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A Situational Awareness Model of Regional Power Demand Based on Stacking Technology

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Abstract:
The effective application of electric power big data can better reflect the influencing factors of electricity demand and its inherent laws. This paper introduces big data and its related technology to the study of electricity demand. By selecting variables from five aspects such as historical electricity consumption by industry, weather, economy, industry attributes, and holidays, stacking fusion technology is used to construct a regional electricity demand situational awareness model to predict industry and regional electricity consumption trends. The empirical evaluations demonstrate that the integration model possesses notable capacity for combining diverse factors, thereby enhancing the precision of electricity consumption forecasts.

Keywords: Power big data, stacking fusion technology, power demand dynamics, industry economic dynamics.

INTRODUCTION

As China's modern market economy surges ahead and international collaboration and rivalry intensify, the significance of electricity data mining and analysis within the power market escalates, playing a pivotal role in the strategic planning and growth of power enterprises. Accurate power demand characterization has not only emerged as a vital aspect of electric power enterprises' production, operation, planning, and management work but also plays a crucial role in guiding their operational planning.[1] There are numerous influencing factors in electricity demand forecasting, and domestic and international economic turbulence further complicates the process, making electricity demand forecasting even more challenging.[2] For instance, economic prosperity, climate, population density, and so forth, are all influential factors in electricity demand forecasting. Furthermore, since this year, international trade disputes have intensified and are expected to continue escalating in the foreseeable future, which will significantly impact regions with a high proportion of exports. At the same time, the acceleration of industrial structure upgrading, driven by strong national policies, has made it more difficult to predict the power demand of various regions and industries.[3]

Electricity, as the cornerstone of national economic development, plays an irreplaceable role in fostering investment, stabilizing growth, adjusting structures, enhancing people's livelihoods, and ensuring security. Consequently, economic growth is the earliest and most frequently cited factor explaining electricity demand or energy demand in existing studies. [4-8] Eldowma et al. (2023)[9] integrated the autoregressive distributional lag-bounds testing approach with econometric methodologies to delve into the interplay among electricity usage, CO_2 emissions, overall population dynamics, and economic expansion in Sudan. Studies have shown that Sudan's growing population has contributed to economic expansion and, in turn, increased electricity demand. Xie Pinjie et al. (2020) [10] established a long-term equilibrium link between China's electricity use, economic expansion, and urbanization trends, utilizing data spanning 1978-2019. Their analysis revealed a bidirectional Granger causality between economic expansion and electricity use, both in the long and short term. Similarly, Adedoyin and Ilhan (2020) [11] investigated the relationship in Sub-Saharan Africa from 1971 to 2017, uncovering a robust positive correlation between electricity use and economic expansion.

In recent years, as meteorological statistics have become increasingly refined, the impact of meteorological factors on power demand has also emerged as a research hotspot for many scholars. Zhang et al. (2023) [12] introduced a CatBoost-PPSO hybrid model, leveraging weather variables to forecast electricity demand with heightened accuracy in short-term scenarios. Xu et al. (2022) [13] utilized structural equation modeling to discern the intricate direct and indirect links between electricity use and economic expansion in China, affirming a positive influence. Zhou (2020) [14] refined short-term load forecasting for power systems by identifying key meteorological factors and developing a method that achieved high precision through error analysis. Guo et al. (2020) [15] employed spatial econometrics to identify the multifaceted drivers of electricity demand in China, uncovering both enhancing (e.g., economic growth, population) and moderating (e.g., technological advancements, industrial structure optimization) factors.

The forecasting of electricity demand is inseparable from reasonable forecasting methods and models. [16-23] Prashanth and Srikanth (2023) [24] devised a predictive model that combines Random Forest (RF) and Bi-Directional Gated Recurrent Unit

(Bi-GRU) for enhanced accuracy. Khan et al. (2022) [25] introduced a short-term electricity load forecasting model, integrating data cleansing and a deep residual convolutional neural network, demonstrating its efficacy. Liu et al. (2020) [26] proposed a short-term bus load forecasting approach, blending XGBoost and Stacking models, with system parameters optimized by particle swarm optimization, validated through case studies.

