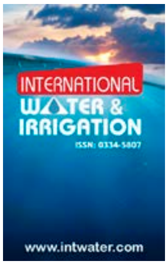

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Research on the Optimization and Development of Low Carbon Energy Economy from the Perspective of Water Conservancy Engineering

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Abstract In order to explore the optimal development path of low-carbon energy economy in universities, this paper proposes a new method based on complex network theory to describe the global evolution and transformation characteristics of multivariate time series correlation patterns. In order to more intuitively see the impact of product extraction inputs as endogenous factors on economic growth, this article explores the relationship between economic growth and product extraction inputs by constructing a Hamiltonian function and using optimization methods. When considering whether the extraction input share of products with different extraction ratios is different, this article found the relationship between the total extraction input of products with different extraction ratios and the input share of green and low-carbon products, and analyzed consumers' preferences; Extractive investment of products under budget constraints and policy constraints. In addition, this article uses the dynamic equation of household utility function and environmental quality to prove that the extractive input of products not only promotes carbon reduction, but also has a positive effect on promoting economic growth. The simulation results show that the low-carbon economic development model based on energy efficiency proposed in this paper can effectively improve the development path of low-carbon energy economy.

Keywords: big data; low carbon; energy economy; model; water conservancy;

1 INTRODUCTION

Energy problem runs through the whole process of social production, such as production, supply and consumption, and involves all aspects of social life, such as life and production. With the rapid development of economy and the gradual deepening of the reform of market economic system, marketization has extended to all walks of life in economic development. However, the energy system established on the basis of planned economy system can no longer meet the current social and economic development. In particular, it cannot meet the development requirements of low-carbon economy.

Under the low-carbon economic development model, it is necessary to establish a goal oriented medium to long-term energy development plan that adapts to the operation of the market system through the comprehensive application of policy and economic means. The comprehensive interaction mechanism between the government, enterprises, and society for energy conservation and emission reduction requires the guidance of the scientific development concept, with the goal of promoting low-carbon economic development, optimizing energy structure, reforming the energy system, and improving energy development planning. Mainly including: fully leveraging the government's leading role in energy management, strengthening supervision and regulation;

Encourage and restrict enterprises to innovate energy technology through policies and economic means, and consciously implement energy conservation and emission reduction; Strengthen publicity, advocate the concept of energy conservation and emission reduction, leverage public efforts to save energy, improve energy utilization efficiency, use as little energy as possible to achieve maximum output, and practice a low-carbon economic development model of low consumption, low pollution, and low emissions

In the research on energy consumption and economic growth, literature [1] adopts multiple cointegration analysis method, incorporating capital and labor variables into the energy economy framework, and finds that energy consumption is an important source of economic growth. Reference [2] studied the relationship between energy consumption and economic growth, and found that there is a bidirectional causal relationship between various types of energy (renewable and non renewable), indicating that both types of energy can significantly promote economic growth and can replace each other. Energy price analysis focuses on studying the impact of energy prices on the economy. Literature [3] found through cointegration analysis that the long-term relationship between oil prices and the economy in the United States, Europe, and G7 economies is constantly evolving, and found that significant price distortions can have a negative impact on economic growth.

The study of the relationship between environment and economy in environmental economy mainly focuses on the analysis of the impact of environmental quality and pollution emissions on the economy, mostly using the environmental Kuznets curve as the main means. Reference [4] analyzed the impact of energy policies on the energy system and proposed that ignoring the impact of climate change may lead to an underestimation of Australia's future energy demand and installed capacity; Reference [5] analyzed the improvement effect of environmental requirements on Tianjin's energy system through the AQI-MTIP model, and found that as environmental requirements become stricter, the substitution effect of clean energy is actually affected

The CGE model absorbs the advantages of the general equilibrium theory model in economics, gradually feeds back the impact of a macro policy into the equilibrium model, gets the equilibrium point before and after the implementation of the policy, and summarizes the impact of the policy on energy consumption. The research literature using the CGE model [6] analyzed the impact of the development of renewable energy, the upgrading of heavy industry, and the improvement of energy efficiency on income inequality. It was found that low-carbon policies have the greatest impact on employment in the energy industry, but have a negative impact on most traditional energy sectors, with a positive impact mainly on most renewable energy sectors; Reference [7] established a multi sector dynamic CGE model to simulate and analyze the dynamic impact of different combinations of resource tax and environmental protection tax rates on macroeconomic output and waste emissions.

With the support of data mining technology, this paper simulates and analyzes the economic optimization development process of low-carbon energy, so as to provide theoretical reference for the sustainable development of low-carbon energy economy.

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2 DATA MODEL OF LOW-CARBON ENERGY ECONOMY

2.1 Carbon footprint data processing

Carbon footprint data processing mainly includes carbon footprint preprocessing, carbon footprint data transformation and carbon footprint data reduction. It mainly processes carbon footprint data of products to meet data mining, and carbon footprint data processing is regarded as ΣDP data processing.

