Research and Application of Association Analysis Model for Power and Economy in Key Industries

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Abstract. Electric power is a 'thermometer' and 'barometer' of the national economy, and key industries are important driving forces for its growth. This paper focuses on the research of the association analysis model between power consumption in key industries and economic development, aiming to grasp the economic development trends from the perspective of power consumption in key industries. Firstly, the correlation characteristics of power consumption in key industries and the economy are analyzed. Then, an association analysis model is constructed, including a model for leading, coincident, and lagging relationships, as well as an economic index calculation model based on power data. Finally, an empirical study is conducted based on the electricity consumption data of a certain province's key industries and industrial value-added data. The results indicate that power consumption in key industries has a certain leading effect on the growth rate of industrial value-added, and it can forecast the changing trend of the year-on-year growth rate of industrial value-added, thus supporting macroeconomic regulation and control.

Keywords: key industries; power-economy; association analysis; economic index; leading effect

1 Introduction

Electricity is the "thermometer" and "barometer" of the national economy [1-2], and changes in electricity demand reflect the activity of economic operation. In addition, industry is the backbone of the national economy, and the growth of industrial production can promote regional economic prosperity[3]. Among them, key industries play an important role in the national economic planning and are the main driving force for industrial development. Therefore, studying the economic development trends from the perspective of power consumption in key industries, will be beneficial for government departments to better formulate policies and macroeconomic regulation.

Since the 1980s, major institutions in China have been conducting research on economic development, but there are problems such as complex calculation of economic statistical indicators and high difficulty in prediction[4]. Power data has many advantages such as comprehensive coverage, fine granularity, high accuracy, good continuity, and strong real-

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time performance[5], providing a data foundation for conducting economic analysis of electricity. With the accumulation of power data, many experts and scholars are gradually shifting their focus to the construction of economic prosperity index based on power data. The economic sentiment index plays an important role in macroeconomic analysis, market research, and policy formulation [6,7]. References [4,8] analyzed the leading, coincident, and lagging relationships between electricity and economic indicators through time difference correlation analysis and K-L information, and synthesized the Economic Prosperity Index based on Power Data (EPI-P). Reference [9] is based on electricity consumption data from various industries, using three methods: price weighting, market value weighting, and equal weight weighting. According to the principle of a base value of 100, the electricity economic prosperity index is established. Existing research has proposed a relatively mature method for calculating the electricity economic prosperity index, laying a solid foundation for our research.

Therefore, this paper first analyzes the correlation characteristics of power consumption in key industries and the economy, and then refers to the practices of references [2] and [8] to construct the association analysis model for the power-economy relationship. Finally, an empirical study is conducted based on the electricity consumption data of a certain province's key indus-tries and industrial value-added data.

2 Correlation characteristics of power-economy in key industries

According to effective statistics, the average annual growth rate of industrial added value in the province from 2018 to 2022 was 9.24. The province includes 11 key industries such as food, non-ferrous metals, steel, and textiles. The electricity consumption of these 11 key industries increased from 41.159 billion kilowatt hours to 62.391 billion kilowatt hours, with an average annual growth rate of 10.96%. Fig. 1 shows the Growth rate of electricity consumption and industrial added value in a certain province. From the graph, it can be seen that from 2018 to 2022, the year-on-year growth rate of industrial value-added in the province showed a high correlation with the year-on-year growth rate of various key industries.

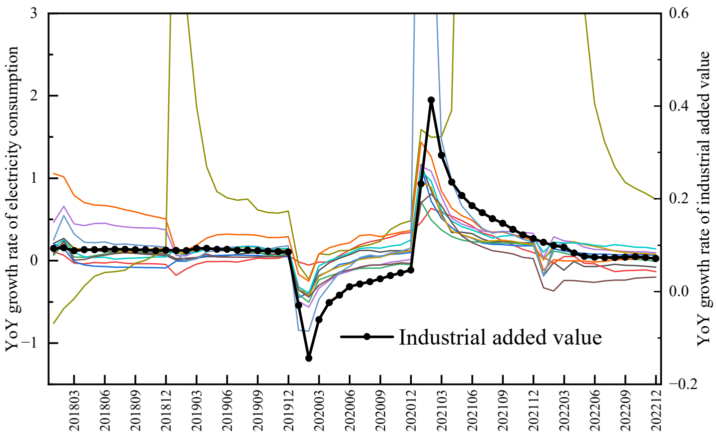

Fig. 1. Growth rate of electricity consumption and industrial added value in a certain province

3 Association analysis model for power-economy in key industries

3.1 A model for leading, coincident, and lagging relationships

Due to the lack of objectivity in a single dimension of evaluation indicators, the approach of references [2] and [8] was adopted to determine the similarity between power indicator sequence data and economic indicator sequence data. The specific calculation methods for the above two indicators are as follows.