In addition to economic growth and climate change, scholars have also explored the impact of a range of factors, including important holidays [27], industrial structure [28], information and communication technology (ICT),[29] oil prices,[30] and urbanization [31], on electricity demand. Consequently, they have improved the forecasting model of electricity demand, leading to more reasonable and accurate predictions.

To enhance the relevance to contemporary power system demands, prior research foundations are expanded by incorporating big data and related technologies into electricity demand analysis. This involves exploring the interplay between electricity use and diverse external economic and meteorological factors. Variables are meticulously selected across five dimensions: historical electricity consumption, weather patterns, economic indicators, industrial characteristics, and holiday effects. Based on the three basic models of XGBoost, support vector regression, and random forest, the regional electricity demand situation awareness model is constructed by using the stacking fusion technology to predict the industry and regional electricity consumption trend. The innovations of this paper are as follows: (1) In terms of the research object, most research on electricity consumption in the industry focuses on the sector, industry, or even regional level, which results in a significant amount of information about individual users remaining unextracted and rarely analyzed in terms of their electricity consumption behaviors. This paper proposes taking the individual enterprise user as the research object, which offers a finer granularity compared to other similar studies, enabling the analysis of the user's electricity consumption behavior. Furthermore, it aims to address the prediction error in the user's prediction results through correction and analysis, which will significantly improve the accuracy of the model. (2) By utilizing stacking technology to construct a fusion model, we aim to compensate for the shortcomings of a single model. This approach ensures that the fusion model's accuracy, reliability, and stability are superior to that of a single model. (3) We innovatively employ relative error as a loss function for model error correction, thereby enhancing the accuracy of the model's prediction results.

MODEL

Principle

Stacking fusion is a multi-layer superposition of the model, and its architecture is usually composed of two layers. Specifically, the first layer is employed in processing the input data. The remaining layer is the inductive meta-learner, which is used to inductively fuse the output of the first layer to obtain the ultimate output.[24] Model fusion technology is used to fuse multiple base models to predict industrial electricity consumption, which can integrate and utilize the strengths of each individual, and avoid the disadvantages. It not only considers many factors for analysis but also deals with some random factors in the problem, which is more systematic and comprehensive than that of a single model. Specifically, the advantages of Stacking fusion technology include: (1) the prediction ability of the fusion model is greater than various single models, and the generalization ability is stronger; (2) can accomplish the transfer of knowledge; (3) can battle overfitting without a lot of parameter adjustment or feature selection; (4) it can improve machine learning effect and shorten operation time.

Input Variables

Since the electricity consumption data are obvious time series data, the historical electricity sales have a great influence on the forecast of electricity consumption in the current period. In addition, weather, economy, industry attributes, holidays, and other factors will more or less affect the size of electricity consumption. Therefore, the power demand situational awareness model selects variables from five aspects, including industrial historical electricity consumption, weather, economy, industrial attributes, and holidays.

Base Models

XGBoost

XGBoost is an integrated model of optimized classification regression trees, described as follows:

$$\hat{y}_i = \sum_{t=1}^{t} f_t(x_i), f_t \epsilon F \tag{1}$$

where t is the count of trees, f_t is one of the functions in F, and F represents the set of CART components. The objective function is shown as follows:

$$Obj^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y_i}) + \sum_{i=1}^{t} \Omega(f_t) \quad (2)$$

The parameter f_t is a control parameter. The difficulty of training f_t is much higher than the training of parameters in general machine learning. Therefore, an addition strategy is adopted: fix the learned model and add one tree to the model at a time. The forecast obtained for the TTH time is denoted as $\widehat{y_i^{(t)}}$, and the objective function is expressed as follows:

$$Obj^{(t)} == \sum_{k=1}^{n} l\left(y_k, \hat{y_i}^{(t-1)} + f_t(x_k)\right) + \Omega(f_t) + C \quad (3)$$

