde{X}=[x_n,x_{n-1},\cdots,x_1] \tag{4}$$

Then the output value $\tilde{y}_t$ of the inverse ITCN at the moment of t is only related to the current value and the future value $x_t,x_{t+1}\cdots,x_n$, and in this way, the inverse features of the input data can be extracted. Finally, the sum of the outputs of the two ITCN modules is taken as the final output, so that the output data of Bi-ITCN fully contains the bidirectional temporal features of the input data, and better improves the completeness and globalization of the features.

2.2.2. Self-attention mechanism model

Attention mechanisms have been widely used in computer vision, natural language processing and other fields, and have achieved remarkable results. Unlike the traditional channel attention mechanism, the self-attention mechanism model is able to capture the dependencies between different elements within the input sequence, thus enabling the model to focus on the relevant contextual information in the sequence and improve the model performance. This is crucial for short-term load forecasting tasks that use past historical data to obtain future data.

The query Q (Query), the key K (Key), and the value V (Value) are three important vectors in the model of the self-attention mechanism, and all three come from the same set of elements. Assuming the input vector is X, Q,K,V is obtained by multiplying the input vector X by the three weight matrices:

$$\begin{cases} Q = W_{\mathrm{Q}} X \\ K = W_{\mathrm{K}} X \\ V = W_{\mathrm{V}} X \end{cases} \tag{5}$$

where W represents the weight matrix.

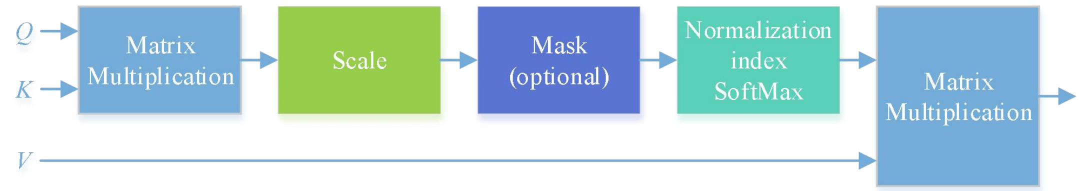

Figure 4. The structure of the self-attention mechanism model

The structure of the self-attention mechanism model is shown in Fig. 4. The self-attention mechanism uses Q, K, V to compute the attention scores between each element and other elements in the input sequence, and finally obtains the final weighted feature by weighted summation, and its output expression $A(Q, K, V)$ is as follows:

$$A(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{6}$$

where d_k is a hyperparameter that helps to alleviate the problem due to the overly large inner product result in the above equation, thus maintaining the stability of the gradient during training.

2.2.3. Prediction Model Based on Bidirectional Improved Temporal Convolutional Networks and Self-Attention Mechanisms

In this section, the residential electricity demand forecasting model Bi-ITCN-Att is constructed based on a bi-directional improved time-volume network with a self-attention mechanism.The model structure of Bi-ITCN-Att is shown in Fig. 5. In this paper, three consecutive Bi-ITCN layers are used in order to gradually extract deeper features from the input data. The size of the convolutional kernel of all three Bi-ITCN modules is 3. To avoid over-parameterization of the model, the last Bi-ITCN module has only 32 convolutional kernel counts, while the remaining Bi-ITCN modules have 64 convolutional kernel counts.The setting of the expansion factors in the Bi-ITCN modules follows the provisions described in the previous section, and are set to $d_1 = [1,2], d_2 = [4,8], d_3 = [16,32]$.

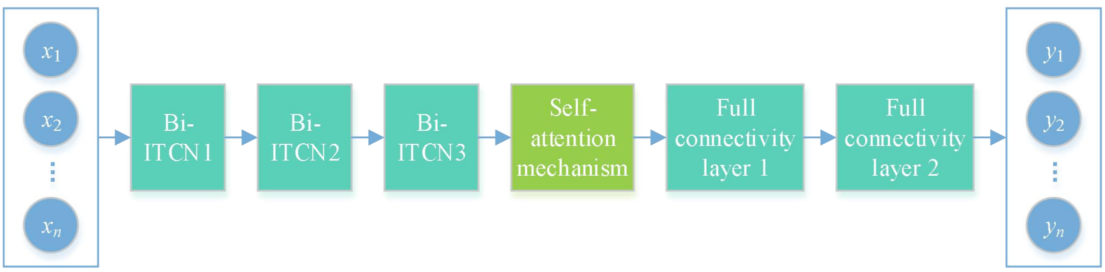

Figure 5. The structure of Bi-ITCN-Att

The self-attention mechanism allows the model to adaptively assign weights based on different parts of the input sequence. For load forecasting, this means that the model can better capture long-term dependencies, such as seasonal variations or the impact of specific events on load. In this paper, the feature information extracted by Bi-ITCN is fed into the self-attention mechanism, and the optimization of the feature vectors is achieved by deeply mining the weight relationships among the load data. Finally, the optimized feature vectors are fed into two fully connected layers to output the final predicted values.