Redundant data generally appears in the integration of multiple data sources. Moreover, some data can only be detected by correlation analysis. If the two attributes are assumed to be x and y, the correlation between the attributes x and y is:

$$r_{x,y} = \frac{\sum (x-\overline{x})(y-\overline{y})}{(n-1)\sigma_x \sigma_y}. \quad (1)$$

In the formula, n is denoted as the number of tuples, $\overline{x}$、$\overline{y}$ is denoted as the mean of x and y respectively, and σ_x、σ_y is denoted as the standard deviation of x and y respectively, then:

$$\sigma_x = \sqrt{\frac{\sum (x-\overline{x})^2}{n-1}} \quad (2)$$

When the value of $r_{x,y}$ is large, it can be determined that the attribute values of x and y are redundant, and one of the attribute values can be removed as redundant data.

The data types of carbon footprint data are divided into real-time data and basic data. By scaling the attribute data, the attribute value falls into a small specific area. Common data transformation methods are as follows:

(1) Minimum-Max normalization

For a given attribute value A, $[\min_A, \max_A]$ is the value range normalized by X, $[\text{new\_min}_A, \text{new\_max}_A]$ is the value range normalized by A, and the minimum-maximum normalization normalizes the value v of A as v 'according to the following formula:

$$\nu' = \frac{\nu - \min_A}{\max_A - \min_A}(\text{new\_max}_A - \text{new\_min}_A) + \text{new\_min}_A \quad (3)$$

(2) Zero-mean normalization

For a given attribute value A, $\overline{A}$ and σ_A are represented as the mean, standard deviation of A, respectively, and zero-mean normalization normalizes the value v of A to v 'by the following formula:

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$$\mathbf{v}' = \frac{v - \overline{A}}{\sigma_A} \quad (4)$$

(3) Decimal scaling normalization

For a given attribute value A, $\max|A|$ is the maximum absolute value of A, j is the smallest integer of $\frac{\max|A|}{10^j}<1$, and decimal scaling normalization normalizes the value v of A to v 'according to the following formula:

$$\text{v}' = \frac{v}{10^j} \quad (5)$$

Figure 1 is a schematic diagram of carbon footprint data reduction, which is mainly divided into attribute reduction and record reduction. If the original data set is assumed to have 100 attributes and 1000 records, the data set is reduced to 50 attributes (attribute reduction) and 100 records (record reduction) after carbon footprint data reduction, which reduces the data amount by 95%.

NO	A1	A2	…	A100
1	a(1,1)	a(1,2)	…	a(1,100)
2	a(2,1)	a(2,2)	…	a(2,100)
…	…	…	…	…
1000	a(1000,1)	a(1000,2)	…	a(1000,1000)

NO	B1	B2	…	B100
1	b(1,1)	b(1,2)	…	b(1,100)
2	b(2,1)	b(2,2)	…	b(2,100)
…	…	…	…	…
1000	b(1000,1)	b(1000,2)	…	b(1000,1000)

Figure 1 Schematic diagram of carbon footprint data reduction

In this article, the relationship between green correlation modes can be expressed as shown in Figure 1.There are connected edges between nodes i and j in the related mode, and the connection relationship between nodes is shown in Figure 2 (a). If the i-th time series and the j-th time series are negatively correlated, that is, $a_{ij}^{(t)} = -1$, there are also connected edges between nodes i and j in the related modes, and the connection relationship between nodes is shown in Figure2 (b). If the related mode consists of four nodes: A, B, c and D, in which there is a positive correlation between A and B, a negative correlation between A and c, a positive correlation between B and c, and there is no correlation between node D and A, B and c, then the internal connection relationship of the related mode is shown in Figure 2 (c).

