Industry correlation chart model for industry chain feature mining and industry screening for demand side response

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Abstract. To broaden the exploration of the latent value of industry electricity data and offer a novel perspective for socio-economic development and demand side management, this study proposes an innovative model for industry chain characteristic analysis. Initially, an industry electric energy correlation model is established, considering the time-lag characteristics of upstream and downstream industrial chains. The research object of this study is the dynamic relationship between industry electricity consumption and socio-economic trends, particularly focusing on how industry chain characteristics influence electricity consumption patterns. A solution method based on quadratic exponential smoothing is proposed to elucidate the interrelations of electric energy demand and supply among various industries. To verify our model, we conducted a comprehensive case study using monthly electricity consumption data from various industries in a certain province from 2004 to 2017. This case study encompasses 8 major industry categories and 29 subsectors, providing a robust dataset for validating our analysis method at multiple industry levels. Subsequently, leveraging the derived industry impact factor matrix, this research innovatively formulates an evaluation model for the electricity consumption characteristics of industries, along with a method to assess their developmental trends. Additionally, industry sensitivity coefficients and radiation intensity coefficients are introduced to quantify the interactive effects of electricity demand among industries and their impact on the overall socio-economic framework. Furthermore, an industry correlation matrix and diagram are developed to facilitate in-depth exploration of the industrial chain conduction relationship and effective screening of demand-side response strategies. Lastly, through case studies, the practicality and efficacy of the model in enhancing energy efficiency and optimizing the allocation of social resources are validated.

Keywords: Industrial Chain, Industry Correlation; Demand Side Response, Correlation Chart; Industry Electricity.

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1 Introduction

In recent years, the interplay between industry-specific electricity consumption and broader socio-economic development has garnered significant attention. Since the COVID-19 in 2020, the industry electricity data has shown great value in the analysis of resumption of work and production, which can timely reflect the changes in the economic correlation intensity and socio-economic development of various industries [1-3]. In reference [4], an analysis of the wholesale and retail industry's position within the industrial chain and its impact on concurrent electricity sales led to the conclusion that the economic activities of this sector are intricately linked with those of its upstream and downstream industries. Reference [5] delves into the construction of a network related to the electricity consumption industry chain, uncovering the mutual dependencies and influences among industries regarding electricity usage. Reference [6] introduces an innovative method for analyzing the leading effect of industry electricity demand, grounded in the relationships within the industrial structure. This approach successfully pinpoints key indicators that influence industry electricity demand and forecasts future trends in this domain. On this basis, how to further explore the multi-dimensional value of industry electricity data, provide guidance and support for social production activities and demand side response, has enormous engineering significance and economic value [7-8].

Demand side response is an important means for the government and power companies to alleviate seasonal and periodic electricity supply and demand contradictions, including measures such as electricity diversion, and load control and power limitation. The implementation process has a long-term nature [9-10]. At present, demand side respondents are often classified and screened by the government and power companies based on their energy consumption behavior and production characteristics [11-12]. The screening rules and basis lack scientific and reasonable [13-14]. Meanwhile, demand side respondents often have strong industry characteristics, and long-term participation in demand side response can lead to long-term adjustments in the production plans of industry users, which will have a profound impact on other industries and social production [15]. If a certain industry has a strong positive correlation with the electricity production and supply industry, when its production activities are reduced, the production intensity of the electricity production and supply industry will also significantly decrease. Adopting long-term and demand side response management for these industries and arranging their production plans reasonably can effectively alleviate the problem of electricity shortage. In addition, the radiation intensity of the industry to the whole society is also an important factor to consider in the selection of demand side response industries. Therefore, analyzing the correlation between various industries and the power production and supply industry plays an important supporting role in screening demand side response industries and users, and formulating reasonable demand side response plans [16-18].

At present, the relationship between the upstream and downstream industrial chains is often simply divided based on the division of labor and order flow of various industries. However, due to the complex production relations in industries, this approach is difficult to accurately reflect the transmission and changes of production activities between industries. In fact, when the electricity demand of a certain industry changes, this change will be transmitted and spread along the production and consumption chain of upstream and downstream industries to other industries, causing corresponding changes in the electricity demand of other industries. Therefore, industry electricity consumption data mining can timely and accurately reflect the changes in industry related relationships [19]. At present, research has used methods such as grey correlation analysis to analyze the correlation between electricity demand in various industries [20-21], but it has not taken into account the time difference characteristics of production activities in upstream and downstream industries, making it impossible to explore the upstream and downstream industry chain correlation between industries, and the value of electricity data has not been fully explored. Reference [22] analyzes the economic development trends of different industries based on the feature index method combined with electricity consumption data and economic data. However, the analysis of industry development trends relies heavily on economic data and has limitations. The input-output table method in reference [23]. heavily relies on economic data. On the one hand, it is susceptible to statistical errors, and on the other hand, due to the delay of statistical data, when the economy is impacted by sudden factors such as epidemics, it cannot timely reflect changes in the correlation between industries.

Based on the above discussion and analysis, in order to support social production activities and demand side response planning, this article proposes an industry electricity correlation model that takes into account the time difference characteristics of production activities in the upstream and downstream industrial chains. A solution method based on the quadratic exponential smoothing method is proposed, and an industry inward and outward electricity consumption characteristic evaluation model and its characteristic development trend evaluation method are proposed. Secondly, to quantify the impact of electricity demand between industries and the radiation intensity of each industry on social production, industry sensitivity coefficients and radiation intensity coefficients were proposed. Then, propose an industry correlation matrix and graph to support the mining of transmission relationships in the industrial chain and the screening of demand side response industries. Finally, the effectiveness of the proposed model was verified through numerical examples.