1) Time difference correlation coefficient

Assuming $x=\{x_1,x_2,\cdots,x_n\}$ is the benchmark indicator sequence, $y=\{y_1,y_2,\cdots,y_n\}$ is a sequence with filtering indicators, the calculation method for the time difference correlation coefficient is as follows [10]:

$$r_l=\frac{\sum_{t=1}^{n_l}(x_{t+l}-\bar{x})(y_t-\bar{y})}{\sqrt{\sum_{t=1}^{n_l}(x_{t+l}-\bar{x})^2\sum_{t=1}^{n_l}(y_t-\bar{y})^2}},\qquad l=0,\pm1,\pm2,\cdots,\pm L \tag{1}$$

Where r_l represents the time difference correlation coefficient corresponding to the number of periods; l indicates the number of delay periods, negative values indicate lag, positive values indicate lead; L indicates the maximum number of delays; n_l is the number of aligned data. Then, select the maximum time difference correlation coefficient, as follows.

$$r=\max_{-L\le l\le L} r_l \tag{2}$$

Where r is the final time difference correlation coefficient between the filtered indicator sequence and the benchmark indicator sequence. The corresponding l is the number of delay periods for the filter indicator.

2) K-L Information Content

The calculation method for the K-L information content of benchmark indicators and the indicators to be screened is as follows [11]:

$$k_l=\sum_{t=1}^{n_l}p_t\ln\left(\frac{p_t}{q_{t+l}}\right) \tag{3}$$

In the formula: k_l represents the K-L information value of the indicator to be screened under the delay period l; q_t represents the sequence of standardized benchmark indicators; p_t represents the sequence of the indicators to be screened after standardization processing; n_l is the number of data after data retrieval. The smaller the K-L information between the selected indicator and the benchmark indicator, the closer it is to 0, indicating that the selected indicator is closer to the benchmark indicator. Then, select the minimum amount of K-L information.

$$k = \min_{-L \le l \le L} k_l \tag{4}$$

In the formula: k represents the final K-L information value of the indicator to be screened, and the corresponding l is the number of delay periods for the screened indicator. Based on experience, when the time difference correlation coefficient between a certain power indicator and an economic indicator is greater than 0.7 or the K-L information content is less than 0.35, it can be preliminarily determined as a certain indicator group.

3.2 An economic index calculation model based on power data

Composite index can not only describe the situation of peaks and valleys, but also serve as a reference for the fluctuation amplitude of the index [4]. Therefore, this paper adopts the composite index method to construct the EPI-P index, and the specific steps are as follows.

1) Calculate the symmetric rate of change for each indicator data based on the leading, coincident, and lagging indicator groups.

$$C_{ij}(t) = X_{ij}(t) - X_{ij}(t-1) \tag{5}$$

Where $C_{ij}(t)$ represents the symmetric change rate of the j indicator in the i group; $t = 1, 2, \cdots, n$; $i = 1, 2, 3$ represent the leading, coincident, and lagging indicator groups, respectively.

2) Calculate the average rate of change for each group of indicators

$$S_{ij}(t) = \frac{C_{ij}(t)}{A_{ij}} \tag{6}$$

Where $S_{ij}(t)$ represents the average rate of change; A_{ij} is the standard rate of change, calculated as follows.

$$A_{ij} = \sum_{t=1}^{n} \frac{|C_{ij}(t)|}{n-1} \tag{7}$$

3) Calculate the standardized average rate of change.

$$R_i(t) = \frac{\sum_{j=1}^{k_i} S_{ij}(t) \bullet w_{ij}}{\sum_{j=1}^{k_i} w_{ij}} \tag{8}$$

Where $R_i(t)$ represents the average rate of change of the i group; k_i is the number of indicators in the i group; w_{ij} is the weight of the j indicator in group i , which can be calculated using the entropy weight method.

4) EPI-P index of composite leading, coincident, and lagging indicator groups

$$I_i(t) = I_i(t-1) \times \frac{200 + V_i(t)}{200 - V_i(t)} \tag{9}$$

Where $I_i(t)$ represents the EPI-P index of the i group. To ensure the consistency of leading indicators, coincident indicators, and lagging indicators, it is necessary to standardize the leading indicators and lagging indicators based on the range and magnitude of changes in consistent indicators, as follows:

$$I_i'(t) = \frac{\max(I_2(t)) - \min(I_2(t))}{\max(I_i(t)) - \min(I_i(t))}(I_i(t) - \overline{I}_i(t)) + \overline{I}_2(t), i = 1,3 \tag{10}$$

Where $\overline{I}_i(t)$ represents the mean of $I_i(t)$. The weighting of indicators will directly affect the final result of index calculation. This section proposes two different weighting methods.