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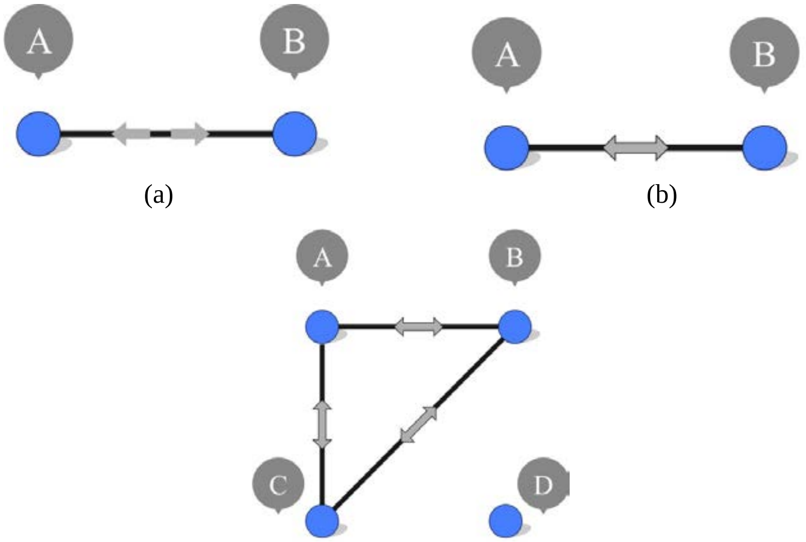
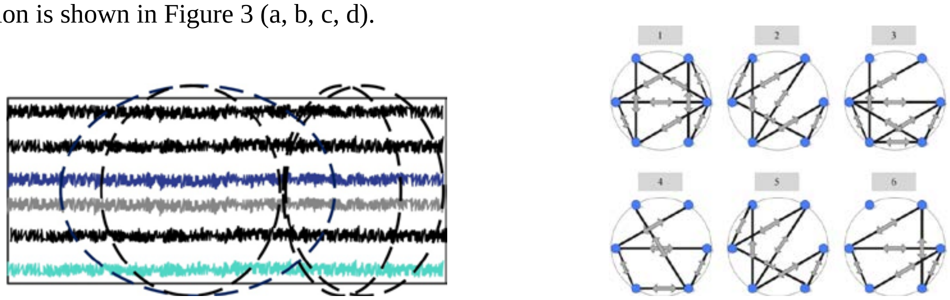


(a) (b)

(c)

Figure 2 Connection relationship within related modes

There is a certain regularity in the transformation between different low-carbon and diversified behavior modes, In order to clearly explain the construction process of the related modal conversion network, taking the six-ary random time series $\mathbf{X}=\left\{x_i\left(t'\right)\right\}, \quad i=1,2,\cdots,6$,a total of six time windows can be obtained, as shown in Figure 3 (a). The related modes are constructed in each time window, so six related modes can be obtained, as shown in Figure 3(b). As can be seen from Figure 3(b), related modes 2 and related modes 5 have the same structure, so the related mode conversion directed network can be constructed by connecting edges according to the time sequence of the occurrence of related modes, and the result is shown in Figure 3 (d). Build the related mode conversion directed network. The whole process of constructing the directed network of related modal conversion is shown in Figure 3 (a, b, c, d).



(a) (b)

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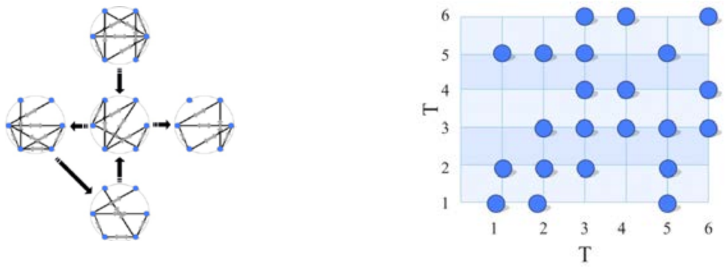


(c) (d)

Figure 3.Schematic diagram of analysis method for evolution and transformation characteristics of related modes in multivariate time series (a) dividing time windows (b) constructing related modes (c) generating recursive graphs (d) constructing directed networks of related modes

For the time series set in the development process of low-carbon economy, it can be decomposed into multiple small fragments in the model in this article. Figure 4 shows the modal sensitivity analysis of different L and 1 obtained under the algorithm in this article.

