Research on Regional Differentiation Allocation Mode of Energy Finance based on Attention Mechanism and Support Vector Machine

Ling Sun[1]*

School of Economics and Management
Nanjing Vocational University of Industry Technology
Nanjing Jiangsu 210023, China

Hao Wu[2]

Jiangsu Suning Bank
Nanjing Jiangsu 210019, China

Abstract—This paper studies the prediction method of regional differentiated allocation mode of energy finance based on attention mechanism and support vector machine to provide scientific guidance for the future development direction of energy finance in each region. Analysis of the key factors influencing the energy consumption, through the attention mechanism to extract the regional factors such features constitute the details of the sample set, the characteristics of the sample set after implementation of fusion and normalized processing, gain new characteristics of sample set as input to construct support vector machine forecasting model, prediction of energy consumption in each region of the output. According to the results, the differentiated allocation patterns of energy finance in each region are predicted. The results show that the prediction model of this method has high training and test prediction accuracy, and the prediction results are consistent with the actual data in historical statistics. Compared with the existing methods, the method of this study can more scientifically and effectively predict the sustainable and stable development of energy finance in various regions of the city in the future. The energy consumption of the experimental city predicted in this study in the next nine years is from high to low in the order of region C, region a and region B. from this, it is predicted that the regions A, B and C of this city in the future will be applicable to the government market dual oriented Government oriented and market-oriented energy finance allocation models. The prediction results can provide scientific guidance for the sustainable and stable development of energy finance in various regions of the city in the future.

Keywords—*Attention mechanism; support vector machine; energy finance; differentiation configuration mode; energy consumption*

I. INTRODUCTION

Energy finance refers to a cooperative model based on the energy system that uses the financial system as a driving force after the integration of energy and finance. It is a brand-new model that promotes the coordinated development of energy and finance [1]. Energy finance is mainly based on the energy industry chain. With the help of financial means, it studies the interaction between the new energy industry and the financial industry from three aspects: the initial financing, the intermediate integration of resources, and the final realization of value-added, and puts forward corresponding safeguard measures. The energy industry is usually dependent on the financial industry in its development. To obtain the highest profit and achieve the highest capital utilization rate, the financial industry also needs to rely on the assistance of the energy industry [2,3]. As the main body of energy consumption in China, the consumption of primary energy in my country has shown an increase year by year in recent years. On the premise of maintaining the sustained and stable development of our country's energy finance, the development level of energy finance is gradually improved in various regions, so that can achieve the coordinated development of energy and finance in various regions. It is necessary to configure a differentiated energy financial model that meets its development characteristics for each region of our country [4]. Therefore, it is necessary to effectively combine the respective advantages of energy and finance in each region to effectively alleviate the financial problems faced by energy development. Meanwhile, new energy financial development paths will be provided to all regions. Regarding the question of how to configure a differentiated energy finance model that applies to each region, the most important thing is to accurately predict the energy consumption of each region. Based on the prediction results, the energy financial allocation models applicable to different regions can be analyzed [5].

The attention mechanism belongs to a type of model that simulates the attention mechanism of the human brain. Its principle is to use the method of attention probability distribution calculation to highlight the effect of a certain main input on the output, and to obtain more feature detail information. When the attention mechanism is used in deep learning models, it can help improve the overall accuracy and efficiency of such models [6, 7]. Meanwhile, the combination of attention mechanisms and machine learning algorithms to solve problems in projects or life has become a development trend. Support vector machine is a relatively important prediction algorithm in machine learning. It can transform the input in the low-dimensional space into the high-dimensional space through the kernel function and slack variables, and obtain the linear sample data in the best classification method [8]. Support vector machine has the advantages of being able to find the optimal solution globally, strong learning ability, and strong pan-China ability. It can be widely used in multi-dimensional function prediction and various recognition problems [9].

---

*Corresponding Author.

The attention mechanism and machine learning methods are applied to study the regional differentiation of energy finance, which can realize the prediction of the regional energy financial differentiation allocation mode. However, the research should analyze the key influencing factors that affect energy consumption and extract the relevant key influencing factors on the basis of a full analysis of the regionally differentiated configuration mode of energy finance. The data under the key influencing factors are formed into a sample set, and the data of the sample set is feature-fused using the normalization method, so that can realize the establishment of the support vector machine feature model. In the entire process, key factors can be determined in terms of economic development degree, urbanization degree, energy efficiency application degree, industrial structure and demographic factors that affect energy consumption, which can realize scientific and effective forecasts. Traditional energy finance regional differentiation research is mainly to analyze the correlation between energy industry projects and energy financial derivatives in various aspects. The process of using correlation to achieve prediction requires constant adjustment of model parameters to improve the accuracy of prediction, and the process is more complicated. This paper combines the attention mechanism and support vector machine to build a scientific prediction model, which can simplify the prediction process. Through the identified key factors, the sample set is input into the support vector machine prediction model, the energy consumption prediction results of different regions are output, and the results of the model output are used to analyze the energy financial configuration modes applicable to different regions. Through the identified key factors, the sample set is input into the support vector machine prediction model, the energy consumption prediction results of different regions are output, and the results of the model output are used to analyze the energy financial configuration modes applicable to different regions.