2 Classification and identification model of enterprises' industries based on power big data

This section proposes an industry classification and identification method based on power big data, establishes the industry identification model of the enterprise, and lays the data foundation for analyzing the characteristics of power consumption in the industry and studying the internal correlation of power demand in the industry.

2.1 Identification model of industry and its main product relationship

Based on the Bert (bidirectional encoder representations from transformers) model, combined with the corpus data of the field, including unstructured data such as industry research reports, news consulting, enterprise annual reports and so on, the field adaptation pre training is carried out to enhance the model's ability to represent the professional vocabulary of the field, and the basic Bert model of the field is constructed. Based on the basic Bert model of the domain, the system uses the Bert bigru CRF structure to identify the two types of entities of industry and business products (as shown in Figure 1), and uses the structure of Bert plus full connection layer to extract the relationship (as shown in Figure 2), so as to identify the industry and its main products, and complete the information collection of the industry and its main products.

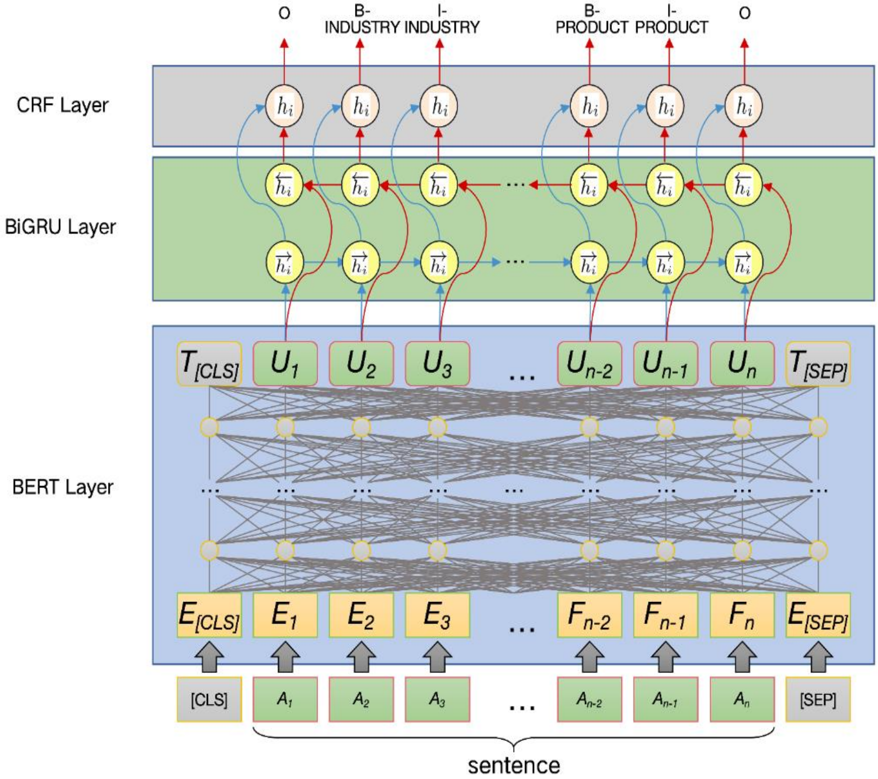

Fig. 1. Structure of Entity Recognition Model.

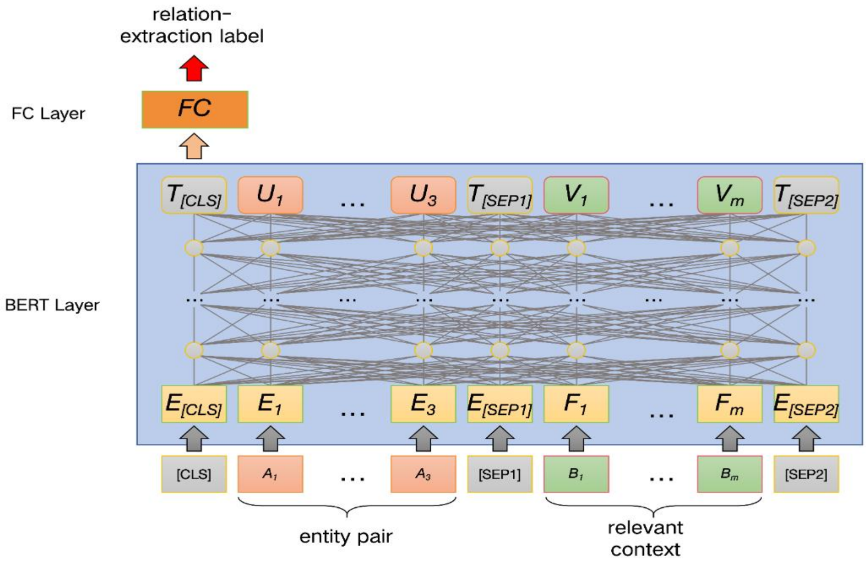

Fig. 2. Relationship Extraction Model Structure.

2.2 Construction of Industry Classification and Identification Model for Enterprises

Based on the massive customer files of power grid enterprises, enterprise users are filtered based on information such as electricity consumption type, user type, voltage level, etc. By associating the corresponding business registration information of the enterprise through web crawlers and data interfaces, the business content of the enterprise is obtained. Combining part of speech tagging and regular expressions, the enterprise's business products and services are effectively identified. Furthermore, it matches the information of the corresponding main products in the existing industry, mainly using word embedding technology. A pre trained domain based BERT model is used to embed words into the enterprise's operating products and the collected industry's corresponding operating product information. The cosine similarity between the two is calculated. When the cosine similarity exceeds a certain threshold, it is considered a match between the two, thus effectively linking enterprise information and industry information, Realize the classification and identification of the industry to which the enterprise belongs.