3. Kano model based on residential electricity demand identification

In order to gain a deeper understanding of what real demand from residents is driving behind load fluctuations. The classic Kano model in management is now introduced. It helps to categorize residents' preferences for community energy services into various elements and probe deeply into the motivations for their electricity behavior.

3.1. Kano Model Questionnaire Design, Distribution and Recovery

In order to construct accurate residential electricity demand forecasting models, it is important to gain a deeper understanding of the intrinsic demand preferences that influence residents' electricity use behavior. In this section, the Kano model is used to conduct a more in-depth look at residents' demand attributes for community electricity-related services and functions.

3.1.1. Content design of the Kano model questionnaire

The first part of the questionnaire was used to collect user background characteristics that may be related to electricity consumption patterns, including subjects' demographic information (age, family structure) and the basis of electricity consumption behavior (major energy-consuming appliances in the home, size of the house, and whether there is a new energy vehicle, etc.).

The main part is designed with 4 factors (electricity consumption cost and feedback, electricity consumption control and scheduling, emergency protection and reliability, green electricity consumption and value-added services) and 22 demand elements. Its demand item indicators are shown in Table 1.

Table 1. Residential electricity demand project indicators

Dimension	**Demand elements**
Electricity Cost and Feedback	ECF1: Precise electricity bills and peak-valley electricity breakdown
	ECF2: AI-based personalized energy-saving suggestions and reports
	ECF3: Active reminders for electricity price fluctuations and package optimization
	ECF4: Household energy efficiency grade assessment and comparison with the same community
	ECF5: Prepaid electricity and reward activities with points
Electrical Control and Dispatching	ECD1: Remote control of major appliances via mobile app
	ECD2: Customized electricity usage scenarios such as leaving home and returning home
	ECD3: Intelligent socket with timed/delayed switch function
	ECD4: Automatically participate in energy conservation to receive subsidies in response to grid demand
	ECD5: Electric vehicles automatically charge during the night's low electricity period
	ECD6: Automatic adjustment of air conditioning temperature based on weather forecast
	ECD7: Automatic shutdown of standby electrical appliances when leaving home
Emergency Support and Reliability	ESR1: Real-time diagnosis and warning for household circuit faults
	ESR2: Precise notification of planned and sudden power outages
	ESR3: Overload protection and reminder when electricity load is too high
	ESR4: 24/7 online electricity consultation and fault repair
	ESR5: Monitoring of abnormal electricity usage of important appliances (such as refrigerators)
	ESR6: Quick access to backup power or emergency power supply guarantee
Green Electricity and Value Services	GE&VS1: Integration of clean energy (such as solar power) and feed-in of surplus electricity
	GE&VS2: Tracking of household electricity carbon footprint and display of emission reduction achievements

	GE&VS3: Subscribe to green electricity to support environmental protection efforts
	GE&VS4: Authorization of electricity usage data to participate in community energy management

3.1.2. Distribution and Collection of Kano Model Questionnaires

After the formation of the formal questionnaire, the questionnaire was distributed in the study community, the distribution point for the district property office, cultural and sports activities center and the community near the park plaza and other places, part of the questionnaire using the community on-site direct distribution to fill out and entrusted to the residents of the online distribution, the data acquisition time from March 14, 2025 to April 1, 2025, the data acquisition time. The online and offline questionnaires were manually screened to remove invalid questionnaires that were obviously filled out indiscriminately, with a large number of blanks and inconsistencies. Finally, 418 questionnaires were obtained, of which 369 were valid, accounting for 88.27% of valid questionnaires.

3.1.3. Reliability Analysis of Kano Model Questionnaire

The reliability of the questionnaire was measured using Cronbacha coefficient for the scales. In this section, the collected Carnot model questionnaires were organized, and SPSS26.0 was used to analyze the reliability feasibility of the forward scale questions, reverse scale questions, and overall scale questions in the questionnaire section, and the results of the test are shown in Table 2, which shows that the Cronbach α coefficient for the forward questions is 0.975; the Cronbach α coefficient for the reverse questions is 0.951; and the overall Cronbach α coefficient is 0.966, indicating that both forward and reverse scale responses are reliable.