Therefore, the purpose of this paper is to combine the attention mechanism and support vector machine to achieve a scientific and accurate prediction of the regional energy finance differential distribution mode, and can guide the development direction of Regional Energy Finance in the future according to the prediction results, promote the sustainable and stable development of Regional Energy Finance in the future, and make up for the shortcomings of existing research.

II. Related Work

The concept of energy finance appeared in the 1880s. As the traditional energy structure upgrades and the capital demand for corporate development has grown, energy finance has gradually developed. However, the issue of energy finance has become the core issue of today's world economic development. It is not only closely related to the security of the country, but also closely related to the development of society [10]. Therefore, the differential analysis of energy finance between countries or regions has gradually become one of the important research hotspots. Many relevant experts and scholars have conducted analysis and research on the differences in energy finance. Some researchers have studied the framework of regional energy finance cooperation under the new normal [11], and they theoretically explain the

importance of forecasting functions to regional energy finance. Some scholars use the GABP algorithm to establish an energy financial risk early-warning model to realize the overall risk prediction of energy finance, but the accuracy of the prediction still needs to be considered [12]. Some researchers analyze the necessity of the association between early warning models and regional energy finance from a theoretical perspective [13]. In terms of the research on the regionally differentiated allocation model of energy finance, most of the existing relevant literature is theoretically analyzed. Some researchers use provincial panel data to analyze financial risks from a differentiated perspective and analyze the potential impact of regional financial risks [14]. Some researchers use the VAR model to study the regional differentiation of rural finance and analyze the correlation between influencing factors [15]. However, the current research on the difference of energy finance is still one-sided, and there are few methods to output scientific and accurate prediction results from the data accumulated in history.

The application of machine learning methods in the financial field is more common, it mainly has stock forecasting, quantitative finance, investment portfolio analysis, etc. [16]. However, there are few studies on regional financial differentiation, which mainly focus on the collection of regional financial data and regional financial risk index. A fuzzy comprehensive evaluation or analytic hierarchy process is applied to evaluate regional financial risks. The analysis of the difference is mainly based on the risk ranking by the evaluation grade [17-18]. There are also a few researchers who study the stability and differences of regional finance [19-21]. However, this type of research is also limited to the use of evaluation methods to obtain results. Few machine learning methods are applied to difference analysis, and data-driven methods are not used to output prediction results.

In summary, the machine learning method has been applied in the financial field, but the existing research on regional financial differentiation mainly focuses on the theoretical level and the correlation analysis between factors. Some studies have made key determination on the economic development degree, urbanization degree, energy efficiency application degree, industrial structure and population factors that affect energy consumption; however, the prediction of regional differentiation of energy finance by means of machine learning is still in the development stage.

Therefore, on the basis of the existing research results and after analyzing the key factors affecting energy consumption, this study uses the attention mechanism to extract the detailed features of these factors in each region, form a feature sample set, and fuse and normalize the feature sample set to obtain a brand-new feature sample set input, build a support vector machine prediction model, and realize scientific and effective research and Analysis on the basis of the existing research, provide auxiliary decision support for relevant management departments.

III. Analysis of the Differential Configuration Mode for Energy Finance Region

To achieve the coordinated development of energy and finance in various regions, it is necessary to configure

differentiated energy financial models in line with their development characteristics for different regions to achieve a more effective combination of the respective advantages of energy and finance. Its model can not only effectively alleviate the financial problems faced in energy development, but also provide brand new development paths to the financial industry in various regions [22]. Generally, the regional energy financial allocation mode can be divided into three types: government-oriented regional energy financial configuration mode, government-market dual-oriented regional energy financial configuration mode, and market-oriented regional energy financial configuration mode. The first configuration mode is suitable for areas with low energy finance levels. The second configuration mode is suitable for areas with a medium level of energy finance. The third configuration mode is suitable for areas with higher levels of energy finance [23]. Therefore, to study the energy financial allocation model applicable to each region, it is necessary to understand the energy financial level of each region. However, the level of energy finance is mainly reflected in the degree of consumption, so it is necessary to analyze the differentiated energy financial allocation models in different regions on the basis of obtaining energy consumption. Meanwhile, to obtain the energy consumption of each region, it is necessary to design an appropriate energy consumption prediction model to realize an effective prediction of the energy consumption of each region. Based on the prediction results, the energy financial level of each region is analyzed, and the differentiated configuration mode of energy finance applicable to each region is predicted. On this basis, the detailed features of such key influencing factors in each region are extracted by combining the attention mechanism. After its features are processed by feature fusion and normalization, they are used as input to the support vector machine prediction model, and the energy consumption of each area is output to realize the prediction of energy consumption in each area.

