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| Team Number : | 2020230040158 |

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| Problem Chosen : | B |



2020 APMCM summary sheet

In order to solve the problem of the impact of the US election results on the Sino-US economy, this paper uses Lagrange interpolation and principal component analysis to complement and reduce the historical data, build a predictive model based on BP neural network, and use the VAR model to analyze the future economy development status, and establish an analytic hierarchy model based on multiple linear regression to evaluate and analyze the results of the general election.

Question 1 requires a quantitative analysis of the impact of the election of different candidates on the US economy. By comparing the similarities and differences between the two candidates’ policy propositions, we extract relevant policy indicators to express their impact on the US economy and collect historical data. For missing data, Lagrange interpolation is used to complete the original data. Due to the large number of policy indicators, it is considered to conduct principal component analysis on policy indicators, and to establish a prediction model based on BP neural network, using historical data of principal component indicators to predict various principal component indicators in the next 4 years. Finally, the VAR model is used to calculate the predicted value of economic indicators using the predicted value of the principal component indicators to analyze the future economic development of US.

Question 2 is to analyze the impact on the Chinese economy. Assuming that only the two candidates' China policy will affect China's economy, four China policy indicators are extracted, and the predicted value of China's economic indicators is calculated based on question 1, and the future economic development of China is analyzed.

Question 3 requires combining the mathematical models of Question 1 and Question 2 to propose economic countermeasures that China should take when Trump and Biden are elected. By constructing an analytic hierarchy model based on multiple linear regression, the index weights are obtained according to the hierarchical ranking method. The results show that Biden's election weight is 0.51, and Trump's election weight is 0.49. There is not much difference between the two, indicating that the policies of the two candidates have similar effects on the China’s economy. Among the ten policy indicators, the top three weighted indicators are the Stock price general 500 index, the trade deficit and the total import and export volume. These indicators mainly correspond to the financial and trade policies of the United States. In response to these policies, appropriate Chinese economic policies are proposed.

The innovation of this paper is to adjust the prediction results of the BP neural network based on the impact of the epidemic to make it more in line with the actual situation, and use the VAR model to analyze and determine the future economic development status. In the analytic hierarchy process, the multiple linear regression method is used to construct the judgment matrix, which avoids the shortcoming ofthe subjectiveness ofthe expert score.

**Keywords:** Lagrange interpolation, principal component analysis, BP neural network, VAR model, multiple linear regression, AHP

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**1** **Problem** **background** **and** **restatement**

**1.1** **Problem** **background**

The US presidential election is held every four years. 2020 is the year of the US presidential election. The 59th President of the United States will be elected. Republican candidate Donald Trump and Democratic opponent Joe Biden will participate in the election. The two sides have held three presidential election debates since September 2020. The general election was officially held on November 3. Candidates on both sides have different policies in finance and trade, economic and financial governance, and other key development areas (such as COVID- 19 fighting measures, infrastructure, taxation, environmental protection, medical insurance, employment, trade, immigration, education, etc.). Given that the United States has a major impact on world development in many aspects, the election of different candidates will shape different strategic models of global economic and financial development, and have a greater impact on the U.S. economy and the global economy (including the Chinese economy). How will different policies affect the economies of the United States and China? How should China respond?

**1.2** **Problem** **restatement**

Based on the above background, on the basis of collecting candidates' policy propositions, policy guidelines and related data in different fields, the following questions are answered:

(1)Establish a mathematical model and use relevant data to quantitatively analyze the possible impact of different candidates elected on the U.S. economy. (You can choose one or several fields to answer this question separately or give a comprehensive answer)

(2)Establish a mathematical model and use relevant data to quantitatively analyze the possible impact of different candidates elected on China’s economy. (You can choose one or several fields to answer this question separately or give a comprehensive answer)

(3)Suppose you were members of China’s Think Tank for Economic Development, combined with the mathematical models of questions 1 and 2, what suggestions would you make to China’s economic countermeasures and policies in related areas in both cases (which party wins)? Please illustrate your points specifically.

**2** **Problem** **analysis**

**2.1** **Problem** **one** **analysis**

Problem one requires the establishment of a mathematical model to quantitatively analyze the impact of the election of different candidates on the US economy through relevant data.

First, it is necessary to compare and analyze the similarities and differences between the

two candidates' policy proposals, which mainly include COVID- 19 fighting measures, infrastructure, taxation, environmental protection, medical insurance, employment, trade, immigration, education, etc.

Secondly, different candidates adopting different policy propositions will result in

different economic development conditions. In order to characterize this impact, select corresponding related policy indicators for each policy, including infrastructure investment, tax income, average CO2 emissions, average domestic general government health expenditure, unemployment rate, total import and export, trade deficit, stock price general 500 index, total international migrants and percentage of education expenditure. On the other hand, in order to quantitatively judge the economic development status, relevant economic indicators such as Gross Domestic Product 、Producer Price Index 、average Gross National Income are selected. Collect historical data for these indicators.

Thirdly, in view of the large number of policy indicators and the fact that not all information is primary, principal component analysis is performed on these indicators to extract comprehensive indicators reflecting policy changes while reducing dimensions.

Fourthly, in order to predict the principal component indicators, a predictive model needs to be established. In view of the many advantages of BP Neural Network, this paper uses BP Neural Network to establish a prediction model, and uses the historical data to predict the various principal component indicators in the next 4 years.

Finally, predicting economic indicators based solely on historical data cannot reflect the impact of policy changes. In order to calculate the predicted value of economic indicators through the predicted value of the principal component indicators, it is necessary to find the relationship between economic indicators and the principal component. This paper analyzes the relationship based on the VAR model. Then substituting the predicted value of the principal component indicators into the model to obtain the predicted value of economic indicators, and then analyze the economic development status.

**2.2** **Problem** **two** **analysis**

Problem two requires the establishment of a mathematical model to quantitatively analyze the impact of different candidates' election on China's economy through relevant data.

Different from problem 1, only two candidates' China policies will affect China's economy in problem 2. Therefore, in problem 2, indicators related to China's policies are selected to characterize the impact of different candidates on China's economy, including China's foreign trade cargo throughput, US imports and exports to China, US dollar to RMB exchange rate and US federal fund interest rate. On the other hand, in order to quantitatively judge the development of China's economy, China's total import and export and customs duties are selected as indicators to measure China's economy. As the first one is similar to other principal component analysis, it is not necessary to extract principal component analysis.

**2.3** **Problem** **three** **analysis**

Problem three requires combining the mathematical model of question 1 and question 2 to put forward the economic countermeasures that China should take when Trump and Biden are elected respectively.

In order to analyze the impact of the two candidates on China’s economy after being elected, this paper uses the analytic hierarchy process model based on multiple linear regression to determine the influence weight of each policy and the influence degree of the two candidates on China’s economy. In order to avoid the subjectivity of analytic hierarchy process (AHP), based on the data of first and second questions, the multiple linear regression method is used to

determine the judgment matrix. Finally, the influence and countermeasures are analyzed according to the results of hierarchical ranking.

**3** **Problem** **hypothesis**

(1) It is assumed that the candidate will implement the published policy proposition after taking office.

(2) According to the development of COVID- 19 vaccine, it is assumed that the epidemic will not last until the end ofthe next tenure.

(3) Ignore the impact of non-policy factors on China’s and the U.S. economy.

(4) It is assumed that the error of BP Neural Network does not affect the solution of the economic model.

**4** **Symbol** **description**

For the convenience of reading and understanding, the important variables in this paper are explained in a unified manner, as shown in Tab.1.

Tab.1 Symbol description

|  |  |  |  |
| --- | --- | --- | --- |
| Symbol | Description | Symbol | Description |
| X1 | Infrastructure investment | Z1 | China's foreign trade cargo throughput |
| X2 | Tax income | Z2 | US imports and exports to China |
| X3 | Average CO2 emissions | Z3 | Exchange rate of US dollar to RMB |
| X4 | Average domestic general government health expenditure | Z4 | US federal funds rate |
| X5 | Unemployment rate | S1 | Problem one training set1 |
| X6 | US total import and export | S2 | Problem one training set2 |
| X7 | Trade deficit | S3 | Problem two training set1 |
| X8 | Stock price general 500 index | S4 | Problem two training set2 |
| X9 | Total international migrants | T | Problem one testing set |
| X10 | Percentage of education expenditure | U | Problem two testing set |

**5** **Model** **and** **solution** **of** **problem** **one**

**5.1** **Comparison** **of** **policy** **propositions**

The election candidates Trump and Biden represent the Republican Party and the Democratic Party respectively. The two parties have very different governing ideas. Therefore, the policy propositions of the two candidates during the election process are very different. Policy propositions are important references for predicting the candidate's ruling situation after winning the election. Therefore, it is necessary to compare and display the main policy propositions of the two candidates, including COVID- 19 fighting measures, infrastructure, taxation, environmental protection, medical insurance, employment, trade, immigration, education, etc.

Tab.2 Comparison of Different Candidates’ Policy Propositions

|  |  |  |
| --- | --- | --- |
| Policy Propositions | Trump | Biden |
| COVID- 19 fighting measures | Passive: No mandatory epidemic prevention policy; Exit WHO | Active: Every people need wear  masks; National Testing; Rejoin  WHO |
| Infrastructure | Invest 1 trillion dollars in the next 10 years | Invest 2 trillion dollars in the next 4 years |
| Taxation | Comprehensive tax cuts for middle- class families and small businesses | Cancel tax cuts |
| Environmental protection | Persist in the development of  traditional energy, withdraw from  the Paris Climate Agreement | Increase clean energy  investment, rejoin the Paris  Climate Agreement |
| Medical insurance | Reduce medical costs through  market competition and abolish  Obamacare policy | Realize affordable medical care  through government intervention  and implement Obamacare  reform |
| Employment | Promote the achievements during the ruling period such as the return of manufacturing and employment | Emphasis on raising the  minimum wage, promoting racial  equality and other government  safeguards |
| Trade | Continue to implement the punitive  tariffs of "unfair dumping and  subsidies" and refuse to join the  TPP | Put pressure on other countries through alliances |
| Immigration | Strengthen border security, repeal  Obama’s immigration reform  executive order, and withdraw from  the global immigration convention | Withdraw Trump's immigration policy |
| Education | Help students in the form of aid | Student loan exemption,  expansion of tuition-free  universities, universal preschool  education, etc. |

**5.2** **Data** **acquisition** **and** **preprocessing**

**5.2.1** **Data** **acquisition**

Question 1 requires a quantitative analysis of the impact of different candidates on the US economy. Obtaining comprehensive and true data is a prerequisite for solving the problem. The data should include two aspects: (1) Policy indicator data that can reflect the impact of policy changes. The data structure is shown in Table 3. It should be noted that since the COVID- 19 epidemic is an emergency, the impact of the epidemic and the corresponding epidemic prevention policy cannot be reflected in the historical data, so it will be considered separately in the model; (2) Economic indicator data that characterizes economic changes. It mainly considers three items: Gross Domestic Product (GDP), Producer Price Index (PPI), and average

Gross National Income (A\_GNI). The data structure is shown in Table 4. After extensive data collection, the complete data results obtained are shown in Attachment 1. The data source is the World Economic Database ofChina Economic Information Network.

Tab.3 Policy indicator data structure

|  |  |  |  |
| --- | --- | --- | --- |
| Time(quarterly) | X2  X1 (billion dollars)  X3(mt /person)  (million dollars) | | X4 (dollar) X5(%) |
| Time(quarterly) | X[7](#_bookmark62)  X6 (million dollars)  X[8](#_bookmark63)  (million dollars) | | X9(person) X10(%) |
|  | Tab.4 Economic indicator data structure | |  |
| Time | GDP（billion dollars） | PPI | A\_GNI （dollar） |

**5.2.2** **Data** **preprocessing**

After checking the acquired data, it is found that some indicators only have partial data values. The main purpose of data preprocessing is to make data interpolation. Commonly used interpolation methods include mean/median/mode interpolation, fixed value, nearest neighbor interpolation, regression method and interpolation method, considering that the results of interpolation method are more accurate and only need to use the information of known points, therefore, using Lagrange interpolation method to impute missing values. Data interpolation can not only improve data quality, but also improve the accuracy of fitting and prediction in the model. The basic steps of Lagrange interpolation are as follows:

Step1: For *n* known points on the plane (no two points are on a straight line), a polynomial of degree *n* − 1 can be obtained *y* = *a*0 + *a*1*x* + *a*2*x*2 + ... + *an*−1*xn*−1 , the curve of the polynomial passes through these *n* points, and substitute the coordinates of the *n* points (*x*1 , *y*1), (*x*2 , *y*2 ),..., (*xn* , *yn*) into the polynomial:

*y*1 = *a*0 + *a*1*x*1 + *a*2*x*12 + ... + *an*−1*x*1*n*−1

*y*2 = *a*0 + *a*1*x*2 + *a*2*x*22 + ... + *an*−1*x*2*n*−1

*yn* = *a*0 + *a*1*xn* + *a*2*xn*2 + ... + *an*−1*xnn*−1

Step2: Solve the Lagrange interpolation polynomial:

*L*(*x*) = *y*1 (*x* − *x*2 )(*x* − *x*3) (*x* − *xn*) + *y*2 (*x* − *x*1)(*x* − *x*3) (*x* − *xn*) (*x*1 − *x*2 )(*x*1 − *x*3) (*x*1 − *xn*) (*x*2 − *x*1)(*x*2 − *x*3) (*x*2 − *xn*)

+ + *yn* (*xn* − *x*1)(*xn* − *x*2 ) (*xn* − *xn* −1) =  *yi* *j**i* *xi* − *xj*

(*x* − *x*1)(*x* − *x*2 ) (*x* − *xn*−1) *n* *n* *x* − *xj*

(1)

(2)

Step3: The approximate value *L*(*x*) of the missing value can be obtained by substituting

the *x* where the data is missing into the interpolation polynomial. Taking percentage of education expenditure as an example, the effect of data interpolation is shown in Tab.5.