Using MSE as the loss function, and then the objective function can be expressed as:

$$Obj^{(t)} = \sum_{k=1}^{n} \left[l\left(y_k, y_k{}^{(t-1)}\right) + g_k f_t(x_k) + \frac{h_k f_t^2(x_k)}{2}\right] + \Omega(f_t) + C \quad (4)$$

Define the complexity $\Omega(f)$ of the model to further improve the definition of $f(x)$:

$$f_t(x) = w_{m(x)}, w \epsilon R^T, m: R^d \to \{1, \dots, T\} \quad (5)$$

where w denotes the scores on a leaf, m is a mapping, and T is the amount of leaves. Furthermore:

$$\Omega(f) = \Upsilon \mathrm{T} + \frac{\alpha \sum_{t=1}^{T} w_t^2}{2} \quad (6)$$

After reconstructing the tree model, the objective function after adding the TTH tree is:

$$\begin{aligned} Obj^{(t)} &\approx \sum_{k=1}^{n} \left[g_k w_{q(x_k)} + \frac{1}{2} h_k w_{q(x_k)}^2\right] + \Upsilon \mathrm{T} + \frac{\alpha \sum_{t=1}^{T} w_t^2}{2} \\ &= \sum_{j=1}^{T} \left[(\sum_{l \in I_j} g_l) w_j + \frac{\sum_{l \in I_j} h_l + \alpha}{2} w_j^2 \right] + \Upsilon \mathrm{T} \\ &= \sum_{j=1}^{T} \left[G_j w_j + \frac{1}{2}(H_j + \alpha) w_j^2\right] + \Upsilon \mathrm{T} \end{aligned} \quad (7)$$

The final objective function is a quadratic function with respect to w_j, and its minimum point and the minimum value are respectively:

$$w_j^* = -\frac{G_j}{H_j + \alpha} \quad (8)$$

$$obj^* = -\frac{1}{2} \sum_{j=1}^{T} \frac{G_j{}^2}{H_j + \alpha} + \Upsilon \mathrm{T} \quad (9)$$

Equation (9) is applied to evaluate the tree structure. More smaller the value is, the better the structure is. Therefore, all possibilities can be tried and the optimum can be selected. However, this method is time-consuming. Therefore, in the process of solving, only one layer of the tree is optimized at a time. Assuming that a leaf splits into two leaves, its score increases as follows:

$$Gain = \frac{1}{2}\left[G_L{}^2 \frac{1}{H_L + \alpha} + G_R{}^2 \frac{1}{H_R + \alpha} + (G_L + G_R)^2 \frac{1}{H_L + H_R + \alpha}\right] - \Upsilon \quad (10)$$

If the gain is less than Υ, we do not split this leaf.

Support vector regression

Support vector regression (SVR) can be formalized as:

$$\min_{\omega, b} \frac{1}{2} ||\omega||^2 + \delta \sum_{i=1}^{m} \zeta_\epsilon(f(x_i) - y_i) \quad (11)$$

where δ is the constant. ζ_ϵ is the ϵ-insensitive loss function,

$$\zeta_\epsilon(z) = \begin{cases} 0, & if\,|z| < \epsilon \\ |z| - \epsilon, & otherwise \end{cases} \quad (12)$$

Introducing the slack variables ξ_m and $\widehat{\xi_n}$, then

$$\min_{\omega,b,\xi_m,\widehat{\xi_n}} \frac{1}{2}||\omega||^2 + \delta \sum_{m=1}^{l} (\xi_{m,} + \widehat{\xi_n})$$

$$s.t. f(x_m) - y_m \leq \epsilon + \xi_m \quad (13)$$

$$y_m - f(x_m) \leq \epsilon + \widehat{\xi_n}$$

$$\xi_m \geq 0, \widehat{\xi_n} \geq 0, m = 1, \dots, l$$

Using the Lagrange multiplier $\mu_m \geq 0, \widehat{\mu_n} \geq 0, \beta_m \geq 0, \widehat{\beta_n} \geq 0$, the dual problem is:

$$s.t. \sum_{m=1}^{l} (\widehat{\beta_n} - \beta_m) = 0$$

$$0 \leq \widehat{\beta_n}, \beta_m \leq \delta$$

Finally, the solution is as follows:

$$f(x) = \sum_{m=1}^{l} (\widehat{\beta_n} - \beta_m) x_m^T x + b \quad (14)$$

Random forest

The process of the random forest (RF) is depicted in Figure 1.