Based on the prediction results, predict the differentiated allocation mode of energy finance in different regions.

A. Analysis of Key Factors Affecting Energy Consumption

The main factors that usually affect energy consumption include the level of urbanization, energy efficiency, demographic factors, industrial structure, and degree of economic development [24]. The demographic factors include two factors: population size and population structure. The degree of economic development includes factors such as the stage and scale of development. The structure of key influencing factors of energy consumption is shown in Fig. 1.

In Fig. 1, the effects of each key influencing factor on energy consumption are as follows.

1) Urbanization level factors: The difference in lifestyle between rural and urban residents has resulted in differentiated energy consumption in the two regions. Meanwhile, in the process of rural urbanization, the construction of transportation and infrastructure can also increase energy consumption. Therefore, the urbanization of the rural population has a promoting effect on energy consumption, and the proportion of the urban population can be used to measure the level of urbanization.

2) Energy efficiency factors: The improvement of energy efficiency can promote the sustainable development of energy, reduce energy waste, and effectively alleviate the contradiction between energy supply and demand, as well as achieve the purpose of saving energy and reducing emissions. The key indicator to measure energy efficiency is the value of energy consumption per unit of GDP, which is inversely proportional to energy efficiency.
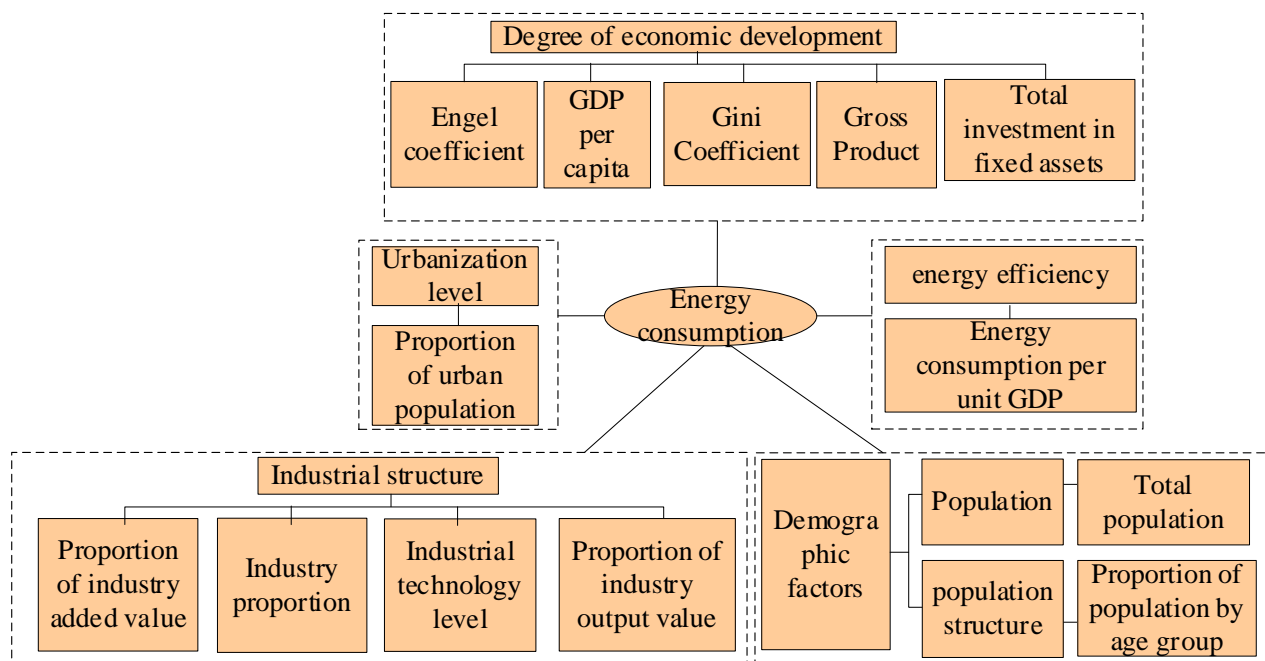

Fig. 1. Structure Diagram of Key Influencing Factors of Energy Consumption.