Tab.5 The effect of data interpolation

|  |  |  |  |
| --- | --- | --- | --- |
|  | Original | After data interpolation | |
| Time | Percentage of education expenditure | Time | Percentage of education expenditure |
| 2009-03  2009-06  2009-09  2009- 12 | 10.88  12.40  missing  13.54 | 2009-03  2009-06  2009-09  2009- 12 | 10.88  12.40  13.25  13.54 |



**5.3** **Principal** **component** **analysis** **of** **policy** **indicators**

Presidential candidates Trump and Biden have expressed different policy propositions in response to the COVID- 19 fighting measures, international trade, and economic development. The election of different candidates will have different effects on economic development. We have selected corresponding indicators for each policy to reflect the impact of the policy. These policy indicators are important basis for describing the policy impact adopted by candidates. Each statistical indicator reflects part of the information about the economic situation under the corresponding policy, but not all the information is the main one, and because there is a certain correlation between the statistical indicators, dimensionality reduction and simplification are needed to extract some potential comprehensive indicators to describe economic conditions. This paper uses principal component analysis to process economic statistical indicators, and uses a few comprehensive indicators to fully reflect the information carried by each indicator.

(1) Principle of Principal Component Analysis

The principal component analysis method aims to remain the most important components in the original data in the process of dimensionality reduction, so as to maximize the variance of the original data, that is, to replace the original more single indicators with fewer comprehensive indicators, it is equivalent to replacing *p* indicators *Xp* with *k* principal components *Yk* in mathematics, generally, these *p* indicators *Xp* are linearly combined to generate *Yk* .

The information contained in a random variable can be measured by the degree of dispersion of its value (that is, the size of the variance), therefore, in principal component analysis, the largest ( *Var*(*Y*1) is largest) variance among all linear combinations is used as the first principal component. If *Y*1 is not enough to represent the original *p* indicators, consider extracting the next comprehensive indicator *Y*2 . In order to ensure the effectiveness of information extraction, make sure *Cov*(*Y*1 , *Y*2 ) = 0 , that is, *Y*1 and *Y*2 are not related, and *Y*2 can independently reflect another aspect of information.

(2) Standardization of indicator variables

Before the principal component analysis, it is usually necessary to standardize each indicator variable, so as to avoid the unreasonable selection of the unit of equally important variables, which makes the variance of the unit huge, thus giving unreasonable principal

component analysis results. Usually *X* = *Xi* − *E*(*Xi*) is used to standardize indicator variables.

(3) Steps ofPrincipal Component Analysis

Step1: Standardize raw index data

*X* *X*

*ij* − *i* *X* =

*i*

*ij* *S*

|  |  |
| --- | --- |
| 1 *n*  *X* =  *x*21 *x*22  *xn*1 *xn*2  *i* *n* *j*=1 *ij*  *X* =*x*  2 1 *n*  *i* *n* *j*=1 *ij* *i*  *s* =(*x* − *x* )  Get standardized data matrix  *x*11 *x*12 | *i* = 1, 2,..., *n*  *x*    2*p*  *xnp*  *i* = 1, 2,..., *n*  *x*1*p* |

(3)

(4)

(5)

(6)

Step2: Calculate the correlation coefficient between each variable, and establish the correlation coefficient matrix *R* between the variables.

Step3: Solve the eigenvalues and eigenvectors of *R* . Solve the characteristic value

1  2     0 from (*I* − *R*) = 0 , and then calculate the characteristic vector *l*1 , *l*2 , , *lp* ,

*li* = (*li*1 , *li* 2 , *lip* )*T* from (*I* − *R*) = 0 .

*p*

Step4: Calculate the contribution rate *pi* = *i* / *i* and cumulative contribution rate

*i*=1

*k* *k* *p*

*pj* = *i* / *i* of each principal component, and determine the number *m* of principal

*j* =1 *i*=1 *i*=1

components to be used according to the 0.85 principle.

Step5: Write the expression of the principal component *Yi* = *li*1*X*1 + *li*2*X*2 + + *lipXp* . In order to make the principal component easier to explain, the load matrix of the principal component is rotated, and the maximum variance method is used to adjust the principal component load matrix after rotation.

Step6: Back to the original data, calculate the score of the selected principal component.

(4) Results of Principal Component Analysis

The KMO (Kaiser-Meyer-Olkin) calculated for 10 policy indicators is 0.754>0.6, and the significance value of Bartlett’s Test of Sphericity is 0.000<0.05, indicating that the data is suitable for principal component analysis.

Through principal component analysis, the principal component contribution rate of 10 statistical indicators is obtained. From Tab.6 and Fig.1, it can be seen that cumulative contribution rate of the first three principal components exceeds 85%. From the gravel map of eigenvalues, Fig.2, it can be seen that eigenvalues corresponding to the first three principal components are all larger than 1. Principal components can use fewer indicators to reflect the information reflected by the original more indicators, so this paper selects the first 3 principal components to represent the original 10 policy indicators.

Tab.6 Principal component contribution rate

|  |  |  |  |
| --- | --- | --- | --- |
| No. | Variance | contribution rate /% | cumulative contribution rate /% |
| 1 | 6.423 | 64.235 | 64.235 |
| 2  3  4  5 | 1.568  1.116  0.392  0.218 | 15.678  11.160  3.921  2.182 | 79.912  91.072  94.994  97.176 |
| 6  7  8  9 | 0.131  0.086  0.046  0.014 | 1.305  0.858  0.457  0.135 | 98.481  99.339  99.796  99.931 |
| 10 | 0.007 | 0.069 | 100.000 |

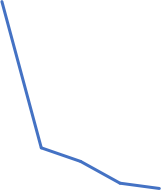
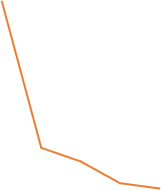
The correlation coefficients between the first three principal components and policy

indicators are shown in Tab.7, and the characteristic values reflected by each principal component are as follows:

1) The first principal component mainly reflects: infrastructure investment, average CO2 emissions, average domestic general government health expenditure, unemployment rate, trade deficit, Stock price general 500 index, total number of international migrants, which are comprehensive indicators reflecting policies.

2) The second principal component mainly reflects: total import and export, trade deficit, and percentage of education expenditure.

3) The third principal component mainly reflects: tax income, unemployment rate, total import and export.



eigenvalue

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 7.0  6.0  5.0  4.0  3.0  2.0  1.0  0.0  1 |  |  |  |  |  |  |  | 10 |
|  |  |  |  |  |  |  |
| 2 | 3 | 4 | 5 6 Component | 7 | 8 | 9 |

|  |  |  |
| --- | --- | --- |
| 100.0  Rate(%)  90.0  80.0  70.0  60.0  50.0  40.0  30.0  20.0  10.0  0.0  1 |  | 10 |
|  |
| 5 6 7 8 9  2 3 4  Contribution rate  Component  Cumulative contribution rate |

Fig.1 Principal component contribution rate analysis

Fig.2 Gravel diagram of principal component analysis

Tab.7 Principal component load matrix after rotation

|  |  |  |
| --- | --- | --- |
| The first principal component | The second principal component | The third principal component |
| 0.947  X1 X2  X3  0.349  -0.928 | 0.259  0.072  -0.176 | 0.064  0.898  -0.104 |
| 0.881  X4 X5 X6 X7 X8 X9  X10  -0.722  0.465  0.685  0.877  0.920  0.007 | 0.391  -0.309  0.716  0.615  0.393  -0.166  0.934 | 0.165  0.534  -0.369  0.071  0.201  0.102  0.097 |

**5.4** **Prediction** **of** **principal** **component** **indicators** **based** **on** **BP**

**Neural** **Network**

This paper uses the BP neural network method to fit and predict the principal component indicators of the two presidential candidates after the election of Trump and Biden respectively, and obtain the prediction results to prepare for the subsequent economic indicator prediction based on the VAR model.

**5.4.1** **Determination** **of** **training** **and** **testing** **sample** **data**

(1) Training sample S1

Considering that Biden served as the vice president of the United States during the Obama administration, and at the same time, combining the policy propositions put forward by Biden during the campaign and comparing them with the policies of Obama, the results obtained are shown in Tab.8. Among them, 1 means that the policies ofBiden and Obama are similar, and 0 means that they are not similar.

Tab.8 Comparison of similarities between Biden and Obama's policies

|  |  |  |
| --- | --- | --- |
| Policy indicators Similarities | Policy indicators | Similarities |
| |  |  | | --- | --- | | immigration | 1 | | trade | 1 | | environmental medical insurance | 1  1 |
| diplomacy 0 | education | 1 |
| economy and employment 1 | infrastructure | 1 |

According to Tab.8, regardless of the impact of COVID- 19, the similarities between Biden and Obama’s policies are as high as 87.5%. Therefore, the data from 2008 to 2016 during the Obama administration is used as the training sample of candidate Biden.

(2) Training sample S2

The collected data from 2008 to 2020 was used as the training sample of candidate Trump. The reason for this is that S2 not only considers the impact of historical policy data, but also considers the characteristics of Trump's governance. Therefore, it is more reasonable to use S2 to predict Trump's policy data after the election.

(3) Testing sample T

In order to test the fitting accuracy of BP Neural Network, it is necessary to select test samples for testing. This paper selects the policy data of Trump's four years in power as the test samples. The main reasons are as follows:

1) T is close to the year of the data to be predicted, which is conducive to the subsequent fitting and prediction.

2) T makes up for the shortcomings of S1, so that the forecast of policy indicators after Biden's election will not deviate from the status quo of Trump's administration.

**5.4.2** **Forecasting** **algorithm** **based** **on** **BP** **Neural** **Network**

BP Neural Network can approximate any non-linear mapping with arbitrary precision, and has learning and self-adaptability. The connection value of the network can be modified to respond to changes in the system. In addition, the multi-input multi-output network constructed by it has good fault tolerance and can generate a system with strong robustness. Because ofthe

above characteristics, BP Neural Network is widely used, can better adapt to the system characteristics of the multi-index variable of this problem, and makes it possible to predict the policy indicators of the two presidential candidates in the next term.

The BP neural network mainly includes three layers: input layer, hidden layer, and output layer. Each layer is composed of many parallel computing neurons. The principle is: the working signal obtains the network error through forward propagation, and the error signal passes back propagation to feed back the adjustment network. In the process of forward propagation, the working signal input by the input layer is transformed by the hidden layer and transmitted to the output layer, and the output signal is obtained at the output end. Ifthe output signal obtained does not meet the given standard, then the error back propagation process is performed. The difference between the actual output value obtained by the forward operation and the expected output value is used as the error signal, which is transmitted from the output layer to the input layer. In this process, the error signal is continuously fed back to adjust the network weight, and the ideal output value is obtained by continuously correcting the weight. The three-layer BP neural network structure is shown in Fig.3.

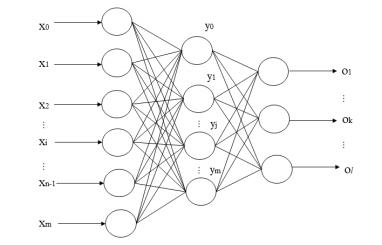


Fig.3 Three-layer BP Neural Network structure

According to the working principle of BP Neural Network, the following algorithm is designed:

Step1: Clarify the input and output variables and corresponding parameters: *Xk* = [*xk*1 , *xk* 2 , *xkM* ] , (*k* = 1, 2, , *N*)represents the input signal of the input layer, Where N is the number of samples (Biden is 32, Trump is 47), M is the number of main modeling variables (10). The weight matrix during iteration is shown in formula (7).

*w*01(*t*)*w*02 (*t*) *w*0*J* (*t*)  *w*01(*t*)*w*02 (*t*) *w*0*K* (*t*) 

*WIJ* (*t*) =  *w*11(*t*)*w*12 (*t*) *w*1*J* (*t*)  *WJK* (*t*) =  *w*11(*t*)*w*12 (*t*) *w*1*K* (*t*) 

    *wI*1(*t*)*wI* 2 (*t*) *wIJ* (*t*)  *wJ* 1(*t*)*wJ* 2 (*t*) *wJK* (*t*) 

(7)

They respectively represent the weight matrix corresponding to the input layer I to the hidden layer J and the weight matrix corresponding to the hidden layer J to the output layer K at the tth iteration.

*On* (*t*) = [*on*1(*t*)*on*2 (*t*) *onp* (*t*)], (*n* = 1, 2,

network at the tth iteration.