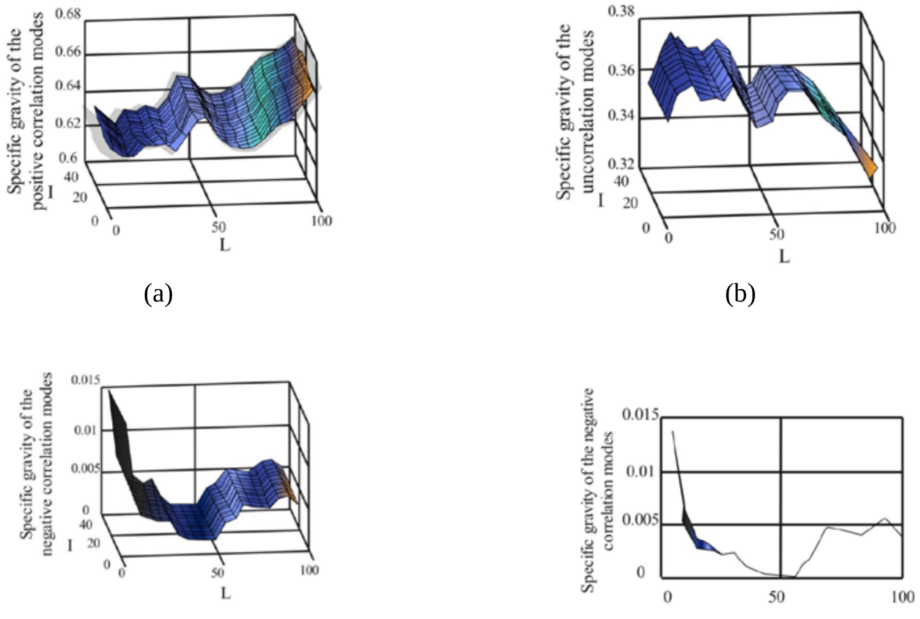


Figure 4 Sensitivity analysis results of L and l

2.2 Data mining model of product carbon footprint

In the field of data mining, Apriori algorithm and Apriori optimization algorithm are the most widely used association rule algorithms. The association analysis of Apriori algorithm is denoted as $\sum AA_{Aprion}$.

Definition of association rules: $I = \{i_1, i_2, \ldots, i_m\}$ is denoted as a set of complete items, and the transaction database is denoted as $D = \{t_1, t_2, \ldots, t_m\}$, where t is a non-empty subset of I, $t \in I$, and each t has a unique identifier TID. Association rules represent the relationship between items, such as an implication expression of $X \to Y$, and X and Y satisfy the following relationship: $X, Y \in I$ and $X \cap Y \neq 0$.

Support degree is an important measure of association rules, and association rules with low support degree have no great significance in actual transactions, which may happen by chance. If we assume that a global itemset is I and the transaction database is D, the support of an itemset $I_1 \subseteq I$ on D is the percentage of transactions containing I_1 on D:

$$\text{support}(I_1) = \frac{|\{t_1| \ I_1 \subseteq t_i, t_i \in D\}|}{| \ D|} \quad (6)$$

For example, the support of association rule for $X \to Y$ is:

$$\sup port\left(X \to Y\right) = \frac{\text{Number of tuples containing X} \cup \text{Y in D}}{\text{Number of tuples in D}} \quad (7)$$

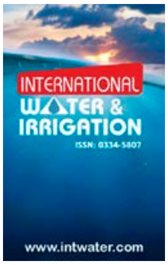
(3) Confidence of association rules

If the association rule of a global itemset I and transaction database d is assumed to be $X \to Y$, and X, $Y \in I$ and $X \cap Y \neq 0$ are satisfied, the confidence is expressed as the ratio of the number of transactions containing X and Y to the number of transactions containing X:

$$confidence\left(X \to Y\right) = \frac{\text{Number of tuples containing X} \cup \text{Y in D}}{\text{Number of tuples containing only X in D}} \quad (8)$$

The formula can also be expressed as $P\left(Y \middle| X\right)$. For association rules, the higher the confidence level, the higher the likelihood that Y will appear in transactions that contain X. Strong association is defined as: the minimum support degree of an association is greater than or equal to the minimum support degree on a given D, and the minimum confidence degree of an association is greater than or equal to the minimum confidence degree on a given D. Only the generated strong association rules are concerned by decision makers.

Among the time series analysis methods, the most common parameter model is ARMA (Auto-Regressive Moving Average). The reference model is established under good working conditions, and the equipment



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working conditions are predicted under time series, so as to realize the prediction of working conditions. Once the structure of equipment or parts changes, the established reference parameter model cannot accurately predict it, which makes the residual error become larger. The residual error is used as the damage index to realize the damage identification of mechanical equipment and parts. We set a stationary and zero-mean time series model $\{x_t\}$, where $t = 1,2,3,\ldots,N$, and the fitted stochastic difference equation is:

$$\begin{bmatrix} 1 & a_1 & a_2 & \cdots & a_{n_q} \end{bmatrix} \begin{bmatrix} x_t \\ x_{t-1} \\ x_{t-2} \\ \cdots \\ x_{t-n_q} \end{bmatrix} = \begin{bmatrix} b_1 & b_2 & \cdots & b_{n_b} \end{bmatrix} \begin{bmatrix} u_t \\ u_{t-1} \\ \cdots \\ u_{t-n_b} \end{bmatrix} + \begin{bmatrix} 1 & d_1 & \cdots & d_{n_d} \end{bmatrix} \begin{bmatrix} e_t \\ e_{t-1} \\ \cdots \\ e_{t-n_d} \end{bmatrix} \quad (9)$$