On this basis, further analyze the energy consumption characteristics of the enterprise. Given that enterprises within the same product category often have similar production equipment and processes, their electricity demand and load curves exhibit certain similarities. Based on historical load data of enterprises, K-means and Dynamic Time Warping (DTW) algorithms are combined to extract typical load curves for all enterprises (as shown in Figure 3), and clustering algorithms are further used based on the typical load curves of all enterprises and their operating products, Form a typical electricity consumption pattern library for each type of business product (as shown in

Figure 4). Match the electricity consumption patterns of each enterprise's operating products, calculate the cosine similarity between the two. When the cosine similarity is below a certain threshold, it is considered that the product is not the main product of the enterprise, and then eliminate the relationship between the enterprise and the corresponding industry of the main product, further improving the accuracy of industry classification recognition of the enterprise.

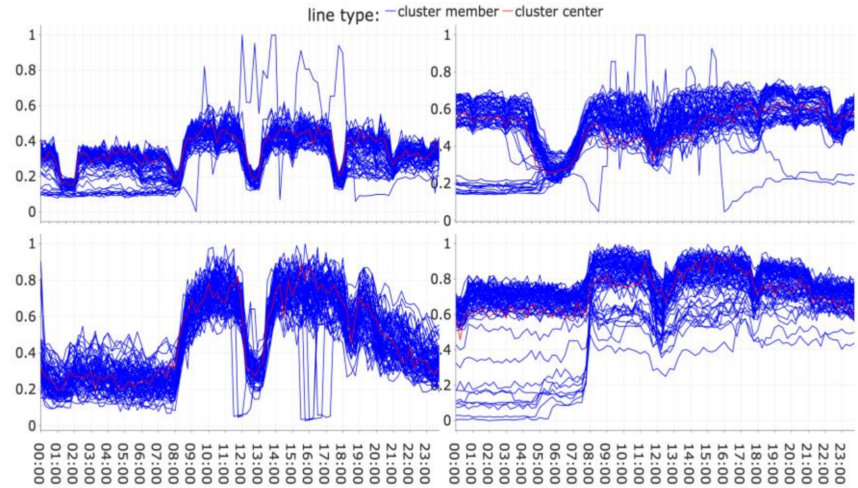

Fig. 3. Example of typical load curve for enterprises.

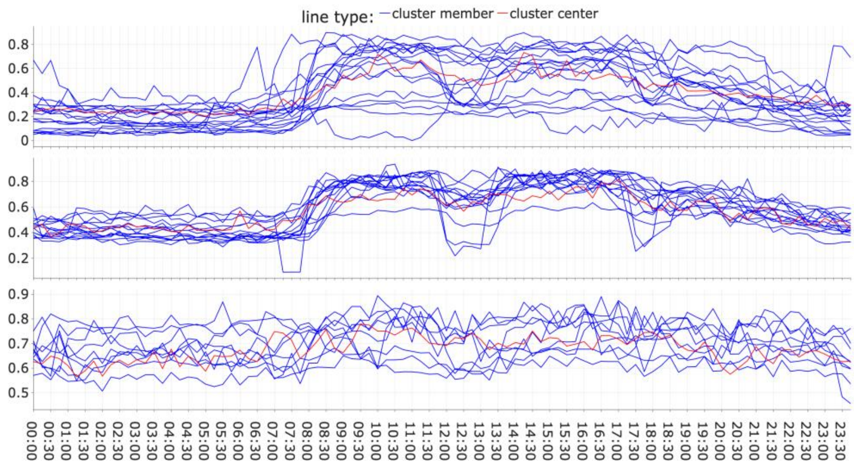

Fig. 4. Example of Typical Electricity Usage Mode Library for Products.

3 Industry Electricity Consumption Correlation Model Based on Supply and Demand Relationship

3.1 The basic model of industry electricity consumption

The electricity consumption $e^{(i)}(k)$ of industry i in a certain region in the k-th month is:

$$e^{(i)}(k) = e_p^{(i)}(k) + e_t^{(i)}(k) + e_o^{(i)}(k) + e_r^{(i)}(k) \tag{1}$$

Where, $e_p^{(i)}(k)$ represents the local production electricity consumption for the current month, which is a positive value; $e_t^{(i)}(k)$ is the final electricity consumption for the current month, which is a positive value; $e_o^{(i)}(k)$ refers to the interactive electrical energy with other regions, including the electrical energy condensed in products or services exported to other regions and the electrical energy condensed in products or services imported to local regions; $e_r^{(i)}(k)$ represents the surplus electricity consumption, representing the surplus of industry production relative to consumption.

3.2 A correlation model of electricity consumption based on industry supply and demand relationship

According to the basic principles of economics, the electricity consumption of an industry is directly determined by the intensity of its production activities, which is determined by three factors: (1) the supply expectations of industry producers towards their suppliers of production materials (upstream industries); (2) The expected demand of industry producers for their target customers (downstream industries and non productive consumer groups); (3) The historical production status of the industry itself. Specifically, if industry producers expect strong supply from their suppliers and demand from their target customers, and the industry itself has a relatively small backlog of historical production, then the industry should choose to engage in high-intensity production.