*Dn* (*t*) = [*dn*1(*t*)*dn*2 (*t*) *dnp* (*t*)], (*n* = 1, 2,

*N*) represents the output vector of the

*N*) represents the output vector that the

*x*max − *x*min

1+ *e*− *x*

*D*

network operation should get.

Step2: Construct the initial network, use the method of randomly assigning smaller values to the network weights, assign the weight matrix *WIJ* (0) , *WJK* (0) to the smaller non-zero

matrix. The input and output data are respectively standardized and transformed into training samples and expected output that can be directly used in calculations. This paper uses linear normalization method to process the data, the formula is as follows:

*x*\* = (*y*max − *y*min )(*x* − *x*min ) + *y*min (8)

Step3: Randomly draw samples *Xk* from the training samples, and the corresponding

expected output *k*

.

Step4: Take the input sample *Xk* as an example, through the forward operation of the neurons in each layer of BP Neural Network, the input signal  and the output signal  are obtained, *onk* (*t*) = *v* (*t*) . The transmission of each signal in the hidden layer needs to pass the activation function. In this paper, the Sigmod function is selected as the activation function, and the formula is as follows:

1

*f* (*x*) = (9)

Step5: Make the difference between the network output *On* (*t*) obtained by the forward operation of the BP neural network and the given expected output *Dn* (*t*) to get the network relative error *E*(*t*) , and judge whether it meets the accuracy requirements, if it meets the requirements, go to Step 8; otherwise, go to Step 6.

Step6: Judge whether (t+1)th iteration meets the termination condition. If it does, go to Step 8. If it does not, use the input sample to calculate the local gradient value of each layer of neurons through the error back propagation process.

*kK* (*t*) = *onk* (*t*)(1 − *onk* (*t*))  (*dnk* (*t*) − *onk* (*t*)) (10)

*K*

*jJ* (*t*) = *f* ' (*J**j* (*t*))*kK* (*t*)  *wjk* (*t*) (11)

*k*=1

Step7: Use the learning rate  to calculate the weight correction and correct the corresponding weight matrix. Go to Step4, and the weight correction method is as follows:

*wij* (*t* +1) = *wij* (*t*) +*jJ* (*t*)  *xni* (*t*)

*wjk* (*t* +1) = *wjk* (*t*) +*kK* (*t*)  (*t*)

(12)

(13)

Step8: Judge whether the training samples are all completed, if yes, end the calculation, otherwise go to Step3.

**5.4.3** **Performance** **optimization** **of** **BP** **Neural** **Network**

(1) Performance optimization of BP Neural Network in training set S1

The number of neurons in the hidden layer of the BP neural network has a great influence on whether the network converges, the speed of convergence, and the accuracy of the results. However, so far there is no sufficient theoretical basis to show how to determine the number, and the selection is generally determined by relying on past experience. In this paper, by adjusting the number of hidden layer neurons and training samples, different neural network structures are constructed, and the number of iterations required by each network and the correlation coefficient R2 are obtained, then find the number of hidden layer neurons that makes the BP neural network performance optimal. Because the relationship between the variables is complicated, after preliminary experiments, this paper sets the number of neurons between [5,20].

Taking the principal component Y1 as an example, Tab.9 shows the corresponding



calculation results of different network structures when the number ofneurons is adjusted. Tab.9 Number of iterations and correlation coefficients of different BP Neural Networks-Y1

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Number of neurons | Number of iterations | Correlation coefficients | Number of neurons | Number of iterations | Correlation coefficients |
| 5  6  7 | 10  8  16 | 0.513486  0.504419  0.476102 | 13  14  15 | 32  19  12 | 0.287622  0.553445  0.53719 |
| 8 | 9 | 0.526028 | 16 | 11 | 0.686481 |
| 9 | 8 | 0.527933 | 17 | 7 | 0.59794 |
| 10 | 9 | 0.530223 | 18 | 9 | 0.496559 |
| 11  12 | 9  8 | 0.555294  0.554874 | 19  20 | 15  23 | 0.552295  0.421812 |

It can be seen from Tab.9 that when the number of neurons in the hidden layer is 16, the correlation coefficient of the BP neural network model reaches the maximum, indicating that the error with the Trump administration is the smallest at this time. Therefore, for the principal component Y1, it is more reasonable when the number of hidden layer neurons is 16.

In the same way, the reasonable number of hidden layer neurons of the principal components Y2 and Y3 can also be obtained by testing. In summary, the performance optimization results of all principal components of the BP Neural Network are shown in Tab.10.

Tab.10 BP Neural Network performance optimization results of each principal component-S1

Principal component

Number of neurons

Number of iterations

Correlation

coefficients

Y1

Y2

Y3

16

20

14

10

10

8

0.6865

0.7567

0.6575

(2) Performance optimization of BP Neural Network in training set S2

The performance of the BP Neural Network is optimized on the training set S2 using the previous method, and the results are shown in Tab.11.

Tab.11 BP Neural Network performance optimization results of each principal component-S2

Principal component

Number of neurons

Number of iterations

Correlation

coefficients

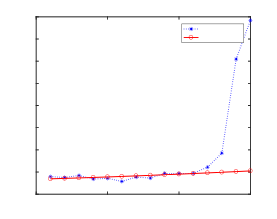
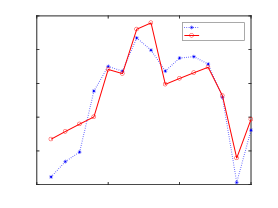
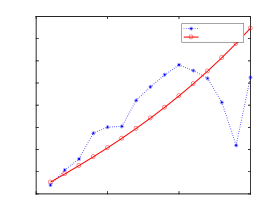
|  |  |  |
| --- | --- | --- |
| Y1  Y2  Y3 | 13  15  11 | 0.6435 0.7835  274  22  21  0.7564 |

**5.4.4** **Neural** **network** **testing** **and** **verification**

For the training sets S1 and S2, the BP neural network performance optimization results determined in Table 10 and Table 11 are used to test the fitting degree of T. Under the training sets S1 and S2, the comparison between the test sample and the prediction result about the three principal components Y1, Y2, and Y3 is obtained, as shown in Fig.4-Fig.6.

As can be seen, the overall gap between the predicted value of each principal component and the actual value is small, and the fluctuation direction of the curve tends to be the same, indicating that the model has high accuracy, good prediction effect, and high reliability of the predicted value data obtained. However, there are also some problems at the same time. For example, there is a gap between the predicted values and actual values in the last three samples ofthe test set in Fig.4 and Fig.6. The main reason is the impact of COVID- 19:

(1) Affected by the epidemic, the overall economic level of the United States has shown a downward trend, which has caused a sudden change in the main component Y1 in March 2020.



(2) Affected by the epidemic, the number of unemployed persons and the unemployment rate in the United States have soared. Y3 mainly reflects the unemployment rate, so Y3 also has a sudden change in March 2020.

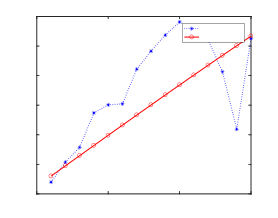


Fig.4 Comparison of test samples and prediction results under the two training sets of Y1

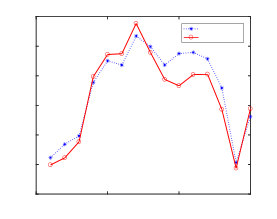


Fig.5 Comparison of test samples and prediction results under the two training sets of Y2

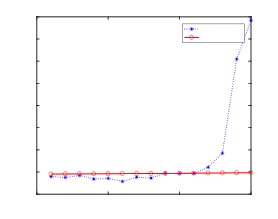
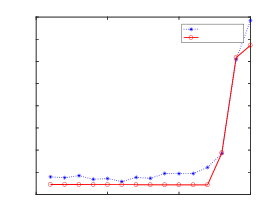
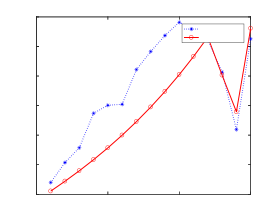


Fig.6 Comparison of test samples and prediction results under the two training sets of Y3

**5.4.5** **Adjustment** **of** **BP** **Neural** **Network** **considering** **COVID-19**

COVID- 19 has caused a sudden change in US policy indicators. In order to add the impact of COVID- 19 to the original results, this article interpolates the values of the three quarters of 2020 on the existing basis and reconstructs BP Neural Network for adjustment. Test the data of the test sample under this adjusted neural network, and the results of Y1 and Y3 are shown in Fig.7-Fig.8.

As can be seen from the figure, the adjusted BP Neural Network takes into account the impact of COVID- 19, which is more consistent with the actual situation.



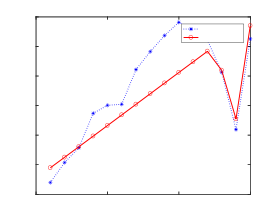


Fig.7 Y1 test results after adjusting the neural network

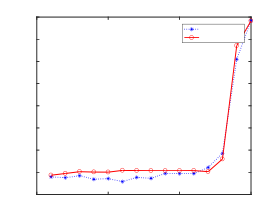


Fig.8 Y3 test results after adjusting the neural network

**5.4.6** **Policy** **indicators** **prediction** **based** **on** **adjusted** **BP** **Neural** **Network**

According to the adjusted BP Neural Network, the subscript of the simulation test is changed to: from the beginning of the forecast quarter to the end of the last quarter of 2024. After Biden and Trump are elected, the predicted values of each principal component of the next four years are shown in Tab.12.

Tab.12 The predicted values of all principal components for the next four years

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Time | Y1 | Biden  Y2 | Y3 | Y1 | Trump  Y2 | Y3 |
| 2020  12  03  06  19  12  03  06  09  12  03  06  09  12  03  06  09  12  -  -  -  -  -  -  -  -  -  -  -  -  -  -  -  -  -  2021  2021  2021  2021  2022  2022  2022  2022  2023  2023  2023  2023  2024  2024  2024  2024 | 2.2028  2.2723  2.3438  2.4180  2.4956  2.5772  2.6636  2.7554  2.8535  2.9586  3.0716  3.1934  3.3249  3.4671  3.6210  3.7877  3.9685 | 2.0065  2.4435  3.0068  3.5992  3.9238  4.2839  4.6829  5.1246  5.6131  6.1524  6.7467  7.4005  8.1182  8.9041  9.7625  10.6973  11.7121 | 0.4706  0.2109  0.0109  -0.3110  -0.4211  -0.4711  -0.4710  -0.4709  -0.4708  -0.4706  -0.4704  -0.4702  -0.4698  -0.4695  -0.4690  -0.4686  -0.4680 | 1.3955  1.5682  1.6337  1.9806  2.0817  2.2203  2.7273  2.9036  3.0502  3.1684  3.2591  3.3237  3.3634  3.3794  3.3731  3.3459  3.2991 | 3.5142  3.7431  3.9803  4.2261  4.4806  4.7443  5.0174  5.3002  5.5930  5.8961  6.2099  6.5346  6.8707  7.2184  7.5781  7.9501  8.3349 | 0.7487  0.8419  0.7122  0.3438  0.1337  0.0351  -0.3386  -0.4442  -0.4422  -0.4402  -0.4392  -0.4342  -0.4042  -0.4014  -0.4012  -0.4011  -0.4011 |



*GDP*(*t*) = −0.45*GDP*(*t* − 1) + 0.84*GDP*(*t* − 2) + 259.10*Y*1(*t* − 1) − 102.19*Y*1(*t* − 2)

**5.5** **Economic** **indicators** **prediction** **based** **on** **VAR** **Model**

This section aims to analyze the relationship between principal component indicators and economic indicators, and then based on the values of the principal component indicators predicted by the BP Neural Network above, the predicted values ofvarious economic indicators in the United States in the next stage can be obtained, and then the economic development trends of the United States when different candidates are elected can be quantitatively analyzed. Vector Autoregressive Model (VAR) is widely used in economics. It mainly uses actual economic data to determine the dynamic structure of the economic system. It is often used to analyze the relationship between interconnected indicators and the impact of random disturbances on the economic system. In view of the built-in VAR model in the economic software EViews10, this paper uses EViews10 software to establish a VAR-based prediction model of US economic indicators. The specific steps are as follows:

Step1: Test the stationarity of the data series, which is the prerequisite for establishing the VAR model. Import historical data of principal component indicators Y1, Y2, Y3 and economic indicators GDP, PPI, and A\_GNI into EViews10, and use the ADF test method to test the stationarity of each item one by one. The criterion for passing the test is that the Prob under level or first difference is less than 0.5. The test results are shown in Tab.13, it can be seen that all the series pass the stationarity test.