Table 2. Reliability test of the positive and negative items in the questionnaire

	Forward questions	**Reverse questions**	**Overall**
Number of items	13	9	22
Cronbach α	0.975	0.951	0.966

3.2. Data processing for the Kano model

3.2.1. Mixed class analysis

The traditional Kano model tends to focus on determining the element attributes of an element by its percentage of the total when defining the type of demand. When an element has the highest percentage, that element is selected as the element attribute of the corresponding service project. However, a significant limitation of this categorization approach is that it fails to adequately consider other key attributes that may be present in the project and their impacts.

Therefore, if the traditional Kano model classification is selected for project analysis, it will result in a large amount of wasted sample data and will not be able to reflect the individual needs of residents. If the final analysis results of the indicators do not show a particular element that can dominate, then the project belongs to the mixed category. The indicators for the mixed category are TS and CS. TS is the total strength, which indicates whether the indicator is satisfactory or not; CS is the strength of the category, which indicates the extent to which respondents perceive an indicator to be categorized into a particular category. When TS ≥ 60% and CS < 6% for a category, the item is categorized as mixed; when CS < 6%, it indicates that the categories are very distinct from each other, as calculated by the following formula:

$$\text{TS(Total strength)} = \frac{\text{Answer the number of M, O, A}}{\text{Total number of responses}} \tag{7}$$

$$\text{CS}(\textit{Category Strength}) = \frac{\max(\text{A,O,M,I,R,Q}) - \text{secong}\max(\text{A,O,M,I,R,Q})}{\text{Total number of responses}} \tag{8}$$

When the value of CS is greater than 6%, the difference between categories is very clear and it is possible to categorize the project into the appropriate category, otherwise, the value of TS must be considered and the project categorized as a mixed category.

3.2.2. Better-Worse coefficient analysis

The traditional Kano model simply determines the final demand level of the service as the most frequent element among the four elements of M (essential element), O (expected element), A (attractive element), and I (irrelevant element), and finds that M>O>A>I demand elements are prioritized to satisfy the sequence, which ignores the impact of the service elements on the overall satisfaction level. The satisfaction of the same demand elements of the impact of the difference in satisfaction. Better coefficient indicates that the product has a certain quality characteristics of the degree of impact on user satisfaction, Worse coefficient indicates that the product does not have a certain in the traditional Kano model on the basis of the introduction of the Better-worse coefficient analysis method, used to distinguish between not a quality characteristic of the degree of impact on user satisfaction.

Eq. (9) yields the Better coefficient value, which is equal to the sum of the charm quality and one-dimensional quality frequencies divided by the total frequency of the four elements.

$$\text{Better Factor} = \frac{A+O}{A+O+M+I} \tag{9}$$

Eq. (10) yields the value of the Worse coefficient, which is equal to the sum of the one-dimensional mass and the required mass frequencies being at the total frequency of the four elements.

$$\text{Worse Factor} = \frac{O+M}{A+O+M+I} \tag{10}$$

4. Multi-dimensional analysis of residential electricity consumption characteristics and validation of Bi-ITCN-Att models

In order to further explore the patterns of electricity consumption habits of community residents, this chapter looks at the two most intuitive dimensions of weather and day type. In this chapter, we start from the two most intuitive dimensions of weather and day type, analyze how weather factors affect electricity load and analyze the different rhythms of electricity consumption on weekdays and weekends.

After figuring out these basic patterns, the Bi-ITCN-Att model is used for residential load forecasting to verify whether the forecasting performance has been improved in comparison with the basic model without the bi-directional and self-attention mechanisms.

4.1. Analysis of environmental factors for residential electricity consumption

Residents' electricity load changes all the time, and the electricity consumption of residents in the whole community is further analyzed by studying the development pattern of residents' load. The residential load characterization in this paper is mainly realized through statistical analysis methods, which capture the electricity consumption patterns of the community residents by counting the typical daily load curves of the residents in summer and winter, as well as the load characterization indexes between weekdays and weekends.

4.1.1. Impact of meteorological factors

Meteorological factors have a significant role to play in the load variations of the residents, and the meteorological data used in this paper were obtained from the NASA MERRA database. The study selected the temperature data of July and December 2024 at the latitude and longitude where a smart community is located, and the load-temperature curves were obtained and analyzed from the daily dimension for 48 moment points per day on the two dates of July 1 and December 1, 2024, and the load-temperature curves for both are shown in Figures 6 and 7, respectively.