These three elements are closely related to electricity consumption. The expectations of industry producers towards their suppliers and demanders are usually determined by the historical production activity intensity of their suppliers and the historical sales situation towards the demanders. The historical production activity intensity of the supply side is closely related to the various components of the supply side's historical electricity consumption, while the historical sales situation of the demand side is closely related to the various components of the industry's historical electricity consumption. In addition, the historical production status of the industry itself is mainly determined by the remaining consumption of electricity in the industry's history. Based on this, the various determining components of industry electricity consumption can be expressed in the form of formulas. If the upstream industry indicator set for industry i is Ui, then:

$$e^{(i)}(k)=\sum_{j\in U_i}\sum_{l<k}\varphi_l^j(e_p^{(j)}(l),e_t^{(j)}(l),e_o^{(j)}(l),e_r^{(j)}(l))+\sum_{l<k}\phi_l(e_p^{(i)}(l),e_t^{(i)}(l),e_o^{(i)}(l),e_r^{(i)}(l))+\sum_{l<k}\psi_l(e_r^{(i)}(l)) \tag{2}$$

Where, $\sum_{j\in U}\sum_{l<k}\varphi_l^j$ is the expected supply function for the k-th month; $\sum_{l<k}\phi_l$ is the demand expectation function for the k-th month; $\sum_{l<k}\psi_l$ is the historical production status function for the k-th month.

4 An Industry Electricity Correlation Model Considering Production Time Difference Characteristics

The industry electricity correlation model described in this section is to model the supply expectation function, demand expectation function, and historical production status function in formula (2) under some basic assumptions.

4.1 Establishment of Industry Electricity Correlation Model

For industry *i*, the actual supply of *k* by supplier j in a certain month is directly related to $e_p^{(j)}(k)$, the production electricity consumption of that supplier in that month; The actual needs met by its target customer k in a certain month are directly related to the productive electricity consumption $e_p^{(i)}(k)$, final electricity consumption $e_t^{(i)}(k)$, and interactive electricity consumption $e_o^{(i)}(k)$ with other regions in industry *i* for that month; And its historical production status in a certain month is directly related to the remaining electricity consumption in the previous month $e_r^{(i)}(k-1)$. Therefore, the supply expectation function, demand expectation function, and historical production status function can be simplified as follows:

$$\sum_{j\in U_i}\sum_{l<k}\varphi_l^j=\varphi^j[e_p^{(j)}(k-1)] \tag{3}$$

$$\sum_{l<k}\phi_l=\phi[e_p^{(i)}(k-1),e_t^{(i)}(k-1),e_o^{(i)}(k-1)] \tag{4}$$

$$\sum_{l<k}\psi_l=\psi[e_r^{(i)}(k-1)] \tag{5}$$

Further, the above simplified function is locally linearized in the time dimension to obtain a multivariate linear model with variable coefficients. The time difference influence factors of five factors affecting the electricity consumption of a certain industry *i* in the k-th month $e^{(i)}(k)$ are defined as: b_{ji} - the time difference influence factor of the productive consumption of electricity consumption of the upstream industry *j* in the *k*-

1st month $e_p^{(j)}(k-1)$ to $e^{(i)}(k)$; b_{ii} - impact factor of time difference between productive consumption electricity consumption $e_p^{(i)}(k-1)$ and $e^{(i)}(k)$ in the k-1st month of industry i; b_{ai} - impact factor of time difference between final consumption power consumption $e_t^{(i)}(k-1)$ and $e^{(i)}(k)$ in the k-1st month of industry i; b_{bi} - impact factor of time difference between $e_o^{(i)}(k-1)$ and $e^{(i)}(k)$ of interactive power consumption in the k-1st month between the field and industry i; b_{ci} - the impact factor of the time difference between the remaining consumption of electricity $e_r^{(i)}(k-1)$ and $e^{(i)}(k)$ in the k-1st month of industry i. The final model expression is:

$$e^{(i)}(k)=\sum_{j\neq i}b_{ji}e_p^{(j)}(k-1)+b_{ii}e_p^{(i)}(k-1)+b_{ai}e_t^{(i)}(k-1)+b_{bi}e_o^{(i)}(k-1)+b_{ci}e_r^{(i)}(k-1)+\varepsilon^{(i)}(k) \tag{6}$$

Where, $\varepsilon^{(i)}(k)$ is the error amount of the model.

4.2 Solution of industry power correlation model

First, deform the model expression so that:

$$e_{tor}^{(i)}(k-1)=e_t^{(i)}(k-1)+e_o^{(i)}(k-1)+e_r^{(i)}(k-1) \tag{7}$$

$$b_{0i}=\frac{b_{ai}e_t^{(i)}(k-1)+b_{bi}e_o^{(i)}(k-1)+b_{ci}e_r^{(i)}(k-1)}{e_{tor}^{(i)}(k-1)} \tag{8}$$

$$c_i=b_{0i}e_{tor}^{(i)}(k-1)-\sum_j b_{ji}e_{tor}^{(j)}(k-1) \tag{9}$$

Combining equations (6) to (9), we can get:

$$\begin{aligned}e^{(i)}(k)&=\sum_j b_{ji}e_p^{(j)}(k-1)+b_{0i}e_{tor}^{(i)}(k-1)+\varepsilon^{(i)}(k)\\&=\sum_j b_{ji}[e^{(j)}(k-1)-e_{tor}^{(j)}(k-1)]+b_{0i}e_{tor}^{(i)}(k-1)+\varepsilon^{(i)}(k)\\&=\sum_j b_{ji}e^{(j)}(k-1)+b_{0i}e_{tor}^{(i)}(k-1)-\sum_j b_{ji}e_{tor}^{(j)}(k-1)+\varepsilon^{(i)}(k)\\&=\sum_j b_{ji}e^{(j)}(k-1)+c_i+\varepsilon^{(i)}(k)\end{aligned} \tag{10}$$