Tab.13 Sequence stationarity test results

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Sequence | Order | | t-Statistic | | Prob |
| GDP  PPI | level  first difference | | -4.211361  -9.192985 | | 0.0090  0.0000 |
| A\_GNI  Y1  Y2  Y3 | level  level  level  first difference | | -4.081910  -3.702587  -3.690424  -3.821201 | | 0.0127  0.0321  0.0333  0.0248 |
| Step2: Determining the optimal lag order is an important problem that the VAR model needs to solve. The larger the lag order, the more fully utilized the information, but the freedom degree of the model will decrease, the lag order can be determined according to criteria such as LR, AIC, and SC. This paper integrates multiple criteria in EViews10 to determine the optimal lag order, assuming that the maximum lag order is 5, the values of each criterion are as shown in Tab.14 (take two decimal places; \* indicates the optimal lag order selected by the corresponding criterion, the order with the most marked times is the optimal value), and the optimal lag order is 2.  Tab.14 Lag order determination result | | | | | |
| Lag LogL | | LR FPE | | AIC SC HQ | |

0

1

2

3

4

5

-351.58

-211.72

- 158.99

- 141.15

- 124.43

-99.43

NA

246.42

82.86\*

24.64

19.90

25.01

265.36

0.73

0.13

0.13

0.14

0.11\*

16.93

11.03

9.29

9.20

9.16

8.73\*

17.10

11.86

10.77\*

11.35

11.98

12.21

16.99

11.34

9.83\*

9.99

10.19

10.01

Step3: Establish a VAR model with a lag order of 2, and get the relationship between GDP and Y1, Y2, and Y3 as shown in the equation (the coefficients retain two decimal places).

+3.02*Y*2 (*t* − 1) − 11.90*Y*2 (*t* − 2) − 142.00*Y*3(*t* − 1) + 37.25*Y*3(*t* − 2) + 2745.08 (14)

Similarly:

*PPI*(*t*) = −0.34*PPI*(*t* − 1) + 0.04*PPI*(*t* − 2) + 0.35*PPI*(*t* − 3) +5.71*Y*1(*t* − 1) − 6.25*Y*1(*t* − 2) +1.95*Y*1(*t* − 3)

−0.83*Y*2 (*t* − 1) + 3.43*Y*2 (*t* − 2) − 1.83*Y*2 (*t* − 3) − 10.85*Y*3 (*t* − 1) − 2.75*Y*3 (*t* − 2) + 5.62*Y*3 (*t* − 3) + 90.23

*A* \_ *GNI*(*t*) = 0.87*A* \_ *GNI*(*t* − 1) − 1.17*A* \_ *GNI*(*t* − 2) − 1.52*A* \_ *GNI*(*t* − 3) +0.15*A* \_ *GNI*(*t* − 4) +1.10*A* \_ *GNI*(*t* − 5) + 8951.40*Y*1(*t* − 1) −6076.37*Y*1(*t* − 2) + 3514.18*Y*1(*t* − 3) − 1322.38*Y*1(*t* − 4) +821.06*Y*1(*t* − 5) − 4080.84*Y*2 (*t* − 1) + 3168.15*Y*2 (*t* − 2) − 1250.89*Y*2 (*t* − 3) +1233.70*Y*2 (*t* − 4) − 1304.08*Y*2 (*t* − 5) −7473.31*Y*3 (*t* − 1) − 4625.25*Y*3 (*t* − 2) +10934.90*Y*3(*t* − 3) −4265.30*Y*3 (*t* − 4) − 6841.72*Y*3 (*t* − 5) + 85461.90

(15)

(16)

Substituting historical data and the predicted values of principal component indicators, the predicted results of each economic indicator are shown in Tab.15 and Fig.9-Fig.11.

Tab.15 The predicted values ofvarious economic indicators

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Time | GDP （billion dollars） Trump Biden | | PPI  Trump Biden | | A\_GNI （dollar） Trump Biden | |
| 2020- 12  2021-03  2021-06  2021- 19  2021- 12 | 5086.81  4805.535  4999.88  4695.577  5124.533 | 5086.81 5049.639 5082.009 5063.232  5144.604 | 101.9951 74.34591 109.8216 91.04404  96.14367 | 101.9951 83.22399 109.3108 99.70397  100.7749 | 47432.59 40863.95 45475.46 45409.56  49034.48 | 47432.59 56321.35 56848.98 51808.63  54164.56 |
| 2022-03 | 4680.776 | 5102.774 | 107.3704 | 110.9566 | 52392.94 | 53456.89 |
| 2022-06 | 5270.522 | 5203.659 | 97.80077 | 103.064 | 46903.04 | 56414.29 |
| 2022-09 | 4796.86 | 5132.503 | 108.8678 | 106.4886 | 55694.66 | 61316.42 |
| 2022- 12 | 5498.171 | 5261.135 | 108.5957 | 108.773 | 57584.03 | 64017.64 |
| 2023-03 | 4798.222 | 5156.069 | 104.8989 | 105.8991 | 58022.41 | 58075.04 |
| 2023-06  2023-09  2023- 12  2024-03  2024-06  2024-09  2024- 12 | 5715.377 4723.659 5944.629 4559.166 6206.385 4295.391  6529.724 | 5324.805  5174.945  5399.478  5189.061  5490.132  5197.08  5602.581 | 109.7317 108.1466 107.8199 109.4828 108.5009 109.1625  109.6949 | 108.7453 109.0967 108.7799 110.6576 110.9594 111.7259  113.1192 | 54046.78 51748.34 54751.49 59258.02 60304.37 68317.84  70634.08 | 64438.78 67423.44 61430.04 68374.59 74748.27 80234.17  79265.53 |

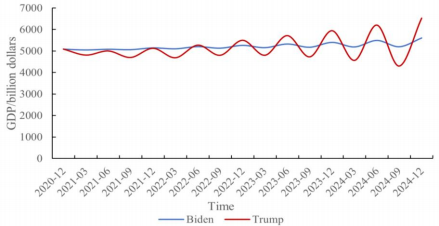


Fig.9 Comparison of GDP prediction results The analysis ofthe impact of different candidates on GDP is as follows:

(1) GDP overall volatility

Comparing Biden and Trump’s overall GDP change trend during the post-election term, we can find that Biden’s overall GDP volatility after election is relatively small. The reason is that Biden pays more attention to the independence of the Federal Reserve and has stricter currency supervision. In other words, Biden's economic policies tend to be more conservative.

(2) Total GDP during the tenure

Comparing Biden's and Trump's total GDP in the post-election terms, Biden's is 8,8660.5 (billion dollars), and Trump's is 8,7731.2. Compared to Trump, Biden’s total GDP is slightly larger. The reason is that Biden has adopted stricter anti-epidemic measures relative to Trump. Therefore, the GDP rebound in 2021 is more obvious, which makes GDP return to normal levels as soon as possible. This also causes the total GDP of Biden to be slightly larger.

(3) GDP comparison at the beginning ofthe tenure

Comparing Biden's and Trump's GDP at the beginning of the tenure, it can be found that Trump's GDP at the beginning of his term is lower than that of Biden. The reason is that Trump continues to adopt loose anti-epidemic policies, which has led to the continued sluggish GDP trend during his tenure.

(4) GDP comparison at the end oftenure

Comparing Biden’s and Trump’s post-election GDP at the end of the term, it can be found that Trump’s GDP is higher than that of Biden. The reason is that Trump adopts loose economic policies, and implements comprehensive tax cuts and loose monetary, fiscal, and financial

supervision policies. Therefore, the economic bubble is higher than that of Biden.

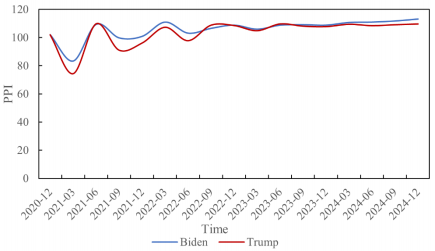


Fig.10 Comparison ofPPI prediction results

The analysis ofthe impact of different candidates on PPI is as follows:

(1)On the macro level, the election of Trump and the election of Biden have basically the same impact on the PPI, because no matter who is elected, there is a high probability that the fifth round of financial relief plan will be required to deal with the impact of the epidemic on the US economy. In the short term, it will increase inflation in the United States, thereby reducing PPI.

(2) At the micro level, Trump’s inadequate attention to the epidemic will lead to greater volatility in his PPI than when Biden is elected. Eventually, with the gradual control of the global epidemic and the acceleration of vaccine research and development, the changes in PPI will gradually stabilize and the US economy will gradually stabilize.

The analysis ofthe impact of different candidates on A\_GNI is as follows:

When Biden is elected president of the United States, the predicted value of A\_GNI is larger than that of Trump. This is because Biden’s plan to increase taxes on the rich and companies and raise the minimum wage is conducive to reducing the gap between the rich and the poor and increasing A\_GNI, while Trump advocates tax cuts that benefit the rich even more, which is not conducive to the increase in A\_GNI.

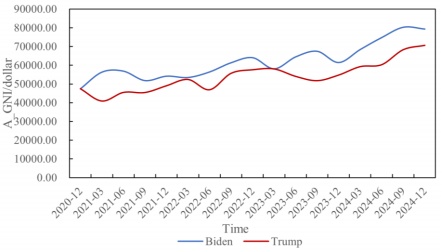


Fig.11 Comparison ofA\_GNI prediction results

**6** **Modeling** **and** **solution** **of** **problem** **two**

**6.1** **Comparison** **of** **policies** **towards** **China**

Biden and Trump have more consensus on China policy, but Biden has a clear welcome attitude towards cooperation in areas of common interests between China and the United States. The following is a comparison ofthe two candidates' views on China policy in terms of COVID- 19 epidemic prevention policy, taxation, energy and environmental protection, science and technology, trade, finance and education.

Tab.16 Comparison of U.S. presidential candidates' views on China Policy

|  |  |  |
| --- | --- | --- |
| Policy | Trump | Biden |
| COVID- 19 epidemic prevention policy | Reducing cooperation  between China and the US in  epidemic prevention | China should be responsible  for the adverse epidemic  prevention, but strengthen the  cooperation between China  and the United States on  epidemic situation |
| Tax revenue | Punitive tariffs on Chinese goods | Against the tariff fortress, but  some aspects still impose  tariffs |
| Energy and environmental protection | Pay attention to the  development of traditional  energy, and do not care about  environmental protection | Cooperation with China on  climate change and clean  energy |
| Science and technology | Imposing scientific and  technological sanctions on  China and suppressing  China's science and  technology industry | Increasing restrictions on  China's technological  progress |
| Trade | Continue the trade war with  China and adhere to trade  protectionism | China and the United States  should ease trade frictions  and put pressure on China  through the cooperation of  trade allies |
| Finance | Reducing investment in China  and preventing Chinese  enterprises from going to the  United States for listing | Oppose financial sanctions against China |
| Education | Against Chinese students going to the United States | Accepting Chinese students |

**6.2** **Data** **acquisition** **and** **preprocessing**

The second question requires a quantitative analysis of the impact of the election of different candidates on China's economy. Therefore, it is necessary to obtain the indicator data that can easily reflect the impact ofthe U.S. policy on China in China's economy.

The data obtained should include two aspects:

(1) Policy index data that can reflect the impact of China's policy changes, and the data structure is shown in Tab.17;

(2) The economic index data representing China's economic changes, mainly considering China's Total Import and Export Trade(TIE) and Customs Duties(CD), and the data structure is shown in Tab.18. After extensive data collection, the complete data results obtained are shown in Attachment 1, and the data source is Zhonghong statistical database.

Tab.17 Data structure of China policy indicators

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Time(quarterly) | Z1(100 million tons) | | Z2(thousands of US dollars) | | Z3 Z4(%) |
| Tab.18 Data structure of China's economic indicators | | | | | |
| Time(quarterly) | | TIE(US $100 million) | | CD(RMB 100 million) | |

Some ofthe data obtained in question 2 also lack some quarterly data values, so the same Lagrange interpolation method is used to interpolate the missing values.

**6.3** **Fitting** **and** **forecasting** **of** **policy** **indicators** **value** **based** **on** **BP**

**Neural** **Network**

Because the number of China policy indicators is small, so it is no longer the same as the first question of principal component analysis, directly using BP neural network to fit and forecast the China policy indicators of Trump and Biden presidential candidates in the next term of office, and get the prediction results, which is prepared for the subsequent prediction of China's economic indicators based on VAR model.

**6.3.1** **Determination** **of** **training** **and** **testing** **sample** **data**

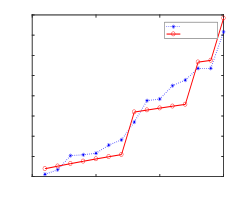
(1) Training sample S3

Considering that Biden served as vice president of the United States during the Obama administration, and combined with Biden's China policy during the election campaign, and compared with the China policy of Obama's period, the results are shown in Tab.19. Among them, 1 represents that Biden's policies are similar to those of Obama, and 0 represents that they are not.

Tab.19 Comparison of policy similarities between Biden and Obama

|  |  |  |
| --- | --- | --- |
| Policy Similar or not | Policy | Similar or not |
| |  |  | | --- | --- | | Tax revenue | 1 | | Energy and environmental protection | 1 | | Science and technology | 1 | | Trade  Finance  Education | 1  0  1 |

Novel coronavirus pneumonia is not considered in the above table. The similarity between Biden and Obama in China during the period of administration is also very high, reaching 83.3%. Therefore, we use the data related to Obama's China policy from 2008 to 2016 as a training sample for Biden, named S3 .



(2) Training sample S4

The collected data on China policy from 2008 to 2020 are used as training samples for candidate Trump, named S4.

(3) Test sample U

Similar to the first question, this paper selects the data of Trump's China policy for four years as the test sample.