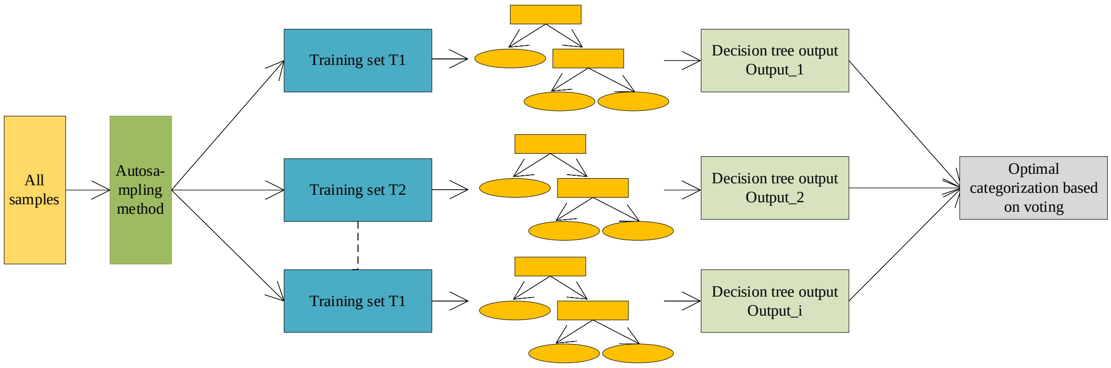

Figure 1. Framework process of random forest algorithm

The random forest uses the bootstrap sampling method with replacement to extract the training samples of each decision tree. In addition, the random forest adds the random selectivity of feature division on the basis of the Bagging method, that is, the decision tree selects the optimal feature according to the attribute division rule when selecting the feature of tree nodes, so there are different features used by each node in each tree.

Construction of Stacking Fusion Model

In this paper, the regional power demand situation awareness model based on Stacking technology is designed as a two-layer framework, which can not only ensure prediction accuracy but also shorten the operation time. The first layer is the basic layer of the system, which is composed of three different basic models, namely the XGBoost model, the SVR model, and the RF model. The second meta-model is multiple linear regression (MLR). The implementation step of the Stacking fusion framework is demonstrated in Figure 2:

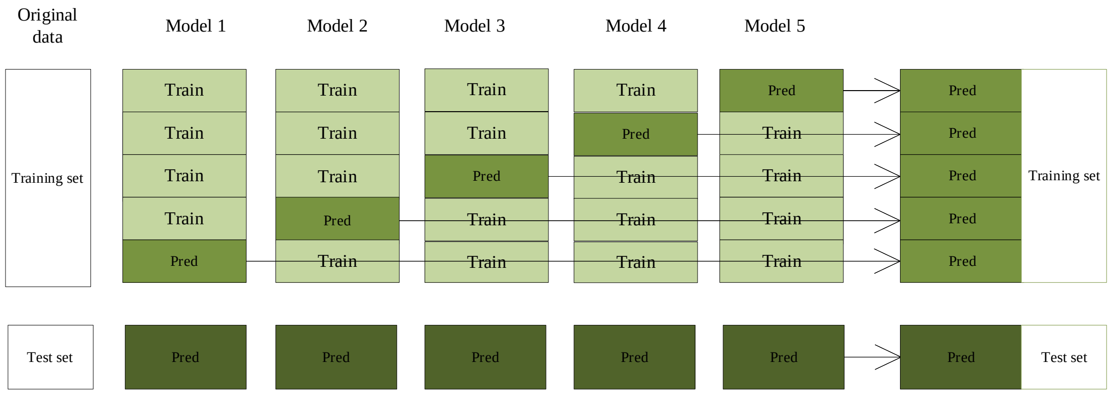

Figure 2. Implementation process of Stacking fusion model method

(1) The XGBoost model, SVR model, and RF model are trained by 5-fold cross-validation, that is, each model will be trained 5 times. The particular training method is as follows: firstly, based on the idea of cross-validation, the input data is split into five segments, four of which are deemed to be training parts, and the other one is deemed to be testing. Four pieces of them were used for training each time, and the corresponding prediction result A was obtained by processing the test data. The prediction result B of the test set was obtained by predicting the test set data. After five training sessions, the five prediction results A are united into a single column, and then results B are averaged. Finally, we get the new data sets A and B, where the amount of A is the same as that of the training data.

(2) Then, the constructed XGBoost, support vector regression, and random forest models obtained three data sets A and three data sets B. By combining the data of three A and three B, we can gain the new training set, as well as the new test set.

(3) This model makes use of the multiple linear regression method to handle the new training set and the new test set. The specific structure is established as follows:

$$y_a = \beta_0 + \beta_1 x_{1a} + \beta_2 x_{2a} + \cdots + \beta_k x_{ka} + \varepsilon \tag{15}$$

where $\beta_0, \beta_1, \beta_2, \cdots \beta_k$ are the regression coefficients to be determined, β_0 is the regression constant, and ε is the error random term.

The pseudo-code for the Stacking algorithm is as follows:

Input: training dataset$D = \{x_i, y_i\}_{i=1}^{m}$
Process 1: Learning sub-classifiers
For t=1,…,T
Learn $h_t(D)$
end
Process 2: Constructing a new dataset for prediction
For t=1,…,m:
$x_i' = \{h_1(x_i), \dots, h_T(x_i)\}$
$D_h = \{X_i', y_i\}$
Process 3: Learning meta-classifiers
Learn $H(D_h)$
Output: integrated learning classifier H

EXPERIMENTS

Data Source and Preprocessing

Source

The power and meteorological data in this paper come from the basic data platform of a power supply company in a certain province of China. Through data access, relevant power and weather information can be collected. The external economic data are mostly collected from the websites of the national, provincial, and municipal Bureau of Statistics and other relevant official websites and other third-party data platforms by means of manual or automatic download/collection or crawler acquisition. In addition, the data can be separated into two segments: the training part and the test part. According to the actual situation of the data, the period from January 2022 to November 2023 is the training set, and the period from December 2023 is the test set.

Preprocessing

Due to the sudden increase and decrease of industrial electricity consumption, which imposes a huge effect on the prediction ability in training processing, it is worthwhile to handle "outlier" treatment for such electricity consumption (outlier here refers to the relative anomaly of model data). However, in order not to affect the test effect of the test set, we only deal with the "outlier" of electricity consumption in the training set.

The lack of electricity consumption imposes a certain effect on the prediction ability. To reduce the impact, we mainly employ the mean before and after to complete the missing part of electricity consumption in the training set and do not process the electricity consumption in the test set.

Selection of input variable

The results of input variable selection are demonstrated in tables 1, 2, 3, 4, and 5.