The weighted least square fitting method was used to solve the model parameters. Assuming that the historical data of n months before the k month are used for fitting, equation (10) is written in the form of matrix:

$$E_n^{(i)}(k)=E_m^{(i)}(k)\bullet B_i+\varepsilon \tag{11}$$

Where:

$$E_n^{(i)}(k)=\left[e^{(i)}(k-n+1) \quad \cdots \quad e^{(i)}(k-1)\right]^T \tag{12}$$

$$E_m(k)=\begin{bmatrix} 1 & e^{(1)}(k-n) & \cdots & e^{(N)}(k-n) \\ 1 & e^{(1)}(k-n+1) & \cdots & e^{(N)}(k-n+1) \\ \vdots & \vdots & \vdots & \vdots \\ 1 & e^{(1)}(k-2) & \cdots & e^{(N)}(k-2) \end{bmatrix} \tag{13}$$

$$B_i=[c_i \quad b_{1i} \quad \cdots \quad b_{Ni}]^T \tag{14}$$

$$\varepsilon=[\varepsilon_1 \quad \varepsilon_2 \quad \cdots \quad \varepsilon_{n-1}]^T \tag{15}$$

Where, N is the number of industries.

Finding structural parameters is essentially an optimization problem, namely:

$$\min_{B_i}\sum_{t=1}^{n-1}(\theta_t\varepsilon_t)^2=[E_n^{(i)}(k)-E_m^{(i)}(k)\bullet B_i]^T\bullet\Lambda^T\bullet\Lambda\bullet[E_n^{(i)}(k)-E_m^{(i)}(k)\bullet B_i] \tag{16}$$

Where, Λ is the weight matrix, where the elements are taken by the method of quadratic exponential smoothing:

$$\Lambda=\begin{bmatrix} \theta_1 & 0 & \cdots & 0 \\ 0 & \theta_2 & \ddots & 0 \\ \vdots & \ddots & \ddots & 0 \\ 0 & 0 & 0 & \theta_{n-1} \end{bmatrix} \tag{17}$$

$$\theta_t=(n-t+1+[\frac{\alpha}{1-\alpha}])\cdot\alpha^{n-t+1+[\frac{\alpha}{1-\alpha}]},0<\alpha<1 \tag{18}$$

Where, $t\in\left[1,2,\cdots,\ n\right]$, represents the serial number of the month from (k-n+1) to k; $[x]$ represents the maximum integer that does not exceed x. The increment $[\alpha/(1-\alpha)]+1$ is to make θ_t always increment. Taking α a larger value can ensure the stability of the model parameters, so this paper takes $\alpha=0.9$.

By combining equations (16) to (18) to solve the industry electricity correlation model, the time difference impact factor combination of other industries on industry i's electricity demand in month t is obtained as $\left[b_{1i}(t),\ b_{2i}(t),\cdots b_{Ni}(t)\right]^{\mathrm{T}}$, and then the time difference impact factor matrix of electricity demand between industries in month t is obtained:

$$\Pi(t)=\left[b_{ij}(t)\right]_{N\times N} \tag{19}$$

Where, $b_{ij}(t)$ is the time difference impact factor of industry *i* on industry *j*'s productive power consumption in month *t* in the industry power correlation model.

5 Association graph model for industrial chain association and demand side response

This section proposes an industry association matrix based on the time difference impact factor matrix, establishes an industry association graph model, and then studies the law of power demand in the internal association of the industry, mining the value of electricity data in the upstream and downstream industry chain feature mining and demand side response industry screening.

5.1 Evaluation model of industry power consumption characteristics based on autocorrelation coefficient

$b_{ii}(t)$ is defined as the industry power demand autocorrelation coefficient to reflect the size of the industry power consumption affected by itself, and its development trend reflects the change law of the industry affected by itself.

Export oriented and inward oriented characteristics of industry power demand.

The average value $\overline{b_{ii}(t)}$ of $b_{ii}(t)$ is used to represent its average size. According to the size of $\overline{b_{ii}(t)}$, the export-oriented and inward oriented industries with power demand can be selected from various industries. If $\overline{b_{ii}(t)}$ is large and the overall impact of other industries on industry *i* is small, it is considered that the development of power consumption in industry *i* is mainly driven by the industry itself, and industry *i* is called an inward looking industry in power demand; If $\overline{b_{ii}(t)}$ is small and the overall impact of other industries on industry *i* is large, it is considered that the development of power consumption in industry *i* is mainly driven by other industries, and industry *i* is called an export-oriented industry with power demand.

Set the threshold value α_1, α_2, β_1, β_2, and record $\lambda_j(t)$ as the proportion of power consumption of industry *j* in the whole industry in month *t*. the screening criteria are:

1) If industry *i* satisfies: $\overline{b_{ii}(t)} = \frac{1}{n}\sum_{t=1}^{n} |b_{ii}(t)| \geq \alpha_1$, $\frac{1}{n}\sum_{t=1}^{n} |\sum_{j \neq i}^{N} [b_{ji}(t) \cdot \lambda_j(t)]| \leq \alpha_2$, then industry i is referred to as an industry with inward electricity demand;

2) If industry *i* satisfies: $\overline{b_{ii}(t)} = \frac{1}{n}\sum_{t=1}^{n} |b_{ii}(t)| \leq \beta_1$, $\frac{1}{n}\sum_{t=1}^{n} |\sum_{j \neq i}^{N} [b_{ji}(t) \cdot \lambda_j(t)]| \geq \beta_2$, then industry i is referred to as an industry with outward electricity demand.