**6.3.2** **Performance** **optimization** **of** **BP** **Neural** **Network**

(1) Performance optimization of BP neural network based on training set S3

Using the first question to adjust the number of neurons and training samples in the hidden layer, the correlation coefficient value corresponding to the number of neurons in each hidden layer is obtained, and the number of neurons with the maximum correlation coefficient is selected to construct the corresponding neural network. The performance optimization results of BP Neural Network for all China policy indicators are shown in Tab.20.

Tab.20 Performance optimization results of BP Neural Network

Policy indicators on China

Number of neurons

Number of iterations

Correlation

coefficient

Z1

Z2

Z3

Z4

15

13

13

20

7

245

8

11

0.995193

0.712234

0.992345

0.822344

(2) Performance optimization of BP neural network based on training set S4

According to the above method, the BP neural network performance optimization of training set S4 is carried out, and the results are shown in the Tab.21.

Tab.21 Performance optimization results of BP Neural Network

Policy indicators on China

Number of neurons

Number of iterations

Correlation

coefficient

Z1

Z2

Z3

Z4

13

20

15

19

35

9

18

172

0.970633

0.631422

0.875645

0.883397

**6.3.3** **BP** **Neural** **Network** **test** **and** **verification**

Aiming at the training set S3 and S4, the fitting degree of U (test sample) is tested according to the optimization results of BP neural network determined in Tab.20 and Tab.21 respectively. Under the training set S3 and S4, the comparison between the test samples and the prediction results on the four China policy indicators Z1, Z2, Z3 and Z4 is obtained, as shown in Fig.12-

Fig.15.

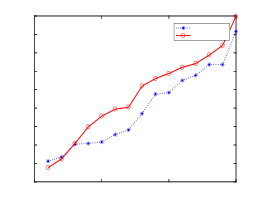
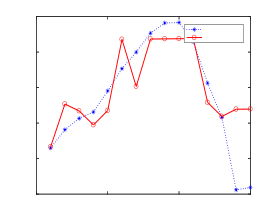
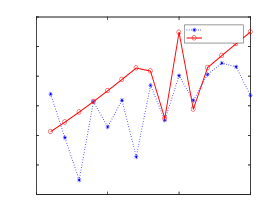
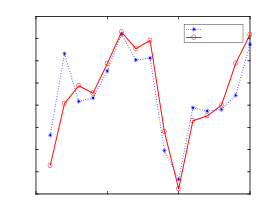


Fig.12 Comparison of test sample and prediction result Z1 under two training sets



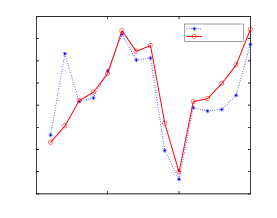


Fig.13 Comparison of test sample and prediction result Z2 under two training sets

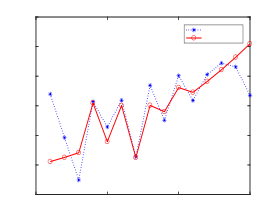


Fig.14 Comparison of test sample and prediction result Z3 under two training sets

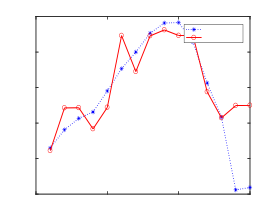
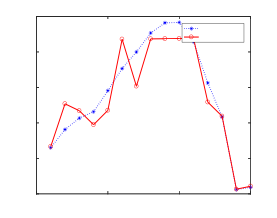
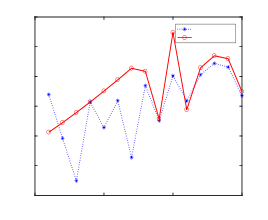


Fig.15 Comparison of test sample and prediction result Z4 under two training sets

It can be seen from the above figure that the overall gap between the predicted value and the actual value of China policy indicators is small, and the fluctuation direction of the curve tends to be consistent, which indicates that the accuracy of the model is high, the prediction effect is good, and the predicted value data credibility is high. Novel coronavirus pneumonia is also the same problem as the first question. For example, there is a gap between the predicted value and the actual value of the final 3 samples ofthe test set 1 and 2. The main reason is the impact ofCOVID- 19 epidemic:

(1) Affected by the epidemic situation, the overall economic level of the United States has



shown a downward trend. Due to the remarkable effect of epidemic prevention and control and rapid economic recovery in China, the exchange rate of US dollar against RMB has declined, the US dollar has depreciated, and the RMB has appreciated, resulting in the mutation of Z3 in March 2020.

(2) Affected by the epidemic, the U.S. economy is going down, and the Federal Reserve adopts a zero interest rate policy, so the federal reserve fund interest rate continues to be low, resulting in a sudden change in Z4 in March 2020.

**6.3.4** **Adjustment** **of** **BP** **Neural** **Network** **considering** **COVID-19**

In order to add the influence ofthe new epidemic situation to the original results, BP Neural Network was adjusted according to question 1, and the test results of Z3 and Z4 after adjustment were obtained as shown in Fig.16-Fig.17.

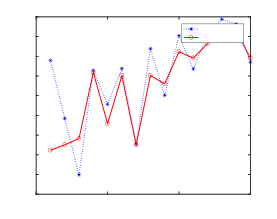


Fig.16 Z3 Test results after adjusting neural network

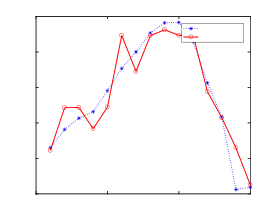


Fig.17 Z4 Test results after adjusting neural network

**6.3.5** **Prediction** **of** **policy** **indicators** **value** **based** **on** **adjusted** **BP** **Neural**

**Network**

According to the above adjusted BP Neural Network, the subscript of simulation test is changed to: from the beginning of forecast quarter to the end of the last quarter in 2024. After Biden and Trump are elected respectively, the forecast values of each China policy indicator in the next term are shown in Tab.22.

Tab.22 The forecast values of China policy indicators of Biden and Trump

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Time |  | Biden |  |  | Trump |  |
| Z1 | Z2 Z3 | Z4 | Z1 | Z2 Z3 | Z4 |
| 2020- 12  2021-03  2021-06  2021- 19  2021- 12  2022-03 | 14.4633 14.4882 14.5121 14.5349 14.5568  14.5777 | 146336890  6.8385 6.8383 6.8381 6.8380 6.8379  6.8378  156456400  144233236  166495358  183191879  161708401 | 0.2059 0.2313 0.2503 0.2644 0.2748  0.2823 | 13.5263 13.6396 13.7467 13.8480 13.9436  14.0337 | 156336890  6.8302 6.8492 6.8687 6.8887 6.9093  6.9304  176456400  184233236  156495358  153191879  161708401 | 1.1543 1.1698 1.1847 1.1991 1.2129  1.2261 |
| 2022-06 | 14.5978 | 163246349 6.8377 | 0.2878 | 14.1185 | 163246349 6.9520 | 1.2388 |
| 2022-09 | 14.6171 | 175448432 6.8376 | 0.2918 | 14.1983 | 165448432 6.9742 | 1.2510 |
| 2022- 12 | 14.6357 | 191955101 6.8375 | 0.2946 | 14.2733 | 161955101 6.9970 | 1.2627 |
| 2023-03 | 14.6536 | 180362600 6.8375 | 0.2966 | 14.3437 | 160362600 7.0203 | 1.2738 |
| 2023-06 | 14.6708 | 181238900 6.8374 | 0.2979 | 14.4097 | 161238900 7.0442 | 1.2846 |
| 2023-09  2023- 12  2024-03  2024-06  2024-09  2024- 12 | 14.6875 14.7036 14.7193 14.7345 14.7493  14.7638 | 189538000  6.8374 6.8373 6.8373 6.8373 6.8373  6.8372  186602383  189603459  186645430  192688457  189926522 | 0.2989 0.2995 0.2998 0.3000 0.3001  0.3001 | 14.4717 14.5297 14.5840 14.6349 14.6825  14.7271 | 169538000  7.0686 7.0936 7.1191 7.1452 7.1718  7.1991  166602383  169603459  166645430  172688457  179926522 | 1.2948 1.3046 1.3140 1.3230 1.3316  1.3398 |

**6.3.6** **China's** **economic** **indicators** **prediction** **based** **on** **VAR** **model**

Referring to the analysis method of question 1, based on the value of each China policy index predicted by BP Neural Network, the vector autoregressive model (VAR) is used to analyze and obtain the forecast value of China's economic indicators in the next stage.

This paper uses EViews10 software to establish a VAR based prediction model of the impact of U.S. policy on China's economic indicators. The relationship between China's economic indicators TIE and China policy indicators is obtained as shown in formula (17) (the coefficient is kept to two decimal places).

*TIE*(*t*) = −0.05*TIE*(*t* − 1) + 0.71*TIE*(*t* − 2) + 0.17*TIE*(*t* − [3)](#_bookmark64)

+204.95*Z*1(*t* − 1) − 41.65*Z*1(*t* − 2) + 991.70*Z*1(*t* − [3)](#_bookmark65)

+3.32*e* − 06*Z*2 (*t* − 1) − 6.52*e* − 05*Z*2 (*t* − 2) − 2.48*e* − 05*Z*2 (*t* − 3) (17) −2322.39*Z*3 (*t* − 1) + 94.20*Z*3 (*t* − 2) + 650.02*Z*3(*t* − [3)](#_bookmark66)

+458.91*Z*4 (*t* − 1) + 4266.21*Z*4 (*t* − 2) − 4856.57*Z*4 (*t* − 3) +14255.72

Similarly, the relationship between China's economic indicator CD and China policy indicators can be obtained, as shown in formula (18).

*CD*(*t*) = 0.24*CD*(*t* − 1) + 0.30*CD*(*t* − 2) − 0.01*CD*(*t* − [3)](#_bookmark66)

+117.14*Z*1(*t* − 1) − 50.66*Z*1(*t* − 2) − 8.19*Z*1(*t* − [3)](#_bookmark67)

− 1.92*e* − 06*Z*2 (*t* − 1) + 4.91*e* − 07*Z*2 (*t* − 2) − 5.68*e* − 07*Z*2 (*t* − 3) (18) +12.35*Z*3 (*t* − 1) − 186.68*Z*3 (*t* − 2) +195.87*Z*3 (*t* − [3)](#_bookmark68)

−86.57*Z*4 (*t* − 1) + 328.85*Z*4 (*t* − 2) − 327.51*Z*4 (*t* − 3) − 3.36

By substituting the historical data and the predicted values of policy indicators for China, the forecast results of China's economic indicators are shown in Tab.23 and Fig.18-Fig.19.

Tab.23 The predicted values ofvarious economic indicators for China

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Time | TIE （US $100 million） Trump Biden | | CD(100 million RMB) Trump Biden | |
| 2020- 12  2021-03  2021-06  2021- 19  2021- 12 | 6890.357  15070.94  13969.15  14941.54  16814.06 | 6890.357  15427.69  10875.76  19357.2  15556.93 | 593.4982  1026.773  1284.623  1110.595  1176.988 | 593.4982  1232.991  1181.862  1335.361  1315.009 |
| 2022-03 | 17328.38 | 20244.78 | 1144.608 | 1337.854 |
| 2022-06 | 19034.96 | 19559.75 | 1164.777 | 1353.997 |
| 2022-09 | 19696.36 | 21774.07 | 1163.094 | 1352.737 |
| 2022- 12 | 20679.85 | 21772.61 | 1164.28 | 1352.034 |
| 2023-03 | 21627.96 | 22182.64 | 1171.361 | 1327.306 |
| 2023-06  2023-09  2023- 12  2024-03  2024-06  2024-09  2024- 12 | 22488.34  23364.2  23658.52  24603.85  24552.95  25552.26  25198.44 | 22970.27  22779.29  23206.92  23363.15  23253.32  23714.81  23211.23 | 1177.487  1184.669  1179.96  1187.201  1180.906  1189.741  1181.768 | 1331.262  1314.779  1307.527  1305.279  1294.381  1297.796  1285.822 |

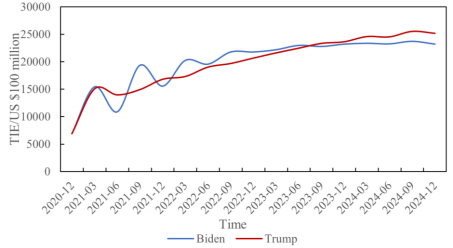


Fig.18 Comparison of TIE prediction results The analysis ofthe impact of different candidates on TIE is as follows:

(1) TIE overall change trend

By comparing the overall change trend of China's total trade volume between Biden and Trump during their term of office, we can find that after Biden's election, China's total trade volume tends to be stable after the initial rapid growth, while after Trump's election, it shows a slow growth trend. The reason is that Biden encourages the elimination of trade barriers, while Trump does the opposite.

(2) TIE initial fluctuation

Comparing the total trade volume of China between Biden and Trump at the beginning of his term of office, it can be found that China's total trade volume fluctuated after Biden's

election, because the change of policies after the election will have a certain impact on Sino US trade.