Table 1. Characteristics of historical electricity consumption

Electricity consumption characteristics	Definition
T_PQ_LAST	Electricity consumption in the past month
T_PQ_2	The mean electricity demand in the recent two months
T_PQ_3	The mean electricity demand in recent three months
T_PQ_4	The mean electricity demand in recent four months
T_PQ_2_STD	The standard deviation of electricity demand in the past two months
T_PQ_3_STD	The standard deviation of electricity demand in the past three months
T_PQ_4_STD	The standard deviation of electricity demand in the past four months
T_PQ_3_CV	Dispersion coefficient of electricity demand in the past three months
T_PQ_4_CV	Dispersion coefficient of electricity demand in the past four months
T_PQ_3_MIN	Minimum electricity demand in the past three months
T_PQ_4_MIN	Minimum electricity demand in the past four months
T_PQ_3_MAX	Maximum electricity demand in the past three months
T_PQ_4_MAX	Maximum electricity demand in the past four months
T_PQ_1_RATE	The rate of increase in electricity demand in the recent month
T_PQ_2_RATE	The rate of increase in electricity demand in the past two months
T_PQ_3_RATE	The rate of increase in electricity demand in the past three months
LAST_SAME_TIME_PQ	Electricity demand in the same period past year
ES	Historical electricity consumption scale
T_PQ_PM	Ranking of historical electricity consumption
RUN_CAP	Increase and decrease capacity

Table 2. Weather characteristic variables

Characteristic of weather	Definition
MAXLAPSERATE	Monthly maximum temperature
MINLAPSERATE	The minimum temperature in a month
AVGLAPSERATE	The mean temperature in a month
AVGHUMIDITY	Monthly mean humidity
SUMPRECIIPITATIONFALL	Accumulated monthly rainfall
SUM10MMPRECIIPITATIONFALL	Days with monthly accumulative rainfall of less than 10mm
SUM25MMPRECIIPITATIONFALL	The cumulative monthly rainfall is 10mm-24.9mm days
SUM50MMPRECIIPITATIONFALL	The cumulative monthly rainfall is 25mm-49.9mm days
OVER50MMPRECIIPITATIONFALL	Days with cumulative monthly rainfall above 50mm

Table 3. Variables of economic characteristics

Economic characteristics	Definition
GDP	Gross regional domestic product
PMI	Manufacturing purchasing managers index
PPI	Ex-factory price indices of industrial product
CPI	Consumer price index
EVA	Added value of industries above designated size
TRSCG	Total retail sales of consumer goods

Table 4. Variables of industry attributes

Industry attributes	Definition
HYLB	Secondary industry categories
SFGY	Whether industrial or not
HYFQ	Industry group number

Table 5. Characteristic variables of holidays

Characteristic	Definition
Year	Year
Mon	Month
Season	Season
Holiday	Number of holidays

Electric Power Demand Forecasting

General situation

Nowadays, the prediction precision to the total electricity sales in a province of China is about 96%, and the average forecasting precision to the electricity sales in various cities in a province of China is about 95%. The main problems affecting the predicted performance are the sudden increase and decrease of electricity sales data in some industries, too many null values (occasionally there is electricity), etc.

Industry electricity sales forecast

General situation

In the current industry electricity sales prediction model, due to the abnormal electricity sales data of some industries, these industries are not brought into this model. After eliminating the abnormal industries, the remaining industries are modeled and predicted. All current average forecast accuracy is about 94%. The specific distribution of industry forecast accuracy is depicted in table 6:

Table 6. Distribution of industry forecast accuracy

Accuracy	Count	Proportion (%)
More than 95%	1122	72.15%
90%-95%	238	15.31%
Less than 90%	73	4.69%
Not included in the model	122	7.85%
Total	1555	100.00%

Forecast accuracy of key industries

Twelve key industries were selected according to the existing circumstances of industry in a province in China, and the forecast results are as follows in table 7. Herein the errors of feathers and its products, leather, footwear, and fur industry mainly come from a city in the province, after analysis, it is found that the trend of electricity sales is abnormal, and the accuracy can reach 95.46% after excluding the data of this city.