In the formula, x_t is the output of the system at time t, u_t is the input of the system at time t, e_t is the error generated, and a_i、b_i,d_i is the model parameter of the system, whose corresponding order is n_a、$\mathrm{n_b}$、n_d, which is transformed into:

$$A(q)x_t = B(q)u_t + D(q)e_t \quad (10)$$

In the formula,

$$A(q) = \begin{bmatrix} 1 & a_1 & a_2 & \cdots & a_{n_a} \end{bmatrix} \begin{bmatrix} 1 \\ q^{-1} \\ q^{-2} \\ \cdots \\ q^{-n_a} \end{bmatrix} \quad (11)$$

$$B(q) - \begin{bmatrix} b_1 & b_1 & b_2 & \cdots & b_{n_b} \end{bmatrix} \begin{bmatrix} 1 \\ q^{-1} \\ q^{-2} \\ \cdots \\ q^{-n_b} \end{bmatrix} \quad (12)$$

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$$D(q)=\begin{bmatrix}1 & d_1 & d_2 & \dots & d_{q_d}\end{bmatrix}\begin{bmatrix}1\\ q^{-1}\\ q^{-2}\\ \dots\\ q^{-n_d}\end{bmatrix} \quad (13)$$

e_t in formula 10 is represented as the extra input of the system. The ARMA model can be changed into AR (Auto-Regressive model) model through $n_b = n_d = 0$, and the mining of time series analysis carried out by formula 10 is denoted as $\sum TSA_{A(\mathrm{q})\mathrm{xt}}$.

At present, clustering analysis has become an important part of the field of data mining, and clustering is mainly the process of dividing the collection of data objects into similar object classes.

Clustering can be expressed as: $D=\{o_1, o_2, ..., o_n\}$ denotes a set of n objects, where o_i is denoted as an i (i=1, 2, …, n)-th object, C_x is denoted as an x (x=1, 2, …, k)-th cluster, and $C_x \subseteq D$. $sim(\mathrm{o_i,o_j})$ is denoted as the similarity between o_i and o_j. Among them, if each cluster C_x is subjected to rigid clustering results, each C_x satisfies the following conditions:

$$\bigcup_{x=1}^{k} C_k = U \quad (14)$$

For $\forall C_x, C_y \subseteq D,$ and $C_x \neq C_y,$ then $C_x \cap C_y = \varnothing$ (15)

$$\begin{aligned}&Min_{\forall o_{x_u}, o_{x_v}} \in C_x; \forall C_x \subseteq D(\mathrm{sim}(\mathrm{o}_{\mathrm{x_u}}, \mathrm{o}_{\mathrm{x_v}})) > \\ &Max_{\forall o_{x_s}} \in C_x, \forall o_{y_i} \in C_y, \forall C_y \subseteq D \,\&\, C_x \neq C_y(\mathrm{sim}(\mathrm{o}_{\mathrm{x}_s}, \mathrm{o}_{y_t}))\end{aligned} \quad (16)$$

For formulas 14 and 15, Q is a partition of D, and formula 14 indicates that the similarity of any object within a cluster is greater than that of any object between clusters. In cluster analysis, similarity between objects is the core of cluster analysis, and the most common similarity measures are distance, density, connectivity and so on. Cluster analysis realized by similarity between objects is denoted as $CA_{\mathrm{Similarity}}$, and common ones are Euclid distance similarity measure, Manhattan distance similarity measure, Minkowski distance similarity measure, etc., which are defined as follows:

(1) The Euclidean distance similarity measure is:

$$d(o_i, o_j) = \sum_{k=1}^{m} |\, o_{ik} - o_{jk}| \quad (17)$$

(2) The Manhattan distance similarity measure is:

$$d(o_i, o_j) = \| o_i - o_j \| = \sqrt{\sum_{k=1}^{m} (o_{ik} - o_{jk})^2} \quad (18)$$

(3) The Minkowski distance similarity measure is:

$$d(o_i, o_j) = \sqrt[q]{\sum_{k=1}^{m} \left| o_{ik} - o_{jk} \right|^q} \quad (19)$$

In order to better mine the product carbon footprint data information, the product carbon footprint data mining model is established to achieve the standardization of product carbon footprint data mining. Real-time data and basic data of product carbon footprint are obtained in manufacturing enterprise information system. After data preprocessing, the correctness of data mining is improved. After data transformation, carbon footprint data is easier to store, and data reduction simplifies product carbon footprint data. After data processing, a data warehouse is established, which is stored in MySQL database and Elasticsearch according to the types of product carbon footprint data, and supports rapid retrieval of real-time data of product carbon footprint. Cluster analysis method evaluates the attributes of carbon footprints through similarity, and excavates the attributes of carbon footprints, the relationship between attributes and predictions through association analysis and time series analysis. Based on the above ideas, a product carbon footprint data mining model is established. Figure 5 shows the product carbon footprint data mining model.