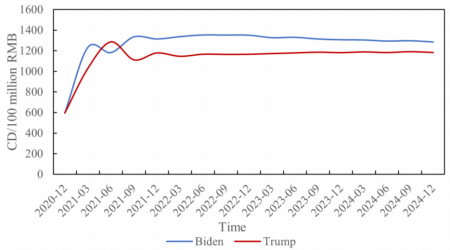


Fig.19 Comparison of CD prediction results

The analysis ofthe impact of different candidates on CD is as follows:

(1) CD overall stable value

Compared with the general changes of China's tariff revenue after Biden and Trump were elected, the trend of the two changes was almost the same, but the final stable value of Biden was larger, because Biden opposed to continue to impose trade tax on China, so China's tariff revenue rose accordingly after Biden took office

(2) CD later changes

Compared with the change trend of China's tariffrevenue at the end of Biden's and Trump's term of office, China's tariff showed a weak downward trend at the end of Biden's term of office, because he exerted trade pressure on China through other channels.

**7** **Modeling** **and** **solution** **of** **problem** **three**

**7.1** **The** **judgment** **process** **of** **AHP**

Based on the basic principle of AHP, this paper first establishes the hierarchical structure model according to the impact ofAmerican presidential candidates' policy indicators on China's economy, and then uses different methods to construct the judgment matrix of criteria-layer and scheme-layer and conduct consistency test. Then, the importance of the policies of the two candidates on China's economy is obtained in order of hierarchy, and finally a conclusion is drawn.



|  |
| --- |
| Joe Biden elected |

|  |
| --- |
| Donald Trump elected |

|  |  |
| --- | --- |
| Establishment of hierarchical structure model  Target layer Criterion layer Scheme layer | |
|  |  |
| |  | | --- | | Consistency check |  |  | | --- | | Criterion-level judgment matrix |  |  | | --- | | Scheme-level judgment matrix |  |  | | --- | | The construction of the judgment matrix | | |
|  |  |
| |  | | --- | | Plan importance |  |  | | --- | | Hierarchical ranking and inspection |      |  | | --- | | Hierarchical sorting | | |

Fig.20 AHP-based process for judging the impact of the US presidential election on China's economy

**7.2** **Establishment** **of** **hierarchical** **structure** **model**

According to the impact of US presidential candidates' policy indicators on China's economy, a three-layer hierarchical structure model with target layer, criterion layer (10 indicators) and scheme layer (2 schemes) is established, as shown in Fig.21.

|  |
| --- |
| Target layer |

One

|  |
| --- |
| Criterion layer |
| Ten |
| Scheme layer |

|  |
| --- |
| Impact on China's economy |



|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  | | --- | | *Proportion* *of* *education* *expenditure* |  |  | | --- | | *Total* *number* *of* *international* *migrants* |  |  | | --- | | *Stockprice* *general* *500* *index* |  |  | | --- | | *Total* *Import* *and* *Export* |  |  | | --- | | *Unemployment* *rate* |  |  | | --- | | *Domestic* *general* *government* *health* *expenditure* *per* *capita* |  |  | | --- | | *Per* *capita* *CO2* *emissions* |  |  | | --- | | *Infrastructure* *investment* |  |  | | --- | | *Tax* *revenue* |  |  | | --- | | *Trade* *deficit* | |



Two

Fig.21 Hierarchical structure model

(1) Target layer

The target layer is the purpose of using AHP, taking the best economic situation of China as the target layer.

(2) Criterion layer

Ten policy indicators affected by the US presidential candidate policy are taken as the standard level indicators, which are infrastructure investment, tax revenue, per capita CO2 emissions, per capita domestic general government health expenditure, unemployment rate, total import and export, trade deficit, stock price general 500 index, total number of international immigrants and proportion of education expenditure.

(3) Scheme layer

The two major US presidential candidates, namely the election of Trump and the election

 *i*  

ofBiden.

**7.3** **The** **construction** **of** **judgment** **matrix**

In AHP, the judgment matrix of each layer represents the relative importance of all indicators of this layer to the corresponding indicators of the upper layer. The hierarchical structure model shown in Fig.21 has three layers: the target layer, the criterion layer and the plan layer. Therefore, there are two types ofjudgment matrices, namely the criterion layer and the plan layer judgment matrix. Among them, the criterion layer needs to construct a judgment matrix. The layer needs to construct 10 judgment matrices.

(1) The construction of criterion-layer judgment matrix

In order to avoid the shortcomings of highly subjective scoring by experts, this article takes the three principal component forecast data for the next term after Trump and Biden are elected, and then normalizes them as sample independent variables to predict data for China policy indicators. After comprehensive averaging, normalization is used as the sample dependent variable, and the multiple linear regression method is used to construct the criterion- layer judgment matrix. Specific steps are as follows:

1)Data normalization

In order to avoid the influence of different index dimensions on the analysis results, it is necessary to normalize the samples. In this paper, the max normalization method is used, that is to make the indexes of each sample *Yi* = *Yiorig* / *Yi*max , where *Yiorig* is the original value of index *Yi* in the sample, *Yi*max is the maximum value of index *Yi* in all samples. Obviously, after normalization, the values of *Yi* in the sample are all located in [0,1].

2)Multiple linear regression



For the selected independent variable *Yi* and dependent variable *Z*

( *Z* = ( *Zi*) / 3,*i* = 1, 2,3 ), use the following equation to perform multiple linear regression:

*Z* = *a*0 + *a*1*Y*1 + *a*2*Y*2 + *a*3*Y*3 (19)

Then multiply the regression coefficients of the three principal components with the correlation coefficients of the ten policy indicators and sum them to obtain the importance of these ten policy indicators.

Let the principal component expression be

*Yi* = *bijXj* , *i* = 1, 2,3, *j* = 1, 2,...,10 (20)

Then the formula for calculating the importance of the ten policy indicators is

*Sj* = min  *aibij* ,9  , *i* = 1, 2,3, *j* = 1, 2,...,10 (21)

Finally, the criterion-layer judgment matrix is constructed according to this importance.

(2) The construction of the scheme-layer judgment matrix

In the same way, according to the above method, the importance of ten policy indicators in the case of two presidential candidates being elected respectively is constructed, and the importance of the two is compared to construct a judgment matrix at the scheme-layer.

(3) Judgement matrix construction result

The multiple linear regression equation is as follows

*Z* = 0.27 +1.36*Y*1 + 0.69*Y*2 + 0.05*Y*3 (22)

The importance results of the ten policy indicators are as follows

Tab.24 Importance of policy indicators

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Policy indicators | 1  *X* | 2  *X* | 3  *X* | 4  *X* | 5  *X* | 6  *X* | 7  *X* | 8  *X* | 9  *X* | 10  *X* |
| Importance | 1 | 3 | 3 | 3 | 3 | 5 | 7 | 9 | 5 | 1 |

The criterion-layer judgment matrix is constructed according to the above-mentioned importance results, and the judgment matrix of the scheme layer can be obtained in the same



*n* *i*=1 *Wi*

*i* *n*

*i*

way. The specific results are shown in Attachment 1.

**7.4** **Hierarchical** **ranking** **and** **inspection**

(1) Hierarchical ranking and inspection steps

Sort the judgment matrices at each layer, calculate the weight vector, and perform consistency testing. To facilitate the introduction of the method, let the currently considered judgment matrix be *An**n* , which is a square matrix of order 1, and its elements are *aij* .

This paper uses the square root method to calculate the weight vector. The calculation steps are as follows:

1)Find the product of each row element of the judgment matrix *M*

*Mi* = *aij* , *i* = 1, 2, , *n* (23)

*j*=1

2)Calculate the nth root of *M*

*Wi* = , *i* = 1, 2, ,*n* (24)

3)Calculate the weight vector and eigenvalue

*n*

*Wi* = *Wi* / *Wj* , *i* = 1, 2, , *n* (25)

*j*=1

 = (26)

1 *n* (*AW*)*i*

The consistency test method for the judgment matrix *A* is as follows:

1)Calculate the consistency index

*C*.*I*. = max (27)

 − *n*

*n* − 1

2)Find the corresponding average random consistency index, see Tab.25 Tab.25 Consistency Indicator *R.I.*

|  |  |  |
| --- | --- | --- |
| *n* 1 2 3 4 5 6 7 | | 8 9 10 11 12 |
| *R.I.* 0.00 0.00 0.52 0.89 1.12 1.26 1.36 | | 1.41 1.46 1.49 1.52 1.54 |
| 3)Calculate the agreement ratio  (28)  *C*.*R*.  0.1 , the  *C*.*I*.  *C*.*R*. =  *R*.*I*.  When *C*.*R*.  0.1 , the judgment matrix is considered acceptable; when judgment matrix should be revised.  (2) Hierarchical ranking and test results  Tab.26 shows the weight of the influence of the two US presidential candidates on China's economy.  Tab.26 The weight of the elements in the scheme-layer to the decision goal Options  Weights  Joe Biden elected 0.51  Donald Trump elected 0.49  It can be seen from Tab.26 that the election of Trump or Biden has little difference in the impact of the Chinese economy. Therefore, it is only necessary to analyze the impact of different policies on the Chinese economy without distinguishing specific leaders. The weight ranking of ten policy indicators is shown in Tab.27.  Tab.27 The weight of policy indicators to decision goals | | |
| Policy  indicators | |  |  |  |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | | *X* | *X* | *X* | *X* | *X* | *X* | *X* | *X* | *X* | *X* | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | | |

Weights 0.025 0.075 0.075 0.075 0.075 0.125 0.175 0.225 0.125 0.025

It can be seen from the table that the weight of *X*8 is the largest, followed by *X*7 , and

*X*6 . The sum of the three weights accounts for more than 50%. Therefore, this paper mainly analyzes the impact of the policies corresponding to the three indicators on China's economy and puts forward countermeasures.

**7.5** **The** **influence** **of** **US** **presidential** **election** **results** **on** **China's**

**economy** **and** **Countermeasures**

From the above analysis, it can be concluded that no matter which U.S. presidential candidate is elected, its impact on China's economy is not much different, because Biden and Trump have more consensus than differences on China policy, and both advocate taking a tough attitude towards China. Therefore, for China's economic development, the countermeasures can be similar.

From the weight of policy indicators on China’s economy, it can be seen that the Stock price general 500 index has the greatest impact on China’s economy, followed by trade deficit and total imports and exports. These indicators mainly correspond to the financial and trade policies of US, and appropriate China's economic policies should be put forward for these policies.

The financial and monetary policies and foreign trade policies of US have a great impact on China's economy, which shows that China's dependence on foreign economy is too strong, which is inseparable from opening up and economic globalization. However, with the sudden change of the international environment, the prevalence of de globalization, the trade war between China and US, the global COVID- 19 epidemic continues to break out, and the uncertainty increases.

In the short term, China should improve its market diversification and expand its markets outside US with the help of the "One Belt One Road" initiative. It is possible to further strengthen cooperation with the European Union, East Asia and other regions in the financial, currency and trade fields, expand the scope of cross-border use and cross-border payments of the RMB, and minimize the excessive dependence of monetary policy on the US monetary policy.

From a long-term perspective, China should focus on domestic demand, deepen supply- side structural reforms, and alleviate imbalances and inadequacy in economic development. Effectively change the situation that has been at the low end of the international industrial chain for many years, change the one-sided export that relies solely on commodity trade, and shift to both commodity trade and service trade. With the domestic big cycle as the main body, the domestic and international double cycles promote each other, and accelerate the formation ofa new development pattern.

**8** **Model** **evaluation** **and** **promotion**

**8.1** **Model** **evaluation**

(1) In terms of data sources, this paper selects data from multiple economic databases to ensure reliable and abundant data sources.

(2) In question 1, this paper first interpolates the missing data, and uses Lagrange interpolation to interpolate the missing values, which can improve the quality of data and the accuracy of fitting and prediction in the model. Then, principal component analysis is used to extract the principal components of ten policy indicators, which effectively retains the parameter information of the original policy indicators on the premise that the principal components are independent of each other. Secondly, through the comparative analysis of BP neural network errors of different parameters, the optimal network parameters are determined.

Based on this, the BP neural network which can accurately predict the main component values is established and adjusted according to the impact of epidemic situation. According to the fitting degree between the adjusted data and the test set, the prediction results are reliable. Finally, based on the VAR model, the relationship between the U.S. economic indicators and the principal components is given, and then the predicted values ofthe U.S. economic indicators in the next four years after the two candidates are elected respectively are obtained. The VAR economic prediction model has been widely used in the economic circles and proved to be reasonable and reliable.

(3) In question 2, this paper adopts the same treatment method as the first one. The main difference lies in the different selection of indicators, which mainly focuses on the selection of indicators for China policy, which conforms to the question hypothesis.

(4) In question 3, the analytic hierarchy process (AHP) model based on multiple linear regression is used to analyze and calculate the influence weight of each policy of the two candidates and their influence on China's economy. Different from the judgment matrix determined by the expert scoring method in the conventional analytic hierarchy process (AHP), this paper analyzes and calculates the policy data of question 1 and the economic data of China in question 2 Meta linear regression, according to the regression coefficient to determine the importance of indicators, and then construct a judgment matrix, to avoid the subjective impact caused by artificial scoring.

**8.2** **Model** **promotion**

In this paper, BP Neural Network adjustment indicators value fitting and forecasting method based on epidemic situation, the economic prediction model based on VAR and the analytic hierarchy process model based on multiple linear regression can be applied to predict the impact of any two presidents on the economy of China and the United States in the future election.

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**Attachment**

**Attachment** **1**

**Question** **1** **raw** **data** **(**data source: the World Economic Database of China Economic Information Network.)