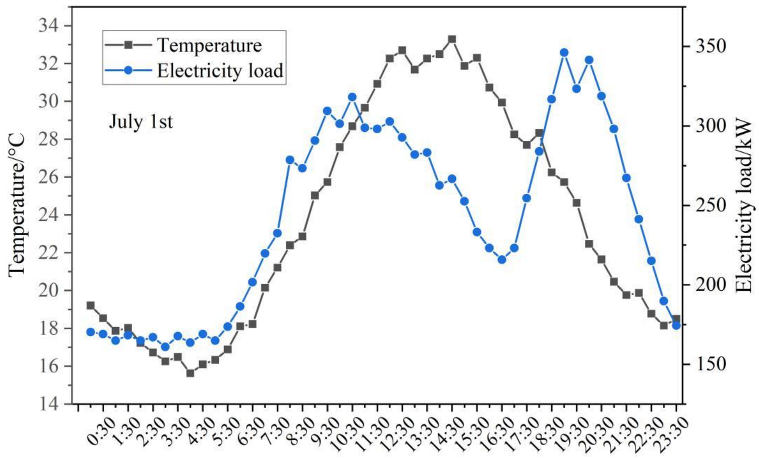

Figure 6. Load-temperature curve on July 1st

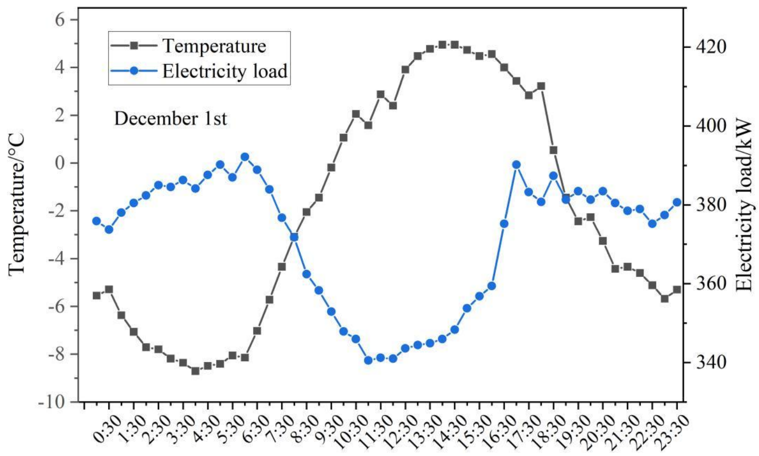

Figure 7. Load-temperature curve on December 1st

It can be clearly seen that both in summer and winter, as the maximum temperature continues to change, the residential load also changes accordingly, and the fluctuation trend of the two is basically the same.

In summer, with the overall increase in temperature, the load of electricity consumption rises, with a slight discrepancy in the afternoon work hours, people are generally out of the house, the community household electricity consumption will be relatively declined, but on the contrary, in the warmer hours of the load of electricity consumption decreases. During the dinner-home interval from 17:00-20:00, as people return home from work, the use of household appliances increases, causing electricity consumption to increase, with a peak load of 350 KW in the neighborhood.

From the typical winter load-temperature curve represented by December 1, it can be seen that the electricity load increases as the temperature decreases. Because the study area is in the north, its heating power consumption will increase as the temperature decreases, and at the same time, because people get off work early in the winter, at 16:30 onwards for the peak period of electricity consumption, the temperature change in this period does not have a great impact on it. The electricity load in winter is higher than that in summer, with a peak of 420 KW, because the electricity load of heating equipment is larger than that of air conditioning, and people have a greater demand for heating.

4.1.2. Impact of day type

This paper analyzes the impact of residential loads using the most common day types, i.e., weekdays and weekends, as examples.

Weekdays and weekends have their own similarities, i.e., load changes are cyclical. In order to reflect the difference between load weekdays and weekends, this paper selects weekdays and weekends with no major changes in meteorological conditions for comparative analysis, and Figure 8 shows the residential load curves from July 1 (Monday) to July 7 (Sunday), 2024.