Analysis method **of industry characteristics change trend**

The inward and outward characteristics of the industry are not immutable. The changing characteristics of the relationship between industry *i* and other industries can be obtained by analyzing the time trend of $b_{ii}(t)$. The $b_{ii}(t)$ time series is fitted by a straight line, and the slope of the straight line and the fitting error are recorded as k_i and err_i, respectively. Set the threshold value δ, ε, μ, η, and then four industry types with typical change characteristics can be screened out: if $err_i \geq \delta$, industry *i* is called power demand related fluctuation industry; If $err_i \leq \varepsilon$ and $k_i \geq \mu$, industry *i* is said to be an industry with weak correlation of power demand; If $err_i \leq \varepsilon$ and $k_i \leq \eta$, industry *i* is said to be an industry with enhanced power demand correlation; If $err_i \leq \varepsilon$ and $\eta < k_i < \mu$, industry *i* is said to be an industry with stable electricity demand correlation.

5.2 Industry power demand sensitivity coefficient and radiation intensity coefficient

This paper puts forward the sensitivity coefficient and radiation intensity coefficient of industry power demand, and analyzes the influence degree of power demand among industries and the radiation intensity of each industry to social production. The power demand sensitivity coefficient g_i of industry *i* is defined as the comprehensive degree to which the power of industry *i* is affected by the power disturbance of other industries $j = 1 \sim N, j \neq i$, and the calculation formula is:

$$g_i = \frac{1}{n}\sum_{t=1}^{n} \left| \sum_{j \neq i}^{N} [b_{ji}(t) \bullet \lambda_j(t)] \right| \tag{20}$$

Where, the larger the index value, the higher the sensitivity of the industry *i* power to the power disturbance of other industries.

The radiation intensity coefficient F_i of industry I to the power demand of the whole society is defined as the comprehensive degree of the impact of the power disturbance of industry I on the power fluctuation of other industries $j = 1 \sim N, j \neq i$, and the calculation formula is:

$$\hat{F}_i = F_i / \sum_i F_i \tag{21}$$

$$F_i = \frac{1}{n}\sum_{t=1}^{n} \left| [\sum_{j}^{N} b_{ij}(t)] \bullet \lambda_i(t) \right| \tag{22}$$

Among them, the larger the index value, the greater the radiation intensity of industry I power to other industry power fluctuations. At the same time, this indicator can be used to reflect the impact of the long-term adjustment of production plan on the overall social production activities due to the long-term participation of an industry in demand side response. The smaller the value of this indicator, the smaller the fluctuation of social production caused by the industry's participation in demand side response, and the more suitable it is to participate in demand side response.

If $\hat{F}_i > \rho_1$, the radiation intensity of demand side response in industry I is strong; If $\hat{F}_i < \rho_2$, the radiation intensity of demand side response in industry I is weak; Otherwise, the radiation intensity of demand side response in industry I is medium.

5.3 Industry power demand correlation matrix and graph

Industry power demand incidence matrix.

Define the industry association matrix S as:

$$S = [s_{ij}]_{N\times N} \tag{23}$$

$$s_{ij} = \frac{k_s}{n}\sum_{t=1}^{n}[b_{ij}(t)\lambda_i(t)] \tag{24}$$

Where, s_{ij} is the correlation coefficient between industry I and industry J; k_s is an adjustable parameter. The industry association matrix can reflect the degree of association between any two specific industries. The industry association coefficient s_{ij} defines the transmission and impact information of industry I on the power consumption of industry J. at the same time, the industry association matrix can also identify the transmission relationship of the industry chain. In addition, by analyzing the relationship between various industries and the power production and supply industry through the industry association diagram, the impact of various industries on the power industry can be obtained, and the value and potential of various industries to participate in demand side response management can be evaluated.

Industry power demand correlation diagram.

In order to better represent the industry chain relationship of industry power demand, this paper proposes a new concept of industry power demand correlation graph to represent the correlation relationship between industry power consumption. The definition of association degree is as follows:

If the power demand correlation coefficient between industry I and industry J meets: $s_{ij} > 0$, then the power demand correlation between industry I and industry J is said to be strong correlation; If: $|s_{ij}| < s_\varepsilon$, the power demand of industry I to industry J is said to be weakly correlated; Otherwise, the power demand of industry I to industry J is generally related.

If the power demand correlation coefficient between industry I and industry J meets: $s_{ij} > 0$, the power demand correlation relationship between industry I and industry J is said to be positive; If $s_{ij} < 0$, it is said that the power demand between industry I and industry J is negatively correlated; If $s_{ij} = 0$, it is said that industry I is not related to industry J in terms of power demand.

Among them, $s_{\lim}$ and s_ε shall be determined according to the actual situation.

In general, the industry electricity demand association diagram uses circles with industry labels to represent the industry electricity consumption, one-way arrows to represent one-way Association, and two-way arrows to represent two-way Association, as shown in the following Table 1:

Table 1. Legend of Industry Electricity Demand Correlation Diagram.

Degree of association	Arrow or circle color	Line type
No association or weak association	white	Solid line
Strong positive correlation	Deep Gold	Solid line
Ordinary positive correlation	Light orange	Solid line
Ordinary negative correlation	Light blue	Dashed line
Strong negative correlation	Dark blue	Dashed line

For weak association relationships, they can be left out of the industry association diagram. To represent them, simply connect them between industries with a line, without indicating the direction and strength of the association relationship.

6 Example analysis

Taking the monthly electricity consumption data of various industries in a province from 2004 to 2017 as an example, this paper verifies the analysis method from two levels of eight categories of industries and 29 sub sectors of industry.

6.1 Industrial Economic Association Analysis Based on Industry Association Model

The values of each threshold parameter are: $\alpha_1 = 0.5$, $\alpha_2 = 0.5$, $\beta_1 = 0.3$, $\beta_2 = 0.2$, $\delta = 0.3$, $\varepsilon = 0.15$, $\eta = -0.001$, $\mu = 0.001$, $k_s = 60$ respectively. The analysis results of industrial power consumption characteristics, sensitivity and radiation intensity of eight categories of industries are shown in Table 2.