3) Demographic factors: With the increase in the number of people, the energy demand has gradually increased, so energy consumption has also shown an increasing trend. From the perspective of demographic structure, different age groups will lead to differences in consumption habits and lifestyles, as well as differences in energy consumption. Therefore, both population size and population structure will have an impact on energy consumption. Generally, the main indicators for measuring demographic factors are the total population, the proportion of the population of each age group, and so on.

4) Industrial structure factors: The differentiation of industrial structure has a direct impact on energy consumption, and the key energy consumption industry in my country is the secondary industry [25]. Common indicators used to measure changes in the secondary industry structure include the proportion of secondary industry's added value, the proportion of the secondary industry, the technical level of the secondary industry, and the proportion of secondary industry's output value. Therefore, the above indicators can also be used to measure the impact of changes in industrial structure on energy consumption.

5) Economic development degree factors: The increase in total energy consumption can promote the degree of economic development, and economic development will also bring about an increase in energy consumption. There is a mutually reinforcing relationship between energy consumption and economic development. Commonly used indicators to measure the degree of economic development include Engel's coefficient, GDP per capita, Gini coefficient, gross production value, and total fixed-asset investment. In which the Engel coefficient is inversely proportional to the living standards of the masses, and the Gini coefficient is directly proportional to the difference in income distribution, both of which can show the degree of economic development.

B. Feature Extraction of Key Influencing Factors for Energy Consumption based on Attention Mechanism

The attention mechanism is the process of extracting more detailed features. Its main principle is to quickly scan the overall scene of its visual interval through the human visual system, and select the key target interval from it through the brain's signal processing mechanism, and put more attention resources into this interval [26]. Feature extraction of factors affecting energy consumption is the key to energy consumption prediction. The attention mechanism can quickly extract more detailed feature information of the key influencing factors of

energy consumption, which can effectively improve the accuracy and efficiency of the final energy consumption prediction in each region. The attention mechanism can search for many key-value pair mappings, and obtain the goodness of such key-value pairs. The goodness of fit is proportional to the number of allocated attention resources. The structure of the attention mechanism is shown in Fig. 2.

In Fig. 2, $L_i - W_i$ represents a key-value pair, which represents the weight of factors affecting energy consumption. The query is represented by Q, which represents energy consumption. The feature information of the key influencing factors of energy consumption extracted by the attention mechanism can be used to construct the prediction model, which can improve the prediction accuracy and efficiency of the model. The calculation process of attention is:

After calculating the goodness of fit between the energy consumption and the weight of each key influencing factor, the weights will be obtained. Here the splicing method is chosen to calculate the coincidence degree. The calculation equation is:

$$g(Q, L_i) = v_\alpha [Q; L_i] \tag{1}$$

In equation 1, the splicing coefficient is represented by v_α.

Step2: Normalization of weights. The weights obtained in step (1) are normalized by the Soft max function, and the calculation equation is:

$$\text{Soft max}[g(Q, L_i)] = [\exp(g(Q, L_i))] / [\sum_j \exp(g(Q, L_j))] \tag{2}$$

Step3: Attention calculation. The weights gained by normalization of weighted and sum, and the weights acquired by factors of influencing energy consumption are used to obtain attention. The calculation equation is:

$$A(Q, L, W) = \sum_i \omega_i W_i \tag{3}$$

In equation 3, ω_i represents the normalized weight.

Based on the key influencing factors of energy consumption extracted by the attention mechanism, the detailed feature information is formed into a feature sample set. The sample set is processed accordingly and then input into the support vector machine prediction model to obtain the output of energy consumption in each region.
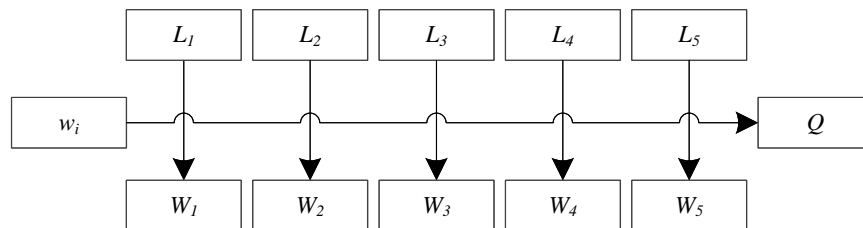

Fig. 2. Structure Diagram of Attention Mechanism.

C. Prediction of Regional Energy Consumption based on Extracted Feature Sample Sets

1) Feature fusion and normalization of the feature sample set: The feature sample set acquired by the attention mechanism can be fused to realize the complementary advantages of each factor feature in the sample set, improve the description performance of the feature, and help to further improve the prediction accuracy of the model [27]. After fusion, due to the dimensional differences of the characteristics of each factor in the feature sample set, it is easy to cause large fluctuations in the prediction results obtained by the prediction model, and the prediction performance is not stable enough. Therefore, it is necessary to further implement normalization processing on the basis of feature fusion to achieve stable prediction of the prediction model.