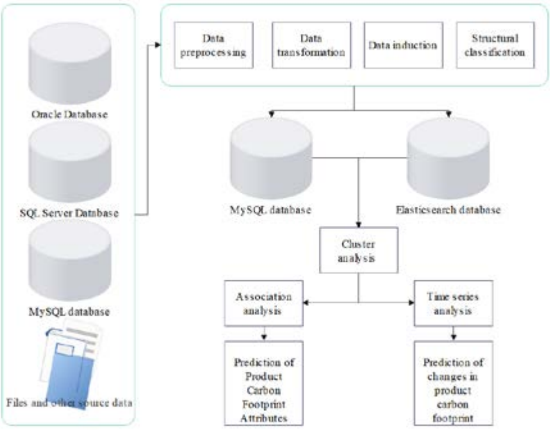

Figure 5 Schematic diagram of product carbon footprint data mining model

As shown in Figure 5, the mathematical expression formula of the product carbon footprint data mining model is:

$$\sum DS_{\text{information system}} \rightarrow \sum DP_{\text{data handling}} \rightarrow \sum DM_{(\text{Basic data+real-time data})} \rightarrow CA_{\text{Similarity}} \rightarrow \sum(\mathrm{AA}_{\text{Apriori}} + \mathrm{TSA}_{\mathrm{A(q)x_i}}) = \mathrm{M}_{\text{Data-mining}}(\text{produci}) \quad (20)$$

In the next step, the product carbon footprint data is stored in the database of corresponding data types after data preprocessing, data transformation, data reduction and data structure classification. Then, the similarity of clustering analysis is used to improve the effect of data mining. Finally, the association between carbon footprint attributes of products is mined by association analysis, and the prediction is made according to strong association rules. The change trend of carbon footprint attributes of products in time dimension is mined by time series analysis.

In practical applications, the product carbon footprint data mining model obtains the corresponding carbon footprint data of products and performs model fitting, and compares the fitting results with the original data, which may lead to model errors. The error produced by the model is not the result needed in this study. Bias is used to evaluate the fitting degree of the model, and variance is used to measure the fitting accuracy of the model, in which mean square error includes bias and variance.

The bias is evaluated by the following expression:

$$E_{\text{bias}} = E(\overline{x}) - x \quad (21)$$

In the formula, x is the true value of the product carbon footprint data, $E(\overline{x})$ is the estimated value, and the mean square error is:

$$MES(\overline{x}) = E_{\textbf{bias}}^2 + \sigma^2 \quad (22)$$

In the formula, $MES(\overline{x})$ is denoted as the mean square error and σ is denoted as the unbiased estimate of the population variance, and its expression is:

$$\sigma^2 = \frac{\sum_i (x - \overline{x})^2}{N - 1} \quad (23)$$

When the given mean square error is constant, the value of variance will decrease with the increase of bias. When the bias decreases, the value of variance will increase. Therefore, the data mining model of product carbon footprint should reduce the mean square error as much as possible, so that bias and variance can reach a reasonable range.

Based on the diversification of green and low-carbon economic behavior, this article combines the construction of a three-layer recursive network to construct a model. The schematic diagram of the multivariate time series in this article is shown in Figure 6.

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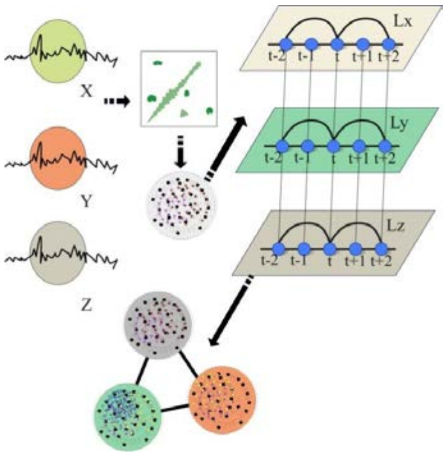

Figure6 Schematic diagram of time-varying multi-layer recursive complex network construction of multivariate time series (M=3)

Based on the construction of time-varying multi-layer recursive network, we introduce the delay parameter $\tau \geq 0$ to construct the time-delay recursive complex network of multi-layer. In particular, when $\tau = 0$, taking the degradation of time-delay recursive complex network of three-layer into a sequence between multi-layer recursive complex networks as an example, the schematic diagram of time-delay recursive network of three-layer is constructed, as shown in Figure 7.

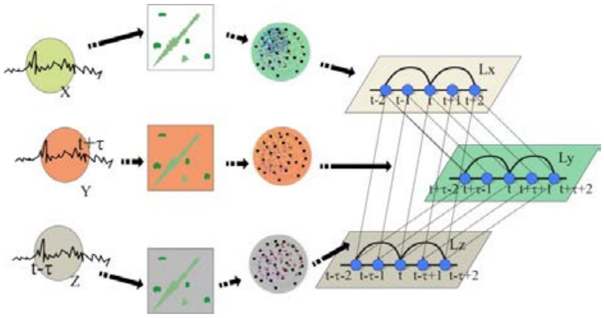

Figure 7 Schematic diagram of constructing multi-layer recursive complex network with time delay and time variation of multivariate time series (M=3)

We can still observe the phenomenon that the cross-correlation index ω jumps with the coupling strength ε. However, with the increase of noise intensity, the jump phenomenon tends to weaken.