Table 2. Analysis results of industry related parameters of eight categories.

Number	Industry name	Industry power consumption characteristics	sensitivity coefficient	Radiation intensity coefficient of electricity consumption to the whole society	Radiation intensity of electricity consumption to the whole society
1	Agriculture, forestry, animal husbandry and fishery	outward	1.0013	0.0215	weak
2	industry	Inward and stable	0.1299	0.8821	strong
3	Construction industry	Inward and stable	0.1935	0.0045	weak
4	Transportation, storage and postal services	outward and weakening	0.5851	0.0229	weak

Number	Industry name	Industry power consumption characteristics	sensitivity coefficient	Radiation intensity coefficient of electricity consumption to the whole society	Radiation intensity of electricity consumption to the whole society
5	Information transmission, computer services and software industry	/	0.1152	0.0036	weak
6	Business, accommodation and catering	outward oriented and intensive	0.5164	0.0169	weak
7	Finance, real estate, business and residential services	/	0.2404	0.0114	weak
8	Public utilities and management organizations	outward	0.8500	0.0372	weak

Taking $s_{\lim} = 0.5$, $s_{\varepsilon} = 0.2$, we can get the power demand correlation diagram of the eight categories of industries, as shown in Figure 5:

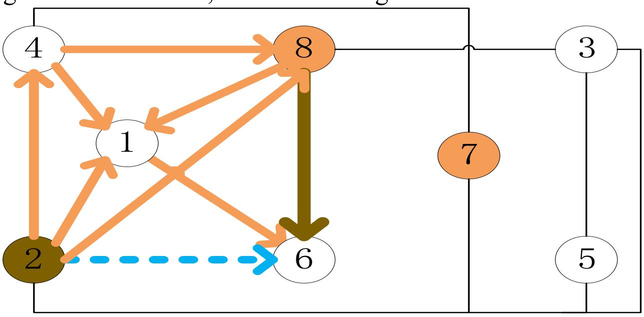

Fig. 5. Industry association diagram of eight categories.

It can be seen from table 2 that industry is an inward oriented industry with stable power demand, and the power of this industry has the greatest radiation intensity to the whole society. The four export-oriented industries are agriculture, forestry, animal husbandry, fishery, transportation, warehousing and postal services, commerce, accommodation and catering, and public utilities and management organizations. Among them, transportation, warehousing and postal services are also weakly related industries, indicating that this industry is gradually developing into an inward oriented industry, while commerce, catering and accommodation are also strongly related industries, It shows that this industry is developing from an inward oriented industry to a deeper one.

It can be seen from Figure 1 that agriculture, forestry, animal husbandry and fishery (industry 1), industry (industry 2) and public utilities and management organizations that maintain the normal operation of society (industry 8), as basic production industries, are widely associated with other industries in terms of power demand. From the perspective of production composition, the electricity consumption of industry 1 is composed of five parts: agriculture, forestry, animal husbandry, fishery, agriculture, forestry, animal husbandry and fishery services. Among them, the electricity consumption of agriculture, forestry, animal husbandry and fishery services accounts for about 45%, which is the main force driving the development of industry 1, and this part is just affected by transportation, warehousing and postal services (industry 4), commerce The accommodation and catering industry (industry 6) is driven by these traditional tertiary industries. The production demand of industry 2 can stimulate the production of industry 1, and industry 8 is also an important guarantee for the development of agricultural service industry. From this, we can see the rationality of the relationship between industry 1 and industries 2, 4, 6 and 8.

Industry 2 accounts for a large proportion of the whole society's electricity consumption and is the basic industry of the national economy. Its electricity consumption growth is mainly driven by itself. The basic production status of industry 2 determines that its power consumption is widely connected with that of industries 1, 4, 6, 8, etc. In addition, industry 4 and industry 6 are also closely related to other industries. The tertiary industry in the province still has the industrial structure characteristics of excessive proportion of traditional service industry. The accommodation and catering industry, wholesale and retail trade industry, transportation, warehousing and postal industry (i.e. industry 4 and industry 6) are highly sensitive. It should be noted that the power consumption of industry 6 is most obviously driven by the power consumption of industry 8, which is a reflection of the fact that the wholesale and retail trade, accommodation, catering and other industries in industry 6 are greatly affected by the development of science, education, culture, health and entertainment industries in industry 8.

Information transmission, computer services and software, finance, real estate, business and residential services are emerging services. In this province, the sensitivity and radiation intensity of emerging services are relatively small. In addition, the power consumption of the construction industry itself is very small, so these three industries have a weak connection with the power demand of other industries.

Therefore, the results of the industry association diagram in this paper are compatible with the production relations under the macroeconomic background, which verifies the great value of the industry association diagram model in the mining of industrial chain economic relations.

6.2 Mining industrial chain transmission relationship based on Industry Association Model

The serial numbers and industry names of the 29 sub sectors are shown in Table 3.