2) Feature fusion: Given that the features in the feature sample set obtained by the attention mechanism are the initial features, denoted by X_i *(i=1,2,...,M)*, where M represents the number of features. The features in the feature sample set after feature fusion processing are represented by X_j *(j=1,2,...,M)*. The feature fusion equation is:

$$X_j = \delta_j [\theta_i \times X_i]$$
(4)

In equation 4, δ_j represents the feature fusion function; the conversion function is represented by θ_i.

3) Normalization: After the fusion processing, the normalization of the feature data in the feature sample set is performed, that is, the value range of the feature data of each factor is unified to 0~1, so that can achieve the unity of dimensions and ensure the stability of the prediction results. The normalized processing equation is:

$$\tilde{x} = (x_i - x_{min}) / (x_{max} - x_{min})$$
(5)

In equation 5, $\tilde{x}$ represents the normalized feature sample set feature data; x_i represents the *i-th* feature data in the feature sample set after fusion processing. The highest value and the lowest value of the feature data in the feature sample set after fusion processing are represented by x_{max} and x_{min}, respectively. Therefore, a new feature sample set $\tilde{X}$ composed of many normalized feature data $\tilde{x}$ can be obtained, which can be used as the input sample set of the prediction model to achieve a stable prediction of energy consumption in each region.

4) Support vector machine prediction model based on the processed feature sample set: Taking the processed new feature sample set XXX as input and the energy consumption of each area as output, a support vector machine prediction model is constructed to realize effective prediction of energy consumption in each area. The differentiated allocation mode of energy finance in each region is estimated by the prediction results.

Each feature $\tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M$ in the input feature sample set $\tilde{X}$ is mapped to a high-dimensional feature space ($\sigma(X_1)$, $\sigma(X_2)$,..., $\sigma(X_n)$). According to statistics, the initial nonlinear model can be changed to the linear regression model of the high-dimensional feature space. Its equation is:

$$f(X_j) = d + \lambda^T \times \sigma(\tilde{X}_j)$$
(6)

In equation 6, d and λ represent the parameters that need to be identified in the linear regression model, where the adjustable weight vector is λ, and the bias is d. Based on the structural risk minimization criteria, the required identification parameters are processed, and the processing formula is:

$$H(f) = \sum_{i=1}^{s} \gamma \|\lambda\|^2 + B(e_i)$$
(7)

In equation 7, $B(e_i)$ represents the loss function; confidence risk is represented by $\|\lambda\|^2$; $H(f)$ represents empirical risk. According to the principle of support vector machine, the solution of formula (7) is equivalent to the operation of the following optimization problem, which is:

$$\begin{cases} \min K = B \sum_{i=1}^{s} (\mu_i + \mu_i^*) + \frac{1}{2} \lambda^T \lambda \\ s.t. \begin{cases} y - (\lambda, \sigma(X_t')) - d \le \mu + \mu_i^* \\ (\lambda, \sigma(X_t')) + d - y \le \mu + \mu_i^* \\ \mu_i^*, \mu_i \ge 0 \end{cases} \end{cases}$$
(8)

In equation 8, the optimized parameters are represented by μ_i and μ_i^*; K represents the classification hyperplane; and the parameters of the inner product function are represented by X_t'.

By converting formula (8) into a dual problem and simplifying the calculation process, the nonlinear function obtained after conversion is expressed as:

$$f(X) = \sum_{i=1}^{k} (c_i - c_i^*) G(X_t', X') + d$$
(9)

In equation 9, $G(X_t', X')$ represents the inner product function; the support vector parameters are represented by c_i and c_i^*. The radial basis function is set by the Mercer condition, which is set the inner product function, and it is expressed as:

$$G(X_t', X') = \exp\left\{ -\left(\|\tilde{X}_j - \tilde{X}_a\|^2 \right) / \varphi^2 \right\}$$
(10)

In equation 10, φ^2 represents the Mercer condition coefficient; the training feature data vector and the test feature data vector in the feature sample set are represented by $\tilde{X}_j$ and $\tilde{X}_a$, respectively.

The equation (10) is substituted into equation (9). After equivalent transformation, it is acquired as:

$$f(X) = \sum_{i=1}^{l} c_j \exp\left\{-\left(\left\|\tilde{X}_j - \tilde{X}_a\right\|^2\right)/\varphi^2\right\} + d \tag{11}$$

In equation 11, c_j represents the parameter value corresponding to the support vector; the output vector set of energy consumption in each region is represented by $f(X)$. The energy consumption prediction parameters d and c_j can be

acquired to obtain the energy consumption output of each region. The differentiated allocation mode of energy finance applicable to each region is predicted by the energy consumption of each region.