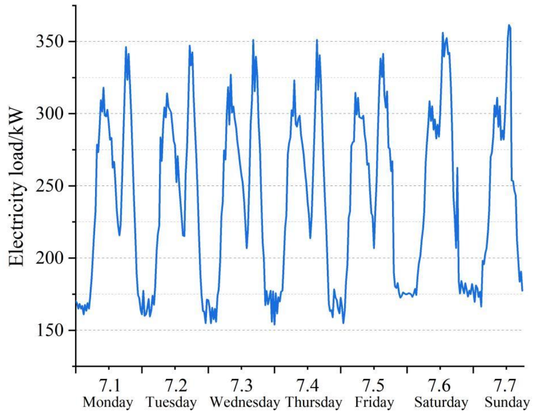

Figure 8. Residential load curve from July 1st (Monday) to July 7th (Sunday)

In this weekly period, the residential load in the neighborhood fluctuates periodically, and under the premise of no major changes in meteorological conditions, the daily load fluctuations are similar over the five weekdays, and the peaks and valleys appear in basically the same time period, which illustrates the regularity of the residents' electricity consumption. However, the electricity loads on weekends and weekdays are quite different, which can change due to people's living habits. Weekend morning load peak delayed growth, mainly due to the weekend, the community residents generally get up later, the use of household appliances slightly delayed due to; coupled with the number of weekend residents at home more, the afternoon peak and the evening peak of the number of electrical appliances used, resulting in an increase in the load peak in the Sunday, July 7, 19:00 or so, even up to the load of 261KW; at the same time, with the increase in the number of people watching TV, playing games and other At the same time, with the increase of people watching TV, playing games and other recreational activities, the night time negative load and electricity consumption time will increase.

4.2. Residential load forecasting based on Bi-ITCN-Att modeling

Continuing with the above obtained electricity load data of a neighborhood as a research sample, the Bi-ITCN-Att model is divided into training set and test set in the ratio of 8:2 for load prediction. At the same time, the original TCN model and the system of two-way improved time-convolution Bi-ITCN without the addition of self-attention machine are used to calculate the two methods respectively, and the results will be compared to verify the effectiveness of the model proposed in this paper, and take the load change of this neighborhood on July 1 as an example, the prediction effect of different methods is shown in Fig. 9 below.

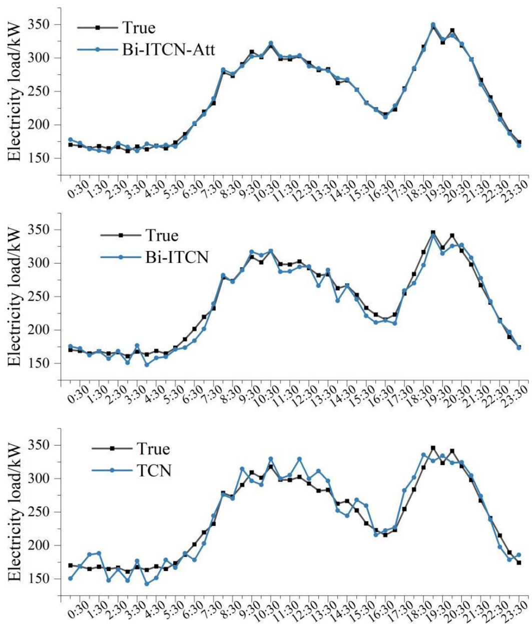

Figure 9. The effects of different methods for predicting the load of residential areas

From the prediction curves of the three models, it can be visualized that the original TCN model has more ups and downs in the prediction of residential users in the early hours of the morning, and the prediction trajectory is a bit sluggish and zigzagging, which is improved by the bidirectional improvement of the temporal convolutional network, but there is still a certain discrepancy between it and the real load curve. In the end, the Bi-ITCN-Att model with self-attention mechanism fits the real load profile most closely, especially at the peaks and troughs of the load, which is captured more accurately with very little error.

In order to show the prediction results among the three algorithms more clearly, the prediction error results of different algorithms are also plotted as shown in Fig. 10.