Table 3. Details of 29 industry segments.

number	Industry name	number	Industry name	number	Industry name
1	Coal mining and washing industry	11	Papermaking and paper products industry	21	Nonferrous metal smelting and rolling processing industry
2	Oil and gas extraction industry	12	Printing and reproduction of recording media	22	Metal products industry
3	Ferrous metal mining and dressing industry	13	Sporting goods manufacturing	23	General and special equipment manufacturing industry

number	Industry name	number	Industry name	number	Industry name
4	Nonferrous metal mining and dressing industry	14	Petroleum processing, coking and nuclear fuel processing industry	24	Transportation, electrical and electronic equipment manufacturing
5	Nonmetallic mining and dressing industry	15	Chemical raw materials and chemical products manufacturing	25	Handicrafts and other manufacturing industries
6	Other mining industry	16	Pharmaceutical manufacturing	26	Waste resources and waste material recycling and processing industry
7	Food, beverage and tobacco manufacturing	17	Chemical fiber manufacturing	27	Power production and supply industry
8	textile industry	18	Rubber and plastic products industry	28	Gas production and supply industry
9	Clothing, shoes and hats, leather down and its products industry	19	Non metallic mineral products industry	29	Water production and supply industry
10	Wood processing and products and furniture products industry	20	Ferrous metal smelting and rolling processing industry		

Taking $s_{\lim} = 0.3$, $s_{\varepsilon} = 0.1$, we can get the power demand correlation diagram of 29 industries, as shown in Figure 6:

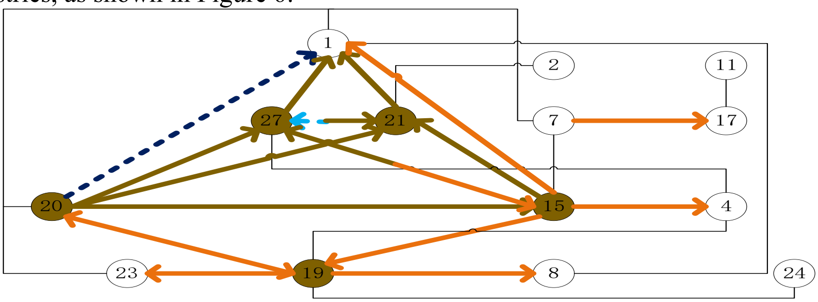

Fig. 6. Association chart of 29 industry segments.

In terms of the transmission relationship between the upstream and downstream industrial chains, it can be seen from Figure 2 that the non-ferrous metal mining and dressing industry (industry 4) is greatly affected by the chemical raw materials and chemical products manufacturing industry (industry 15), because the raw materials of the chemical raw materials and chemical products manufacturing industry are mainly non-ferrous metals. The general and special equipment manufacturing industry (Industry 23) is also mainly affected by the power growth of the non-metallic mineral products industry (industry 19), because the non-metallic mineral manufacturing process requires a large number of general and special equipment, such as boilers and prime movers, metal processing machinery, lifting and transportation equipment, etc. In the middle and lower reaches of the industrial chain, the transmission relationship between the food, beverage and tobacco manufacturing industry (industry 7) and the chemical fiber manufacturing industry (industry 17) is more significant. The path of this transmission chain is that the growth of food, beverage and tobacco manufacturing has led to the growth of the demand for plastic products, which has led to the rapid increase of the demand for chemical fibers. Therefore, the association graph model in this paper can effectively mine the industrial chain characteristics and transmission relationship of the upstream and downstream association relationship of the industry.

6.3 Demand side response industry screening based on Industry Association Model

It can be seen from Figure 2 that the industrial chains with strong transmission relationship with power and other production and supply industries (industry 27) include ferrous metal smelting and rolling processing industry (industry 20) ->industry 27, industry 20->chemical raw materials and chemical products manufacturing industry (industry 15) ->industry 27, industry 15->non-metallic mineral products industry (industry 19) ->industry 20->industry 27. Therefore, the industries with strong correlation with power production and supply industry are industry 20 Industry 15 and industry 19. According to the transmission relationship of the industrial chain, when the production activities of these industries are reduced, the production intensity of the power production and supply industry will also be significantly reduced. Taking long-term demand side response management for these industries and reasonably arranging their production plans can effectively alleviate the problem of power shortage. Therefore, the above three industries can be regarded as the preferred industries for demand side response.

Further, as shown in Table 4, among the above three industries, the power consumption of industry 19 and industry 20 has a weak radiation intensity to the whole society, and their participation in demand side response brings less fluctuation to social production, while the power consumption of industry 15 has a strong radiation to the whole society, so industry 19 and industry 20 are the best industries for demand side response.

Table 4. Radiation intensity coefficient of industrial power consumption to the whole society.

Industry number	Radiation intensity coefficient of electricity consumption to the whole society	Radiation intensity of electricity consumption to the whole society
21	0.1829	strong
15	0.1829	strong
1	0.1558	secondary
20	0.1023	weak
19	0.0998	weak

7 Conclusion

(1) The industry classification and identification model of the enterprise in this paper can effectively identify the industry classification of the enterprise, correct the wrong

industry classification information, and help improve the accuracy of industry electricity.

(2) The correlation graph model in this article can effectively explore the characteristics of the industry chain related to upstream and downstream relationships, such as the food, beverage, and tobacco manufacturing industry and chemical fiber manufacturing industry, the non-ferrous metal mining and selection industry and chemical raw material and chemical product manufacturing industry, and the non-metallic mineral products industry and general and specialized equipment manufacturing industry, showing highly correlated characteristics and significant transmission relationships.

(3) The industry correlation graph model in this article effectively selects the optimal industries for demand side response through the analysis of the correlation between various industries and the power industry. The black metal smelting and rolling processing industry, chemical raw material and chemical product manufacturing industry, and non-metallic mineral products industry are the optimal industries for demand side response. The black metal smelting and rolling processing industry, as well as the non-metallic mineral products industry, have less social production volatility due to their participation in demand side response, making them the optimal choice for demand side response.

(4) The results of the industry correlation diagram presented in this paper vividly delineate the intricate interdependencies and mutual influences among various industries, harmoniously aligning with the broader macroeconomic context. This emphatically underscores the monumental significance of our industry correlation diagram model in unveiling the profound and expansive economic relationships within the industrial chain, marking a significant advancement in the realm of economic analysis.

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