IV. ANALYSIS OF EXPERIMENTAL RESULTS

Take a city as an example, the city is divided into three regions (a~c), and the method in this paper is used to study the differentiated configuration mode of energy finance in each region. Taking the period from 2011 to 2020 as an example, the historical statistics of energy consumption and key influencing factors in each area of the experimental city during the period are used as the basis. The proportion of the urban population, energy consumption per unit GDP, total population, the proportion of secondary industry added value, gross production value and energy consumption in each region of the city can be obtained, which is as Table I.

TABLE I.   HISTORICAL STATISTICS OF ENERGY CONSUMPTION AND VARIOUS INFLUENCING FACTORS IN EACH REGION OF THE EXPERIMENTAL CITY FROM 2011 TO 2020

| Number	Year	Proportion of urban population /%	Energy consumption per unit GDP /tce/ 10 thousand yuan	Total population/10 thousand people	Proportion of added value of secondary industry /%	GDP/100 million yuan	Energy consumption/10 thousand tce
a	2011	48.8	4.7×10^{-5}	60.1	45.1	208.2	98.7
	2012	50.1	5.2×10^{-5}	60.8	44.8	211.5	110.3
	2013	52.4	5.6×10^{-5}	61.7	46.1	218.7	122.6
	2014	53.6	5.8×10^{-5}	62.5	45.8	225.4	130.7
	2015	54.8	6.3×10^{-5}	64.1	43.7	229.2	145.8
	2016	56	6.9×10^{-5}	65.7	41	233.4	162.4
	2017	57.9	7.3×10^{-5}	67.3	42.3	237.6	175.4
	2018	59.1	7.9×10^{-5}	69.2	44.5	241.7	191.1
	2019	59.8	8.2×10^{-5}	71	45.1	252.1	208.3
	2020	60.4	8.5×10^{-5}	72.5	42.5	260.4	221.6
b	2011	45.1	4.6×10^{-5}	55.7	43.7	199.5	93.2
	2012	46.4	5.1×10^{-5}	56.1	42.1	203.7	102.6
	2013	47.1	5.6×10^{-5}	56.9	45.1	208.9	118.5
	2014	47.8	5.8×10^{-5}	58.1	45.3	215.3	126.3
	2015	48.6	6.0×10^{-5}	59.2	41.4	220.7	133.8
	2016	50.1	6.1×10^{-5}	60.3	41.8	229.4	141.9
	2017	52	6.7×10^{-5}	62.7	43.8	233.6	156.9
	2018	53.8	7.1×10^{-5}	64.1	46.1	238.8	169.3
	2019	55.1	7.3×10^{-5}	65.8	44.3	246.4	180.4
	2020	56.7	8.1×10^{-5}	68	43.2	252.2	206.2
c	2011	50.6	4.9×10^{-5}	65.2	46.3	212.4	105.2
	2012	52	5.3×10^{-5}	66.7	45.5	220.6	117.3
	2013	52.8	5.5×10^{-5}	68.1	46.2	227.8	126.9
	2014	54.1	5.8×10^{-5}	69.7	44.1	236.3	138.5
	2015	55	6.2×10^{-5}	71.2	43.7	244.2	151.3
	2016	56.3	6.4×10^{-5}	72.8	47.1	251.7	162.4
	2017	57.8	6.8×10^{-5}	74.1	46.8	258.9	176.9
	2018	59.1	7.2×10^{-5}	76.3	42.1	267.3	192.6
	2019	60.5	7.7×10^{-5}	77.9	46.1	274.2	211.1
	2020	61.3	7.9×10^{-5}	79.5	45.8	285.2	226.9

Using historical statistical data from 2011 to 2015 as the training sample set, and historical data from 2016 to 2020 as the test sample set, the prediction model of this paper is used to implement training and testing, which can obtain the training effect and testing effect, as shown in Fig. 3.

It can be seen from Fig. 3 that the training results and testing results of the prediction model of the method in this paper are in close agreement with the actual energy consumption in historical statistics, and the maximum error value does not exceed 15,000 tce. Therefore, the training effect and test effect of the prediction model in this paper are relatively ideal, and the obtained prediction results have high accuracy, which can be applied to the actual energy consumption prediction in the study of the differential configuration mode of energy finance for different regions.