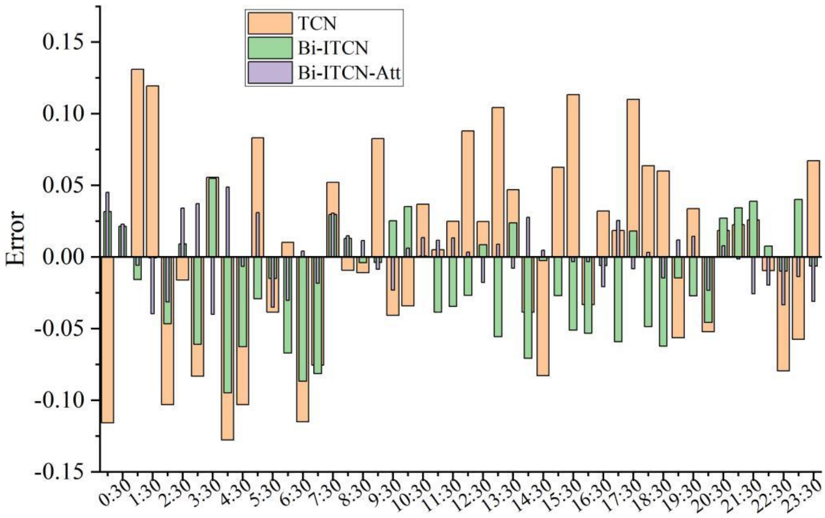

Figure 10. Different algorithm prediction error results

The prediction advantage of the Bi-ITCN-Att model is further evidenced by the error data. It can be noticed that the prediction errors of Bi-ITCN-Att are stably controlled at very low levels of 0.0229 and 0.0148 at several moments, such as late at night 1:00 p.m. and 8:00 a.m., and their fluctuation ranges are significantly smaller than those of the other two models.The average absolute percentage error MAPE of the Bi-ITCN-Att model is only 1.86%, and the root-mean-square error RMSE is 0.027, which is much lower than 1.083 for the TCN model and 0.062 for the Bi-ITCN model.Strongly demonstrates that the strategy of combining bi-directional temporal feature extraction with the self-attention mechanism is successful. It allows the model to understand the context of power usage from both past and future directions, thus making a judgment closer to the real situation.

5. Kano model based residential electricity demand identification and hybrid analysis

The Kano model, a needs decoder, is now introduced to process and interpret the collected needs of the residents. Identify what is the bottom line that must be safeguarded and what are the plus points that can bring surprises.

5.1. Two-dimensional attribute categorization analysis

In this study, the standardized analytical framework of KANO model was used to identify the demand attributes of the 369 valid questionnaires obtained on residential electricity demand. Based on the two-dimensional demand attribute discriminant matrix, the demand sensitivity parameter (SI) of each indicator was calculated by the Better-Worse coefficient method. In the attribute categorization process, the plurality determination method was used to determine the dominant attribute types.

The attribute law table of 2D electricity demand in the community is shown in Table 3.

Table 3. The attribute patterns of 2D electricity demand in the community

Dimension	Indicator	A	O	M	I	R	Demand attribute
Electricity Cost and Feedback	ECF1	58	121	95	88	7	O
	ECF2	132	85	48	98	6	A
	ECF3	45	155	92	72	5	O
	ECF4	118	64	51	129	7	I
	ECF5	146	78	42	98	5	A
Electrical Control and Dispatching	ECD1	72	98	65	126	8	I
	ECD2	135	88	55	87	4	A
	ECD3	81	142	76	65	5	O
	ECD4	92	105	83	84	5	O
	ECD5	128	91	49	96	5	A
	ECD6	95	131	68	70	5	O
	ECD7	62	139	102	60	6	O
Emergency Support and Reliability	ESR1	35	92	187	52	3	M
	ESR2	28	85	201	52	3	M
	ESR3	41	105	158	62	3	M
	ESR4	55	122	98	91	3	O
	ESR5	68	144	85	69	3	O
	ESR6	126	88	79	73	3	A
Green Electricity and Value Services	GE&VS1	151	75	38	100	5	A
	GE&VS2	88	72	45	156	8	I
	GE&VS3	78	65	52	167	7	I
	GE&VS4	95	81	48	139	6	I

A=Attractive demand, O=Expected demand, M=Must-have demand, I=Indifferentiated demand, R=Reverse demand

Through the data in Table 3 we can clearly see the real expectations of community residents for electric service, and their demand mapping presents a vivid and diversified picture. In the dimension of Emergency Security and Reliability, more than 50% of the residents categorize services like ESR1 (Circuit Failure Warning) and ESR2 (Precise Notification of Power Outage) as must-have attributes, indicating that they consider a stable and reliable power supply to be the most important, and is the default configuration for community life. The cost and control of electricity consumption is a game of "expected attributes (O)" and "attractive attributes (A)", with ECF3 (tariff reminder) as an expected demand, which is a clear demand of the residents, and it will add points if it is done well, and deduct points if it is not done well. As for ECF2 (AI energy saving report) and ECD2 (customized scenario), which are charming demands, residents mostly attribute them to the category of "no harm, no foul" and "icing on the cake". In addition, some of the green electricity services are undifferentiated attributes for residents.