1) Weight partitioning method based on correlation coefficient

Assuming r_{ij} is the time difference correlation coefficient of the j indicator in the i indicator group, the weights of each indicator in the indicator group can be calculated based on this.

$$u_{ij} = \frac{r_{ij}}{\sum_{j=1}^{J} r_{ij}} \tag{11}$$

Where J represents the number of indicators in the indicator group; u_{ij} is the weight of the j indicator in the i indicator group under this method. This method effectively avoids the fluctuation of a single power indicator sequence data through the comprehensive operation of multidimensional power indicator data, and the calculated index can better fit the trend of economic indicators.

2) Weight partitioning method based on electricity consumption

Assuming D_{ij} is the annual electricity consumption of the j indicator in the i indicator group, the weights of each indicator in the indicator group can be calculated based on this.

$$v_{ij} = \frac{D_{ij}}{\sum_{j=1}^{J} D_{ij}} \tag{12}$$

Where v_{ij} is the weight of the j indicator in the i indicator group under this method. This weight division method comprehensively considers the actual impact of each indicator in the indicator group on economic indicators, and the calculated prosperity index can more objectively reflect the trend of changes in the economic indicator sequence.

4 Empirical analysis

4.1 Analysis of the leading, coincident, and lagging relationship

This section is based on the year-on-year growth rate of industrial value-added in a certain province from 2018 to 2022 and the year-on-year growth rate of electricity consumption in 11 key industries. The results of the leading or lagging periods of each key industry relative to industrial value-added are shown in Table 1. When l is negative, it indicates leading, when l is positive, it indicates lagging, and the range of l values is $[-12,12]$.

Table 1. Leading, Lagging periods for each key industry relative to industrial value-added

Number	Time difference correlation coefficient		K-L Information Content	
	l_r	r_l	l_k	r_k
Food	-1	0.84	0	0.18
Steel	0	0.62	-12	0.51
Nonferrous metals	-1	0.88	-1	0.16
Textile	0	0.89	0	0.1
Equipment	0	0.87	0	0.15
Chemical industry	0	0.91	0	0.09
Medicine	-1	0.88	0	0.14
Cement	0	0.82	0	0.28
Photovoltaic	5	0.7	9	0.8
Electronic information	-1	0.65	0	0.38
Furniture manufacturing	0	0.91	0	0.12

According to Table 1, food, nonferrous metals, pharmaceuticals, electronic information and furniture manufacturing were ultimately determined as the leading indicators of industrial added value in the province. The leading period was one month, and textile, equipment, chemical and cement were the coincident indicators of industrial value-added in the province. The specific results are shown in Table 2. In addition, there is a significant difference between the sequence data of photovoltaics and steel and the industrial value-added sequence data, which will not be considered. The possible reason is that the energy consumption of the steel industry is mainly primary energy such as coal, and its electricity consumption is not the main characteristic that affects industrial value-added; The photovoltaic industry is an emerging industry, and its growth trend differs significantly from the changing trends of other industries.

Table 2. Leadin, coincident and lagging indicators for industrial value-added

Leading indicators	Coincident indicators	Lagging indicators
Food	Textile	
Nonferrous metals	Equipment	
Medicine	Chemical industry	
Electronic information	Cement	
Furniture manufacturing		

4.2 Economic index calculation based on power data

Using the weighting method based on correlation coefficient and electricity consumption, the leading index and coincident index of industrial value-added in the province were calculated, and the results are shown in Fig. 2 and Fig. 3, respectively. Among them, the key industry electricity consumption data and industrial value-added data from January to September 2023 were used for testing. It can be seen that the weight of each key industry calculated by the former is relatively balanced, while the weight calculated by the latter varies greatly due to the consideration of the actual impact of each key industry on industrial added value.