This paper studies the differentiated energy financial allocation modes of the experimental cities from 2022 to 2030 in the future, and further uses the proposed prediction model to predict the energy consumption of the experimental cities from 2022 to 2030. The future energy financial differentiated allocation mode of each region is studied by the obtained prediction results. The prediction results of energy consumption in each region of the experimental city from 2022 to 2030 are shown in Fig. 4.
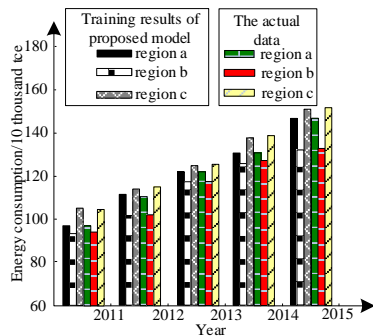
(a) The Training Effect of the Prediction Model for the Proposed Method by the Paper.
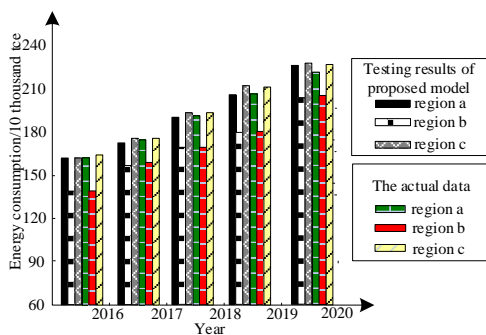
(b) The Testing effect of the Prediction Model for the Proposed Method by the Paper.

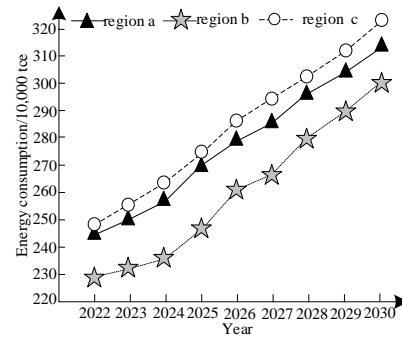Fig. 3.   The Training and Testing Effect of the Prediction Model in the Method of this Paper.

Fig. 4.   The Prediction Results of Energy Consumption in each Region of the Experimental City from 2022 to 2030.

From Fig. 4, it can be concluded that the annual energy consumption of each region for the experimental city from 2022 to 2030 will show an upward trend. On the whole, energy consumption in region *c* is higher, energy consumption in the region *a* is at a medium level, and energy consumption in region *b* is the lowest. Combining this prediction result, the future energy financial level of the three regions of the experimental city is ranked *c-a-b* from high to low. Therefore, the energy financial allocation models corresponding to each region from 2022 to 2030 in the future should be: region-c-market-oriented, region-a-government-market of dual-oriented, and region-b-government-oriented. Based on the predicted different regional energy finance allocation models in the future, it can provide a clear development direction for the future development of energy finance in each area of the experimental city. It also improves the future development level of energy finance and provides help to effectively avoid bottlenecks in future development.

V.   CONCLUSION

This paper focuses on the research on the prediction method of regional differential allocation pattern of energy finance based on attention mechanism and support vector machine. It extracts many detailed features of key influencing factors of energy consumption by using attention mechanism, and after fusing and normalizing them, the feature sample set obtained is input into the support vector machine, constructs the support vector machine prediction model, and outputs the prediction results of regional energy consumption. According to this result, the energy finance allocation mode applicable to each region is analyzed. The proposed prediction model has high training prediction accuracy and test prediction accuracy, and has a good prediction effect on the historical sample set. It can provide a scientific guidance path for the sustainable and stable development of energy finance in various regions of the city in the future.

REFERENCES

[1] F. E. A. Mills, J. Dong, L. Yiling, M. A. Baafi, B. Li and K. Zeng, "Towards sustainable competitiveness: How does financial development affect dynamic energy efficiency in Belt & Road economies?," Sustainable Production and Consumption, 2021, 27, pp. 587-601.

[2] C. Zhang, J. Fu and Z. Pu, "A study of the petroleum trade network of countries along The Belt and Road Initiative," Journal of Cleaner Production, 2019, 222, pp. 593-605.

[3] W. E. I. Li, "The Threshold Effect of Clean Energy Development on Employment Based on the Perspective of Financial Scale," Economic Theory and Business Management, 2021, 41(9), pp. 99.

[4] S. Saud and S. Chen, "An empirical analysis of financial development and energy demand: establishing the role of globalization," Environmental Science and Pollution Research, 2018, 25(24), pp. 24326-24337.

[5] H. Fan, Q. Q. Yuan and J. Deng, "Two-stage capacity optimization configuration method for multi-region integrated energy system," Modern Electric Power, 2020, 37(5), pp. 441-449.

[6] Z. LIU and P. WAN, "Pedestrian re-identification feature extraction method based on attention mechanism," Journal of Computer Applications, 2020, 40(3), pp. 672-676.