5.2. Mixed class analysis

Based on the formula described in section 3.2.1, the data were processed to calculate the TS (Total Score) value and CS (Category Score) value of each relevant element, and the letter H was used to identify the hybrid category (H). Through the application of the mixed category analysis method, the statistical results of the functional attributes of the dimensions of the demand for electricity in this community were obtained as shown in Table 4.

Table 4. The results of the functional attributes of residential electricity demand

Dimension	Indicator	Traditional attributes	TS	CS	Improved attributes
Electricity Cost and Feedback	ECF1	O	0.74	0.07	O
	ECF2	A	0.72	0.09	A
	ECF3	O	0.79	0.17	O
	ECF4	I	0.63	0.03	H(A+I)
	ECF5	A	0.72	0.13	A
Electrical Control and Dispatching	ECD1	I	0.64	0.08	I
	ECD2	A	0.75	0.13	A
	ECD3	O	0.81	0.18	O
	ECD4	O	0.76	0.04	H(A+O)
	ECD5	A	0.73	0.09	A
	ECD6	O	0.80	0.10	O
	ECD7	O	0.82	0.10	O
Emergency Support and Reliability	ESR1	M	0.85	0.26	M
	ESR2	M	0.85	0.31	M
	ESR3	M	0.82	0.14	M
	ESR4	O	0.75	0.07	O
	ESR5	O	0.80	0.16	O
	ESR6	A	0.79	0.10	A
Green Electricity and Value Services	GE&VS1	A	0.72	0.14	A
	GE&VS2	I	0.56	0.18	I
	GE&VS3	I	0.53	0.24	I
	GE&VS4	I	0.61	0.12	I

In terms of overall intensity, the TS values for most of the demands are solidly above 0.60, indicating that residents still generally expect upgraded community electricity services, especially in the emergency protection category, where the TS value is as high as 0.85. However, by exploring the intensity of each indicator category, we find that the ECF4 (comparison of household energy efficiency ratings) and ECD4 (responding to the grid demand for subsidies), two programs, despite being arbitrarily categorized as I and O according to the traditional method, have unusually low CS values of 0.03 and 0.04, respectively, which are below the 0.06 threshold. This reflects the fact that residents' attitudes towards these two services are significantly divergent and do not form a consensus. They are no longer simply undifferentiated or desired goods, but a mixed demand with multiple attributes, which is adjusted to categorize them as a mixture of A+I and A+O. For this type of crowded demand, community managers can no longer follow a one-size-fits-all management strategy, but need to adopt a more flexible program to achieve service provision.

5.3. Better-Worse Satisfaction Index Analysis

The Kano questionnaire to categorize the community residents' demand for electricity can determine which category of the Kano model each demand belongs to, but it cannot determine the degree of satisfaction sensitivity of the public to each demand. Therefore, it is necessary to continue to analyze the satisfaction sensitivity of the public to each index attribute of electricity demand, calculate the satisfaction coefficient Better and dissatisfaction coefficient Worse, so as to determine which demand attributes in this study will have a higher satisfaction sensitivity and increase the public's satisfaction.Better-Worse satisfaction coefficient is shown in Table 5.

Table 5. Better-Worse Satisfaction Index

Dimension	Indicator	Better	Worse
Electricity Cost and Feedback	ECF1	0.494	0.597
	ECF2	0.598	0.366
	ECF3	0.549	0.679
	ECF4	0.503	0.318
	ECF5	0.615	0.330
Electrical Control and Dispatching	ECD1	0.471	0.452
	ECD2	0.611	0.392
	ECD3	0.613	0.599
	ECD4	0.541	0.516
	ECD5	0.602	0.385
	ECD6	0.621	0.547
	ECD7	0.554	0.664
Emergency Support and Reliability	ESR1	0.347	0.762
	ESR2	0.309	0.781
	ESR3	0.399	0.719
	ESR4	0.484	0.601
	ESR5	0.579	0.626
	ESR6	0.585	0.456
Green Electricity and Value Services	GE&VS1	0.621	0.310
	GE&VS2	0.443	0.324
	GE&VS3	0.395	0.323
	GE&VS4	0.485	0.355

Services like ECD6 (automatic pre-conditioning of air conditioning) and GE&VS1 (clean energy access) have very high Better coefficients, and investing resources in them reaps tangible kudos from residents. On the other hand, all the services in the Emergency Security category (ESR1, ESR2, ESR3) show appallingly high Worse coefficients of 0.762, 0.781, and 0.719, respectively, suggesting that these services are the absolute bottom line for the residents, and that a lack of them will trigger strong dissatisfaction among the masses, and that their destructive power is far greater than the others.