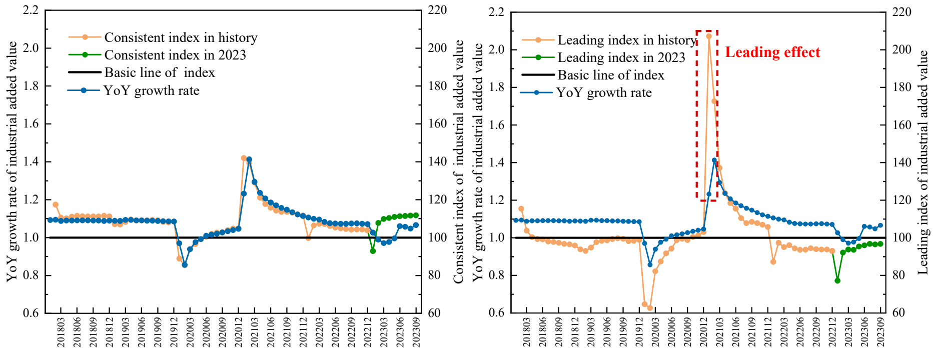

Fig. 2. Leading index and coincident index of industrial value-added calculated by the weight division method based on correlation coefficients

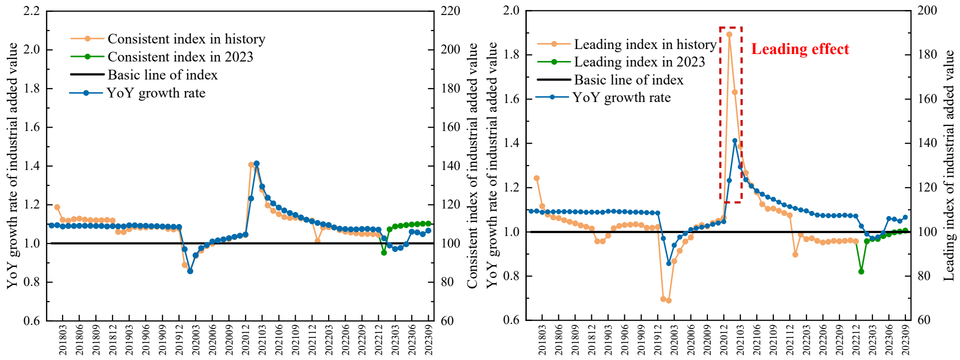

Fig. 3. Leading index and coincident index of industrial value-added calculated based on the weight division method of electricity consumption

From Fig. 2 and Fig. 3, it can be seen that the coincident index results are well fitted with the year-on-year growth rate of industrial value-added, but there is a certain degree of error in predicting the actual value for 2023; The trend of the preliminary index results roughly fits well with the year-on-year growth rate of industrial value-added, but there is a certain deviation in the magnitude of the change, and there is also some error in predicting the actual value for 2023. This is mainly because for the overall industry in the province, the number of key industries is relatively small, and in fact, the total electricity consumption of key industries only accounts for about half of the total industrial electricity consumption in the province. Therefore, relying solely on the electricity consumption data of key industries is difficult to accurately reflect the trend of year-on-year growth in industrial value-added. In addition, there is not much difference in the results obtained for the two different weight calculation methods.

Importantly, according to the results, during the post pandemic recovery phase, the leading index reached its peak one month ahead of the year-on-year growth rate of industrial value-added, and the coincident index also to some extent preceded the year-on-year growth rate of industrial value-added, but the leading effect was not as significant as the leading index. This indicates that key industries have a certain leading role in increasing industrial value, but the leading role in food, non-ferrous metals, medicine, electronic information, and furniture manufacturing is more obvious. From the above analysis, it can be concluded that the electricity consumption of key industries can roughly reflect the changing trend of the year-on-year growth rate of industrial value-added in the province, and can to some extent predict the changes in the year-on-year growth rate of industrial value-added.

5 Conclusion

This paper constructs an association analysis model for the power-economy relationship in key industries. Based on the actual data of a certain province, the leading and coincident indexs of industrial value-added based on power data are calculated. The main conclusions are as follows:

1) Time difference correlation coefficient and K-L information content effectively select the leading and coincident indicators of industrial value-added in a certain province from the electricity consumption data of various key industries.

2) The economic index based on power data can to some extent reflect the trend of changes in the original economic data. The empirical results show that the leading index and coincident index of industrial value-added can roughly fit the trend of year-on-year growth rate of industrial value-added. However, due to the fact that the electricity consumption of key industries only accounts for about half of the total industrial electricity consumption, their impact on industrial value-added is relatively limited. Therefore, there is still a certain deviation between the predicted results on the test set and the actual values.

3) The consumption of electricity in key industries has a certain leading role in the growth rate of industrial value-added, which can to some extent predict the changes in year-on-year growth rate of industrial value-added. It can be used to analyze the short-term development trend of industrial value-added and support the government's macroeconomic regulation.

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