[7] X. Qin, J. Jiang, C. A. Yuan, S. Qiao and W. Fan, "Arbitrary shape natural scene text detection method based on soft attention mechanism and dilated convolution," IEEE Access, 2020, 8, 122685-122694.

[8] F. Kaytez, "A hybrid approach based on autoregressive integrated moving average and least-square support vector machine for long-term forecasting of net electricity consumption," Energy, 2020, 197, pp. 117200.

[9] D. Koschwitz, J. Frisch and C. Van Treeck, "Data-driven heating and cooling load predictions for non-residential buildings based on support vector machine regression and NARX Recurrent Neural Network: A comparative study on district scale," Energy, 2018, 165, pp. 134-142.

[10] M. S. Islam, A. Q. Al-Amin and M. S. K. Sarkar, "Energy crisis in Bangladesh: Challenges, progress, and prospects for alternative energy resources," Utilities Policy, 2021, 71, pp. 101221.

[11] W. Bishan, "Development mechanism of energy industry cluster in new normal economy," Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 2019, 41(23), pp. 2853-2860.

[12] X. Zhong and J. Tu, "Study on Energy Finance Risk Warning Model---Based on GABP Algorithm," In 2017 3rd International Conference on Economics, Social Science, Arts, Education and Management Engineering (ESSAEME 2017). Atlantis Press (2017, July).

[13] D. Y. Peng, "Empirical Study on Coupling and Coordinated Development of"Energy-Finance-Environment" in the Middle Reaches of Yangtze River," Proceedings of 2019 4th International Conference on Advances in Energy and Environment Research (ICAEER 2019), 2019, pp. 912-917.

[14] J. Puck and I. Filatotchev, "Finance and the multinational company: Building bridges between finance and global strategy research," Global Strategy Journal, 2020, 10(4), pp. 655-675.

[15] O. L. A. N. I. Y. I. Evans and O. R. Alenoghena, "Financial inclusion and GDP per capital in Africa: A Bayesian VAR model," Journal of Economics & Sustainable Development, 2017, 8(18), pp. 44-57.

[16] Y. Ma, R. Han and X. Fu, "Stock prediction based on random forest and LSTM neural network. In 2019 19th International Conference on Control," Automation and Systems (ICCAS) IEEE. 126-130 (2019, October).

[17] S. Ma, H. Wang, B. Xu , H. Xiao, F. Xie, H. N. Dai and T. Wang, "Banking Comprehensive Risk Management System Based on Big Data Architecture of Hybrid Processing Engines and Databases," In 2018 IEEE Smart World, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (Smart World/SCALCOM/UIC/ATC/CBD Com/IOP/SCI) IEEE. 1844-1851 (2018, October).

[18] S. Li, L. Yuan and L. Wenjun, "China's Regional Financial Risk Spatial Correlation Network and Regional Contagion Effect: 2009-2016," Management Review, 2019, 31(8), pp. 35.

[19] R. Shaidullin, E. Bulatova, L. Kurmanova, R. Khabibullin and J. Zhuzhoma, "Evaluation of financial stability of Russian companies," In E3S Web of Conferences (Vol. 110, p. 02044). EDP Sciences (2019).

[20] W. Dariusz, "Financial geography II: The impacts of FinTech – Financial sector and centres, regulation and stability, inclusion and governance," Progress in Human Geography, 2021, 45(4).

[21] M. G. Caldas, V. Matheus, D. M. C. Oliveira, "Impacts of the sovereign risk perception on financial stability: Evidence from Brazil," Quarterly Review of Economics and Finance, 2021, 81.

[22] D. Gao, G. Li, Y. Li and K. Gao, "Does FDI improve green total factor energy efficiency under heterogeneous environmental regulation? Evidence from China," Environmental Science and Pollution Research, 2021, 1-14.

[23] G. Shi, D. Liu and Q. Wei, "Energy consumption prediction of office buildings based on echo state networks," Neurocomputing, 2016, 216, pp. 478-488.

[24] X. Y. Zhou and A. L. Gu, "Impacts of household living consumption on energy use and carbon emissions in China based on the input–output model," Advances in Climate Change Research, 2020, 11(2), pp. 118-130.

[25] D. Fang and B. Yu, "Driving mechanism and decoupling effect of PM2.5 emissions: Empirical evidence from China's industrial sector," Energy Policy, 2021, 149, pp. 112017.

[26] H. Wang, J. Shi and Z. Zhang, "Semantic relation extraction of LSTM based on attention mechanism," Computer application research, 2018, 35(5), pp. 143-146.

[27] H. S. Shin, H. Y. Kwon and S. J. Ryu, "A new text classification model based on contrastive word embedding for detecting cybersecurity intelligence in twitter," Electronics, 2020, 9(9), pp. 1527.