We consider two Rossler systems coupled with each other.

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$$\begin{cases} \dot{x}_1 = -\left(1+U\right)x_2 - x_3 \\ \dot{x}_2 = \left(1+U\right)x_1 + ax_2 + \mu\left(y_2 - x_2\right) \\ \dot{x}_3 = b + x_3\left(x_1 - c\right) \end{cases}, \begin{cases} \dot{y}_1 = -\left(1-\upsilon\right)y_2 - y_3 \\ \dot{y}_2 = \left(1-\upsilon\right)y_1 + ay_2 + \mu\left(x_2 - y_2\right) \\ \dot{y}_3 = b + y_3\left(y_1 - c\right) \end{cases} \quad (24)$$

In this coupling system, the variables x_2 and y_2 are coupled with each other, and the parameters a=0. 2925, b=0. 1, c=9. 5, υ=0. 2, μ=0. 03 are taken, and the simulation step size is Δt=0. 02. The evolution images of variables x_2 and y_2 are shown in Figure 8 (a). The variable x_2 is selected to change for [100,1100], and the variable y_2 is selected to change for [180,1180]. As shown by the curve shown in the thick line in Figure 8 (b), the change of variable y_2 leads the change of variable x_2 in terms of the selected time period. Next, we calculate the values of q (t, τ) and q (t, τ) in the selected time period, and the calculation results are shown in Figure 8(c, d).

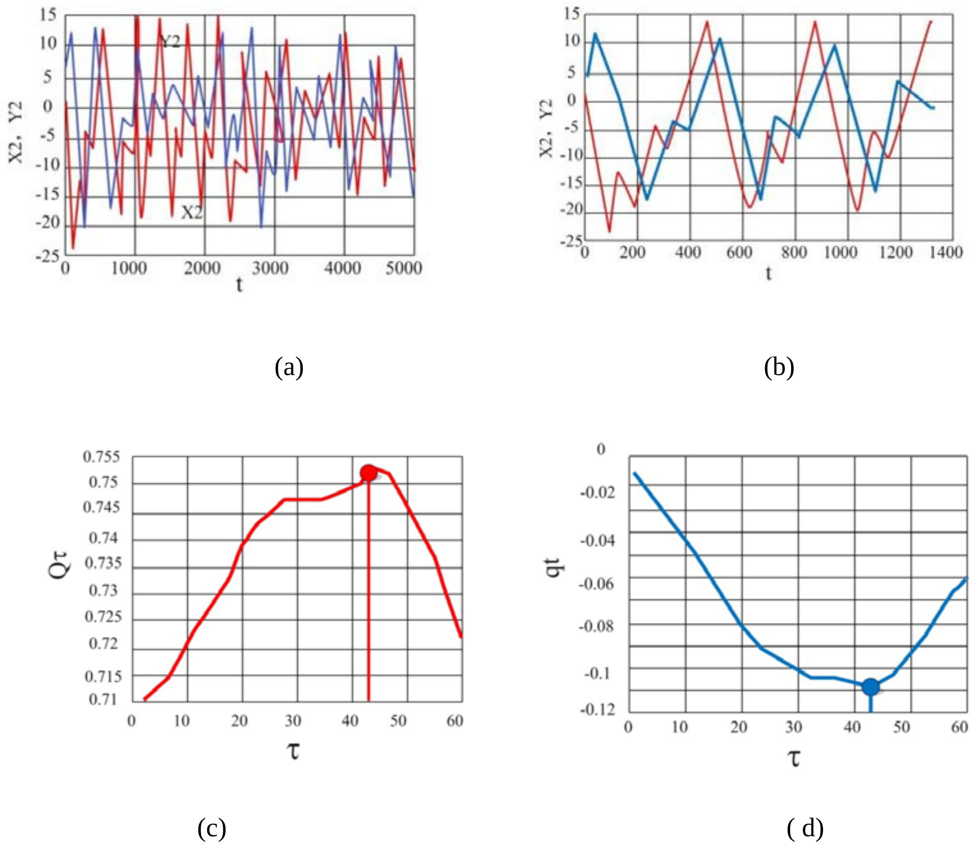

Figure 8 Simulation results of guiding relationship metrics

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As can be seen from Figure 8 (c), when the time delay τ=42, the maximum value of Q_{τ} is obtained. This means that the two systems are synchronized, and at this time , $q_{\tau}<0$, and this means that the second Rossler system (y_2) leads the first Rossler system (x_2).