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Indicator | Policy indicator | | | | | | | | | | Economic indicator | | |
| Time | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 | GDP | PPI | A\_GNI |
| 2009-03 | 107.9592 | 291705 | 4.00 | 854.19 | 8.80 | 623600 | 122000 | 797.87 | 13907427 | 10.88 | 3598.64 | 86.18 | 42572.29 |
| 2009-06 | 107.6463 | 280858 | 4.07 | 929.65 | 9.13 | 611700 | 111300 | 919.32 | 11500592 | 12.40 | 3588.21 | 83.82 | 44406.70 |
| 2009-09 | 108.1524 | 281105 | 4.29 | 949.89 | 9.60 | 662300 | 127700 | 1057.08 | 10957104 | 13.25 | 3605.08 | 86.41 | 45195.36 |
| 2009- 12 | 109.7103 | 290590 | 4.37 | 953.17 | 9.53 | 718100 | 142700 | 1115.10 | 10932390 | 13.54 | 3657.01 | 86.48 | 46936.26 |
| 2010-03 | 103.0495 | 307843 | 4.38 | 953.75 | 10.40 | 752700 | 149900 | 1169.43 | 10972209 | 13.52 | 3680.34 | 88.20 | 47982.05 |
| 2010-06 | 104.4826 | 318291 | 4.36 | 954.57 | 9.47 | 786400 | 161600 | 1030.71 | 10994386 | 13.15 | 3731.52 | 90.03 | 48219.81 |
| 2010-09 | 105.5594 | 327832 | 4.35 | 965.45 | 9.47 | 810300 | 165700 | 1141.20 | 11045910 | 12.79 | 3769.98 | 92.22 | 48206.80 |
| 2010- 12 | 106.6859 | 334587 | 4.36 | 974.11 | 9.13 | 842700 | 158300 | 1257.64 | 11111204 | 12.65 | 3810.21 | 91.23 | 48902.93 |
| 2011-03 | 103.1794 | 367183 | 4.36 | 976.28 | 9.50 | 889800 | 178600 | 1325.83 | 11143363 | 12.64 | 3821.46 | 91.81 | 49428.12 |
| 2011-06 | 104.5994 | 371446 | 4.36 | 975.87 | 8.90 | 921100 | 182500 | 1320.64 | 11147548 | 12.65 | 3874.05 | 92.26 | 49526.68 |
| 2011-09 | 105.2449 | 370203 | 4.23 | 991.33 | 9.07 | 934800 | 179600 | 1131.42 | 11056016 | 13.02 | 3897.96 | 94.60 | 49484.49 |
| 2011- 12 | 106.6262 | 379195 | 4.09 | 1009.37 | 8.33 | 944700 | 184900 | 1257.60 | 10948954 | 13.47 | 3949.12 | 94.25 | 50816.43 |
| 2012-03 | 108.1334 | 385405 | 4.03 | 1016.92 | 8.63 | 958600 | 191200 | 1408.47 | 10903053 | 13.67 | 4004.94 | 95.19 | 52292.41 |
| 2012-06 | 109.0276 | 392598 | 4.05 | 1021.81 | 8.00 | 959800 | 184400 | 1362.16 | 10941343 | 13.69 | 4038.06 | 95.82 | 52878.78 |
| 2012-09 | 109.7358 | 397587 | 4.06 | 1022.27 | 8.13 | 951400 | 175600 | 1440.67 | 11015916 | 13.46 | 4064.29 | 97.01 | 52904.48 |
| 2012- 12 | 110.4224 | 411034 | 4.06 | 1021.02 | 7.50 | 952000 | 179000 | 1426.19 | 11055516 | 13.19 | 4089.72 | 96.19 | 53119.84 |
| 2013-03 | 111.8448 | 430034 | 4.06 | 1020.41 | 8.07 | 957500 | 175500 | 1569.19 | 11061239 | 13.07 | 4142.4 | 96.95 | 53243.31 |
| 2013-06 | 112.3060 | 438405 | 4.09 | 1056.23 | 7.40 | 958200 | 173800 | 1606.28 | 11058766 | 13.06 | 4159.48 | 97.57 | 53230.83 |
| 2013-09 | 113.7291 | 445426 | 4.13 | 1089.52 | 7.33 | 960000 | 174600 | 1681.55 | 11010122 | 13.23 | 4212.19 | 99.09 | 53201.40 |
| 2013- 12 | 115.3111 | 451627 | 4.15 | 1100.14 | 6.70 | 970900 | 165700 | 1848.36 | 10884071 | 13.44 | 4270.78 | 98.38 | 54355.19 |
| 2014-03 | 115.4558 | 469701 | 4.15 | 1099.56 | 6.93 | 982500 | 181700 | 1872.34 | 10801681 | 13.53 | 4276.14 | 99.30 | 55425.32 |
| 2014-06 | 117.6722 | 480166 | 4.11 | 1098.54 | 6.10 | 1001100 | 186700 | 1960.23 | 10784481 | 13.40 | 4358.23 | 100.62 | 55763.40 |
| 2014-09 | 119.6211 | 481762 | 4.07 | 1135.45 | 6.17 | 999700 | 181300 | 1972.29 | 11158829 | 13.25 | 4430.41 | 102.37 | 55742.70 |
| 2014- 12 | 120.4870 | 485241 | 4.06 | 1172.74 | 5.47 | 994500 | 184700 | 2058.90 | 11587363 | 13.19 | 4462.48 | 101.73 | 56730.86 |
| 2015-03 | 121.5230 | 516906 | 4.06 | 1186.12 | 5.83 | 955300 | 187900 | 2067.89 | 11765912 | 13.22 | 4500.85 | 101.08 | 57861.96 |
| 2015-06 | 123.0090 | 516851 | 4.00 | 1204.33 | 5.30 | 949200 | 185600 | 2063.11 | 11656775 | 13.26 | 4555.89 | 99.77 | 58321.11 |
| 2015-09 | 123.8452 | 514227 | 3.93 | 1222.18 | 5.23 | 937100 | 188900 | 1920.03 | 11510812 | 13.28 | 4586.86 | 100.97 | 58343.75 |
| 2015- 12 | 124.0569 | 511043 | 3.91 | 1229.45 | 4.80 | 910600 | 183000 | 2043.94 | 11457511 | 13.28 | 4594.7 | 98.19 | 58335.20 |
| 2016-03 | 124.6736 | 508459 | 3.91 | 1229.86 | 5.20 | 889100 | 180100 | 2059.74 | 11457726 | 13.28 | 4617.54 | 97.58 | 58334.96 |
| 2016-06 | 125.9294 | 518804 | 3.91 | 1229.27 | 4.77 | 898600 | 182200 | 2098.86 | 11646748 | 13.25 | 4664.05 | 97.40 | 58323.07 |
| 2016-09 | 127.0442 | 531188 | 3.88 | 1245.50 | 4.97 | 918300 | 183900 | 2168.27 | 11840956 | 13.21 | 4705.34 | 99.04 | 58310.92 |
| 2016- 12 | 128.4701 | 534506 | 3.83 | 1262.74 | 4.53 | 932300 | 189100 | 2238.83 | 11911860 | 13.19 | 4758.15 | 98.15 | 58974.07 |
| 2017-03 | 129.8527 | 557873 | 3.82 | 1269.01 | 4.87 | 955500 | 192100 | 2362.72 | 11906859 | 13.19 | 4809.36 | 98.73 | 59850.31 |
| 2017-06 | 130.8099 | 573078 | 3.82 | 1284.82 | 4.23 | 955700 | 198500 | 2423.41 | 12251437 | 13.19 | 4844.81 | 99.78 | 60278.08 |
| 2017-09 | 132.4166 | 547934.2 | 3.79 | 1306.36 | 4.40 | 962500 | 193900 | 2519.36 | 12708147 | 13.27 | 4904.32 | 101.01 | 60269.65 |

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 2017- 12 | 134.5812 | 503537.1 | 3.74 | 1318.44 | 3.90 | 1013100 | 207900 | 2673.61 | 12925297 | 13.38 | 4984.49 | 101.75 | 61018.95 |
| 2018-03 | 136.6349 | 479022.1 | 3.72 | 1319.33 | 4.33 | 1036400 | 216000 | 2640.87 | 12914293 | 13.44 | 5060.55 | 102.42 | 62509.12 |
| 2018-06 | 138.7303 | 494738 | 3.72 | 1316.96 | 3.83 | 1049000 | 202800 | 2718.37 | 12862428 | 13.44 | 5138.16 | 103.36 | 63634.60 |
| 2018-09 | 140.0134 | 532165.4 | 3.70 | 1329.87 | 3.87 | 1057900 | 224700 | 2913.98 | 13365367 | 13.40 | 5185.68 | 105.83 | 63799.27 |
| 2018- 12 | 141.1414 | 552266.4 | 3.65 | 1354.05 | 3.57 | 1060100 | 228500 | 2506.85 | 14299783 | 13.34 | 5227.46 | 105.47 | 63783.73 |
| 2019-03 | 142.5284 | 534166.4 | 3.61 | 1370.77 | 3.87 | 1046800 | 213600 | 2834.40 | 14981057 | 13.30 | 5278.83 | 105.27 | 64522.58 |
| 2019-06 | 143.9767 | 495679.6 | 3.61 | 1372.07 | 3.63 | 1039300 | 222100 | 2941.76 | 15078855 | 13.29 | 5332.47 | 104.42 | 65956.08 |
| 2019-09 | 145.3972 | 513835 | 3.61 | 1374.24 | 3.63 | 1035700 | 218300 | 2976.74 | 14580249 | 13.30 | 5385.08 | 105.98 | 67061.04 |
| 2019- 12 | 146.7950 | 724876.7 | 3.58 | 1393.11 | 3.53 | 1018800 | 200400 | 3230.78 | 13701584 | 13.31 | 5436.85 | 104.77 | 65881.75 |
| 2020-03 | 145.5376 | 1324264 | 3.53 | 1423.60 | 3.83 | 992700 | 189300 | 2584.59 | 12885902 | 13.30 | 5390.28 | 103.12 | 59529.98 |
| 2020-06 | 131.7608 | 2566670 | 3.52 | 1443.84 | 13.03 | 794000 | 217000 | 3100.29 | 12800359 | 13.30 | 4880.03 | 89.17 | 44184.98 |
| 2020-09 | 142.8141 | 4765984 | 3.70 | 1419.29 | 8.83 | 838900 | 213900 | 3363.00 | 14336219 | 13.31 | 5289.41 | 98.13 | 45093.45 |