With the satisfaction coefficient Better as the horizontal coordinate and the dissatisfaction Worse as the vertical coordinate, the average value of the satisfaction influence is 0.519 , the average value of the dissatisfaction influence is 0.504, and the demand attribute matrix is drawn with the point (0.519, 0.504) as the origin as shown in Figure 11.

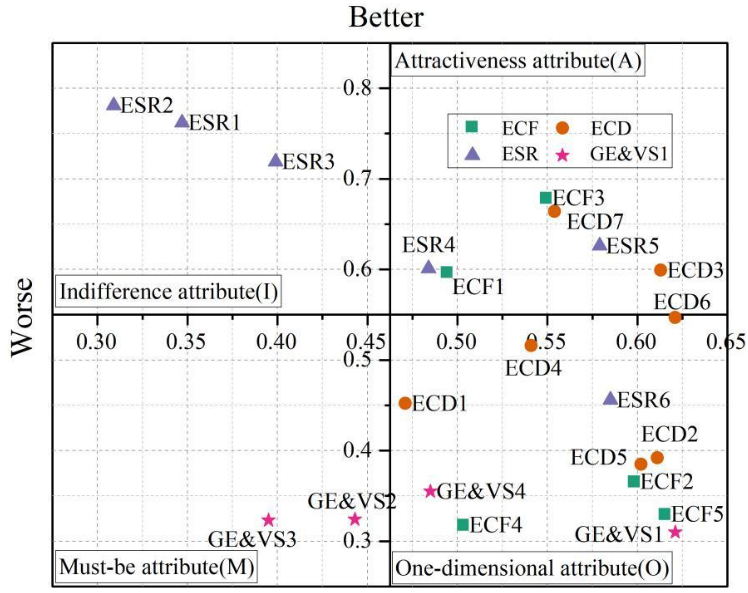

Figure 11. Residential electricity demand Better-Worse coefficient quadrant diagram

The quadrant map in Figure 11 lays out the community's residential electricity strategy visually by placing all needs in four strategic quadrants.

The upper right corner (High Better-High Worse) is the key focus area, where desired needs such as ECF3 (tariff reminder) and ECD7 (automatic appliance switching off) are clustered, which can either significantly increase satisfaction or, if not done well, can significantly cause dissatisfaction, and are the core services that the community needs to focus on maintaining and optimizing.

Bottom right (High Better-Low Worse) is the area of desired surprises, where things like ECF5 (pre-stored rewards) and GE&VS1 (clean energy) fall. High Satisfaction, Low Dissatisfaction, doing it right can greatly improve resident happiness and satisfaction, and it doesn't matter if you don't.

The upper left corner (Low Better-High Worse) is the Basic Security area, where all emergency security type needs fall. This is the bottom line of the community's responsibility, and must be foolproof.

The lower left corner (Low Better-Low Worse) is the Low Priority Zone, where some of the green services are located, meaning that they can be appropriately prioritized at this time.

6. Conclusion

The Bi-ITCN-Att model performs excellently in practice. The prediction curve can be said to closely match the actual curve, and the MAPE is only 1.86%, which is far better than the original TCN and the improved time convolutional network Bi-ITCN-Att comparison model that does not incorporate the self-attention mechanism in both directions, which fully proves the powerful advantages of the architecture in capturing the complex temporal patterns of residential electricity consumption.

The Kano model-based residential electricity demand identification and mixing analysis clearly categorizes the services into A attractive, O expected, M necessary and I undifferentiated demands. It also reveals the existence of hybrid classes like Comparison of Home Energy Efficiency Ratings (ECF4) and Responding to Grid Demand with Subsidies (ECD4) H. Better-Worse coefficient analysis further quantifies these perceptions into a map of actions, with a high Worse coefficient of 0.762 for real-time warning of ESR1 circuit failures, suggesting that the community must safeguard this type of must-have demand; ESR6 The Better coefficient of 0.598 for quick access to backup power supply guarantees suggests that providing this aspect of the charismatic needs will increase resident satisfaction with half the effort.

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