3 OPTIMIZATION OF LOW-CARBON ENERGY ECONOMY BASED ON BIG DATA

Technological progress has a dual impact on energy consumption and economic development. This paper takes other measures to adjust the cost of energy use and environmental pollution in order to achieve the purpose of adjusting the substitution of energy and other elements, and finally promote consumers to choose more other elements, and truly achieve energy conservation and emission reduction. Figure 9 reflects the development model of low-carbon economy based on energy efficiency supported by technology and supplemented by other energy efficiency regulation means.

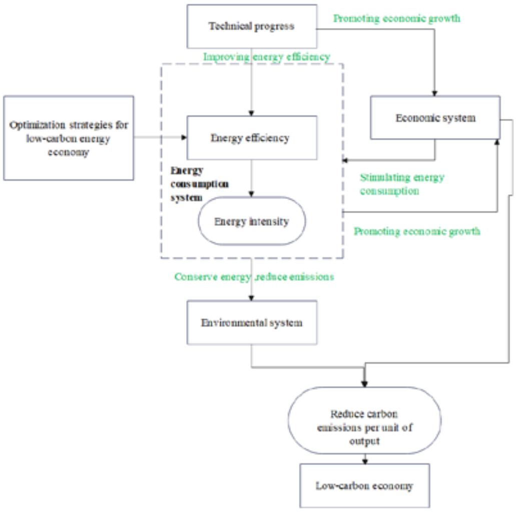

Figure 9 Low-carbon economy development model based on energy efficiency

Figure 9 shows the optimized development model of low-carbon energy economy proposed in this paper. This paper combines the algorithm proposed in the second part to study this model, and the data of this paper comes from statistical yearbook. On the basis of the analysis of this paper, the model proposed in this paper is verified, and the analysis effect of low-carbon energy economic data and the optimization development effect of low-carbon economy are evaluated. Through the simulation analysis of 2000 groups of data, the results shown in Figure 10 are obtained.

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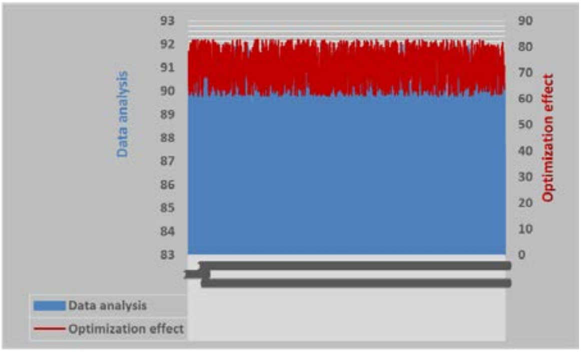


Figure 10 Simulation of low-carbon energy economic development based on big data analysis

From the experimental results in Figure 10 above, we can see that the low-carbon economic development model based on energy efficiency proposed in this paper can effectively improve the development path of low-carbon energy economy.

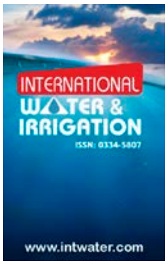
4 CONCLUSION

Compared with high-carbon economy, low-carbon economy is a sustainable economic development model characterized by low energy consumption, low emission and low pollution. Its essence is to use technological progress and institutional innovation to change the way of energy utilization, improve energy efficiency and optimize energy structure, so as to achieve the goal of promoting economic development and reducing carbon dioxide emissions. According to the understanding of the connotation of low-carbon economy, we put carbon dioxide emissions per unit GDP, that is, carbon intensity, to reflect the development goal of low-carbon economy, and build a multi-layer recursive complex network of carbon market-energy market and a time-delay recursive complex network. Moreover, based on the microscopic topology of complex networks, we introduce new metrics to measure the correlation and mutual leading relationship between systems. In addition, we empirically study the linkage and leading relationship between energy market and carbon market in different stages of EU carbon market from the perspective of recursive complex network. The simulation results show that the low-carbon economic development model based on energy efficiency proposed in this paper can effectively improve the development path of low-carbon energy economy.

The combination of water conservancy engineering and low-carbon energy economy has significant advantages.

One is clean energy production. Hydroelectric power in hydraulic engineering is a high-quality low-carbon energy source that can further improve power generation efficiency through technological improvements. Pumped storage power stations can effectively regulate energy supply and demand, help stabilize the power grid, reduce dependence on thermal power, and lower carbon emissions.

The second is efficient utilization of resources. Developing precise water conservancy in irrigation and other areas, reducing water resource waste, and lowering pumping energy consumption. At the same time, water



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conservancy facilities can collaborate with other low-carbon energy sources, such as wind, solar, and water complementarity, to optimize energy layout.

Thirdly, it is eco-friendly. The construction of water conservancy projects is shifting towards low-carbon, adopting environmentally friendly materials and processes to reduce carbon emissions during construction. Some water conservancy projects can also help with ecological restoration and enhance carbon sequestration capacity.

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