Table 7. Average accuracy table of key industries

Industry	Error	Accuracy
Feathers and their products, leather, fur, and footwear industry	0.1107568	88.92%
Chemical fiber manufacturing industry	0.0586388	94.14%
Metal products industry	0.0372169	96.28%
Communications, manufacturing of computers, and other electronic equipment	0.0314198	96.86%
Rubber and plastic products industry	0.0341399	96.59%
Textile industry	0.0397362	96.03%
Manufacture of non-metallic mineral products	0.0401938	95.98%
Ferrous metal smelting and calendering processing industry	0.0763865	92.36%
Farm and sideline food processing industry	0.0296712	97.03%
Wood processing and wood, bamboo, rattan, palm, grass products industry	0.031945	96.81%
Non-ferrous metal smelting and rolling processing industry	0.0530533	94.69%
Chemical raw materials and chemical products manufacturing	0.0348428	96.52%

Based on the analysis of the above experimental outcomes, it is apparent that the poor prediction accuracy of electricity sales in the industry mainly has the following reasons: 1) the historical data of electricity sales in the industry are basically missing; 2) Abnormal sudden increase or decrease of electricity sales trend in the industry; 3) The trend of industry electricity sales fluctuates greatly.

Prediction results of prefecture-level cities

The forecast results of the prefecture and city come from the forecast of industry electricity sales. According to the summary of the prefecture and city, the research is divided into monthly and quarterly dimensions.

Monthly forecast accuracy

From the dimension of prefecture-level cities, taking the results of December 2022 as an example, the forecasting precision of electricity sales in various cities is basically above 90%, and some cities have large errors. The predicted precision of electricity sales by industry in 2022 is as follows in table 8:

Table 8. Predicted precision table of electricity sales in certain cities in China in 2022

Cities	Real value	Predicted value	Accuracy
A city	5602316498	5901210311	94.66%
B city	1447550787	1513664867	95.43%
C city	1426469129	1419300963	99.50%
D city	2268863678	2292719537	98.95%
E city	910086565	1077794127	81.57%
F city	6857721124	7043096918	97.30%
G city	1861809929	1561334615	83.86%
H city	2065845769	2185792147	94.19%
I city	1820036593	1916855375	94.68%

Quarterly forecast accuracy

Taking the results of the fourth quarter of 2022 as an example, the prediction accuracy of all cities is basically above 90%, and some cities have large errors. The predicted accuracy of electricity sales in cities of a certain province in China in the fourth quarter of 2022 is as follows in table 9:

Table 9. Forecast accuracy table of electricity sales in cities of a province in China in the fourth quarter of 2022

Cities	Real value	Predicted value	Accuracy
A city	1.79E+10	1.92E+10	92.64%
B city	4.4E+09	3.99E+09	90.61%
C city	4.25E+09	4.21E+09	99.02%
D city	7.88E+09	7.96E+09	98.94%
E city	3.09E+09	3.56E+09	84.75%
F city	2.15E+10	2.17E+10	99.06%
G city	5.6E+09	5.12E+09	91.29%
H city	7E+09	7.53E+09	92.46%
I city	7.79E+09	9.29E+09	80.73%

The above experimental results show that the prediction of the regional power demand situational awareness method based on Stacking technology for the total electricity sales of a province in China reaches about 96%, and the average prediction accuracy for the total electricity sales of cities in a province in China reaches about 95%. Data problems such as sudden increases and decreases of electricity sales data in some industries and too many null values affect the predicted capacity. Therefore, the average predicted precision of the remaining industries is about 94% after eliminating the abnormal industries. After eliminating the data with obvious abnormal problems and then modeling and forecasting the remaining electricity consumption type data, the average prediction accuracy is about 87.4%.

CONCLUSION

This paper proposed the regional power demand situational awareness model, including the selection of variables, the selection of variables, the selection of base models, and the construction of the Stacking fusion model. Then based on the model, the empirical analysis was fulfilled on the data of a province in China. Moreover, the prediction outcomes demonstrate that this method achieves a high precision of 96% in predicting the total electricity sales of the province. However, there are still shortcomings to be improved. For example, the internal and external power, climate and economic index data collected in this paper have not been fully used, which can be collected into the database after data governance. After analysis, exploration, and development, the industrial power economic operation report and data interface can be formed, and more information can be mined and shared with the government and enterprises to help the government control the national development trend. In addition, it is necessary to further improve the adaptive ability of the power demand situation awareness model for policy factors and contingency events that affect the power demand situation, such as natural disasters.

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