**Question** **2** **raw** **data** **(**data source: Zhonghong statistical database.)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Indicator | China's policy indicators | | | China's economic indicators | | |
| Time | Z1 | Z2 | Z3 | Z4 | TIE | CD |
| 2009-03 | 4.09 | 62085844 | 6.8360 | 0.20 | 4288.00 | 324.02 |
| 2009-06 | 4.89 | 70079173 | 6.8257 | 0.20 | 5182.24 | 333.10 |
| 2009-09 | 5.18 | 79764321 | 6.8296 | 0.13 | 6115.99 | 403.73 |
| 2009- 12 | 5.23 | 86436024 | 6.8273 | 0.10 | 6491.53 | 469.49 |
| 2010-03 | 5.45 | 78112622 | 6.8263 | 0.11 | 6181.20 | 482.53 |
| 2010-06 | 5.67 | 93905264 | 6.8116 | 0.16 | 7366.20 | 539.69 |
| 2010-09 | 5.58 | 106607198 | 6.7577 | 0.18 | 7943.21 | 543.34 |
| 2010- 12 | 6.08 | 106810224 | 6.6428 | 0.18 | 8248.84 | 461.45 |
| 2011-03 | 5.92 | 97670404 | 6.5750 | 0.14 | 8012.23 | 711.46 |
| 2011-06 | 6.16 | 108800318 | 6.4782 | 0.09 | 9027.32 | 638.77 |
| 2011-09 | 6.40 | 119450775 | 6.3994 | 0.08 | 9733.62 | 667.90 |
| 2011- 12 | 6.78 | 120787627 | 6.3426 | 0.08 | 9644.66 | 540.81 |
| 2012-03 | 6.67 | 106733734 | 6.3003 | 0.10 | 8594.54 | 780.20 |
| 2012-06 | 7.04 | 124531472 | 6.3441 | 0.14 | 9796.49 | 662.84 |
| 2012-09 | 6.75 | 124345462 | 6.3317 | 0.12 | 10027.15 | 679.44 |
| 2012- 12 | 7.20 | 129267512 | 6.2314 | 0.14 | 10250.67 | 660.30 |
| 2013-03 | 7.32 | 118245755 | 6.2170 | 0.13 | 9753.89 | 565.53 |
| 2013-06 | 7.49 | 125941779 | 6.1458 | 0.10 | 10217.27 | 646.57 |
| 2013-09 | 7.63 | 134942375 | 6.1233 | 0.07 | 10631.22 | 680.10 |
| 2013- 12 | 8.06 | 141618754 | 6.0806 | 0.07 | 10998.73 | 756.22 |
| 2014-03 | 7.92 | 122550141 | 6.1411 | 0.06 | 9648.28 | 664.57 |
| 2014-06 | 8.09 | 133914738 | 6.2370 | 0.09 | 10549.80 | 733.58 |
| 2014-09 | 7.97 | 148212218 | 6.1519 | 0.07 | 11411.96 | 744.85 |
| 2014- 12 | 7.78 | 150690967 | 6.1540 | 0.07 | 11420.32 | 700.19 |
| 2015-03 | 7.89 | 126258555 | 6.2397 | 0.06 | 9043.02 | 608.02 |
| 2015-06 | 8.08 | 140560656 | 6.2007 | 0.08 | 9780.29 | 643.02 |
| 2015-09 | 8.29 | 147275828 | 6.3144 | 0.08 | 10314.71 | 643.08 |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| 2015- 12 | 7.90 | 146462157 | 6.4033 | 0.12 | 10518.53 | 660.88 |
| 2016-03 | 8.03 | 112737552 | 6.5264 | 0.28 | 8031.31 | 540.53 |
| 2016-06 | 8.42 | 125262241 | 6.5683 | 0.30 | 9247.69 | 663.22 |
| 2016-09 | 8.52 | 138436286 | 6.6627 | 0.30 | 9733.20 | 683.06 |
| 2016- 12 | 8.37 | 148475811 | 6.8692 | 0.39 | 10343.19 | 716.19 |
| 2017-03 | 8.56 | 126495358 | 6.8788 | 0.65 | 9007.70 | 700.02 |
| 2017-06 | 9.04 | 143246349 | 6.8282 | 0.91 | 10136.30 | 758.42 |
| 2017-09 | 9.08 | 155448432 | 6.6566 | 1.07 | 10650.70 | 778.69 |
| 2017- 12 | 8.67 | 163191879 | 6.5848 | 1.16 | 11432.30 | 760.87 |
| 2018-03 | 9.02 | 141708400 | 6.2984 | 1.45 | 10434.14 | 744.15 |
| 2018-06 | 9.41 | 160362600 | 6.4548 | 1.77 | 11647.80 | 709.74 |
| 2018-09 | 9.28 | 171955100 | 6.8377 | 2.00 | 12317.10 | 762.20 |
| 2018- 12 | 9.85 | 161238900 | 6.9382 | 2.27 | 11960.70 | 631.57 |
| 2019-03 | 10.38 | 119538000 | 6.7023 | 2.41 | 10285.60 | 623.35 |
| 2019-06 | 10.75 | 138808700 | 6.8356 | 2.42 | 11348.10 | 711.00 |
| 2019-09 | 11.18 | 144448600 | 7.0631 | 2.14 | 11911.40 | 744.00 |
| 2019- 12 | 10.89 | 137352200 | 7.0117 | 1.56 | 12163.00 | 740.00 |
| 2020-03 | 10.42 | 106602383 | 7.0037 | 1.08 | 10930.15 | 627.21 |
| 2020-06 | 11.18 | 138051500 | 7.0882 | 0.06 | 10866.50 | 594.00 |
| 2020-09 | 12.08 | 167480200 | 6.8705 | 0.09 | 12670.40 | 707.00 |

**Criterion** **layer** **judgment** **matrix**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| 1 | 1 | 1/3 | 1/3 | 1/3 | 1/3 | 1/5 | 1/7 | 1/9 | 1/5 | 1 |
| 2 | 1/3 | 1 | 1 | 1 | 1 | 3/5 | 3/7 | 3/9 | 3/5 | 3 |
| 3 | 1/3 | 1 | 1 | 1 | 1 | 3/5 | 3/7 | 3/9 | 3/5 | 3 |
| 4 | 1/3 | 1 | 1 | 1 | 1 | 3/5 | 3/7 | 3/9 | 3/5 | 3 |
| 5 | 1/3 | 1 | 1 | 1 | 1 | 3/5 | 3/7 | 3/9 | 3/5 | 3 |
| 6 | 1/5 | 3/5 | 3/5 | 3/5 | 3/5 | 1 | 5/7 | 5/9 | 1 | 5 |
| 7 | 1/7 | 3/7 | 3/7 | 3/7 | 3/7 | 5/7 | 1 | 7/9 | 7/5 | 7 |
| 8 | 1/9 | 3/9 | 3/9 | 3/9 | 3/9 | 5/9 | 7/9 | 1 | 9/5 | 9 |
| 9 | 1/5 | 3/5 | 3/5 | 3/5 | 3/5 | 1 | 7/5 | 9/5 | 1 | 5 |
| 10 | 1 | 3 | 3 | 3 | 3 | 5 | 7 | 9 | 5 | 1 |

**Biden** **and** **Trump's** **comparison** **often** **policy** **indicators**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Policy indicator | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 |
| Scale comparison | 9 | 1 | 1 | 1 | 1 | 1/2 | 1/3 | 2 | 3 | 1 |

**Attachment** **2**

**code** **1:** **Lagrange** **interpolation**

**lagrange\_newton\_interp.m**

clc;

clear;

%Parameter initialization

inputfile=xlsread('C:\Users\Admin\Desktop\DATA.xls',’raw data’);

for i=1:size(inputfile,2)

index=i;

data = inputfile(:,index);

la\_data = ployinterp\_column(data,'lagrange'); %Call Lagrange for interpolation

%The results are written to a file

rows = size(data,1);

result = cell(rows+1,2);

result{1,1}='original value';

result{1,2}='Lagrange interpolation';

result(2:end,1)= num2cell(data);

result(2:end,2)= num2cell(la\_data);

xlswrite('C:\Users\Admin\Desktop\DATA.xls',’after data’);

end

**ployinterp\_column.m**

function outputdata= ployinterp\_column(columndata,type)

nans = isnan(columndata);

notzeroIndexes = find(nans);

%zeroIndexes = find(nans==0);

rows=size(columndata);

%currentValues=zeros(size(zeroIndexes));

for i=1:size(notzeroIndexes)

pre5=findPre5(notzeroIndexes(i),columndata);

last5=findLast5(notzeroIndexes(i),rows(1),columndata);

[~,pre5cols]=size(pre5);

[~,last5cols]=size(last5);

if strcmp(type,'lagrange')

missingValue=lagrange\_interp([1:pre5cols,pre5cols+2:last5cols+pre5cols+1],...

[pre5,last5],pre5cols+1);

end

columndata(notzeroIndexes(i),1)=missingValue;

end

outputdata=columndata;

end

function pre5=findPre5(index,columndata)

if index<=0

disp('error');

exit;

end

num=5;

pre5=nan(1,5);

for i=index- 1:- 1:1

if isnan(columndata(i))==0

pre5(num)=columndata(i);

num=num- 1;

end

if num==0

break;

end

end

pre5=pre5(~isnan(pre5));

end

function last5=findLast5(index,rows,columndata)

if index<=0 || index>rows

disp('error');

exit;

end

num=0;

last5=nan(1,5);

for i=index+1:rows

if isnan(columndata(i))==0

num=num+1;

last5(num)=columndata(i);

end

if num==5

break;

end

end

last5=last5(~isnan(last5));

end

**lagrange\_interp,m**

function [ yi ] = lagrange\_interp (X,Y,xi)

n=length(X);

m=length(xi);

yi=zeros(size(xi));

for j=1:m

for i=1:n

temp=1;

for k=1:n

if(i~=k)

temp=temp\*(xi(j)-X(k))/(X(i)-X(k));

end

end

yi(j)=Y(i)\*temp+yi(j);

end

end

end

**code2:** **BP** **neural** **network**

**BPmain.m**

R=zeros(20,N);

I=zeros(20,N);

for i=1:N

index=i;

for j=1:20

num\_neurons=i;

[error,R2,a]=BPTrain(index,num\_neurons);

R(j,i)=R2;

I(j,i)=a;

end

end

**BPTrain,m**

function [error,R2,a] = BPTrain(index,num\_neurons)

%% Input training set and test set

%Training set 1 (data from Obama's eight years in office)

Train1=xlsread('C:\Users\Admin\Desktop\ExportData.xls',' Training set 1');

%Training set 2 (data from Obama's 8 years + Trump's 4 years)

Train2=xlsread('C:\Users\ Admin \Desktop\ExportData.xls',' Training set 2);

%Test set (data from Trump's four years in power)

Test=xlsread('C:\Users\ Admin \Desktop\ExportData.xls',' Test set ');

% Prediction set

%PY=xlsread('C:\Users\ Admin \Desktop\ExportData.xls','Sheet2');

%P\_Y=PY';

%py=mapminmax('apply',P\_y,ps\_input);

%Training set and Test set selection

P\_train=Train2(:,1)';

T\_train=Train2(:,index)';

P\_test=Test(:,1)';

T\_test=Test(:,index)';

%Data normalization

[p\_train, ps\_input]=mapminmax(P\_train,0,1);

[t\_train, ps\_output] = mapminmax(T\_train,0,1);

p\_test = mapminmax('apply',P\_test,ps\_input);

%Neural network creation

net=newff(P\_train,T\_train,num\_neurons); %Number of hidden neurons

%Set training parameters

net.trainParam.epochs=1000; %Number of iterations

net.trainParam.goal=1e-3; %Training objectives

net.trainParam.lr=0.01; %Learning rate

%Training network

[net,tr]=train(net,p\_train,t\_train);

%Simulation test

t\_sim=sim(net,p\_test);

% t\_sim=sim(net,py);

%Data inverse normalization

T\_sim=mapminmax('reverse',t\_sim,ps\_output);

%%Performance evaluation

%Relative error

error=abs(T\_sim-T\_test)./T\_test;

%Coefficient of determination R2

R2=(size(T\_test,2)\*sum(T\_sim.\*T\_test)-sum(T\_sim)\*sum(T\_test))^2/((size(T\_test,2)\*sum((T\_sim).^2)- (sum(T\_sim))^2)\*(size(T\_test,2) \* sum((T\_test).^2)-(sum(T\_test))^2));

%Comparison ofresults

result=[T\_test' T\_sim' error'];

%Number ofiterations

a=tr.num\_epochs;

end

**code3:** **VAR** **model** **prediction**

**VAR\_GDP.m**

BG=xlsread('C:\Users\ Admin \Desktop\predicted data.xlsx','Sheet1');

for i=1:size(BG,1)

BG(i+2,5)=(-0.45\*BG(i+1,5)+0.84\*BG(i,5)+259.10\*BG(i+1,2)- 102.19\*BG(i,2)+3.02\*BG(i+1,3)- 11.09\*BG(i,3)- 142.00\*BG(i+1,4)+37.25\*BG(i,4)+2745.08);

end

**VAR\_PPI.m**

BP=xlsread('C:\Users\ Admin \Desktop\ predicted data.xlsx','Sheet2');

for i=1:size(BP,1)

BP(i+3,5)=(-0.34\*BP(i+2,5)+0.04\*BP(i+1,5)+0.35\*BP(i,5) ...

+5.71\*BP(i+2,2)-6.25\*BP(i+1,2)+1.95\*BP(i,2) ...

-0.83\*BP(i+2,3)+3.42\*BP(i+1,3)- 1.83\*BP(i,3) ...

- 10.85\*BP(i+2,4)-2.75\*BP(i+1,4)+5.62\*BP(i,4)+90.23);

End

**VAR\_A\_GNI.m**

BGN=xlsread('C:\Users\ Admin \Desktop\ predicted data.xlsx','Sheet3');

for i=1:size(BGN,1)

BGN(i+5,5)=(0.87\*BGN(i+4,5)- 1.17\*BGN(i+3,5) - 1.52\*BGN(i+2,5)+0.15\*BGN(i+1,5)+1.10\*BGN(i,5) ...

+8951.40\*BGN(i+4,2)-6076.37\*BGN(i+3,2)+3514.18\*BGN(i+2,2)-

1322.38\*BGN(i+1,2)+821.06\*BGN(i,2) ...

-4080.84\*BGN(i+4,3)+3168.15\*BGN(i+3,3)- 1250.89\*BGN(i+2,3)+1233.70\*BGN(i+1,3)- 1304.08\*BGN(i,3) ...

-7473.31\*BGN(i+4,4)-4625.25\*BGN(i+3,4)+10934.90\*BGN(i+2,4)-4265.30\*BGN(i+1,4)-6841.72\*BGN(i,4) +85461.9);

end

**VAR\_TIE.m**

BTIE=xlsread('C:\Users\ Admin \Desktop\ predicted data.xlsx','Sheet4');

for i=1:size(BTIE,1)

BTIE(i+3,6)=- 0.045\*BTIE(i+2,6)+ 0.71\*BTIE(i+1,6)+ 0.17\*BTIE(i,6) ...

+ 204.95\*BTIE(i+2,2)- 41.65\*BTIE(i+1,2)+ 991.70\*BTIE(i,2) ...

+3.32e-06\*BTIE(i+2,3)-6.52e-05\*BTIE(i+2,3)- 2.48e05\*BTIE(i,3) ...

- 2322.39\*BTIE(i+2,4)+ 94.20\*BTIE(i+1,4)+ 650.02\*BTIE(i,4) ...

+458.91\*BTIE(i+2,5)+4266.21\*BTIE(i+1,5)-4856.57\*BTIE(i,5)+14255.72;

end

**VAR\_CD.m**

BCD=xlsread('C:\Users\ Admin \Desktop\ predicted data.xlsx','Sheet4');

for i=1:size(BCD,1)

BCD(i+3,6)= 0.24\*BCD(i+2,6)+ 0.30\*BCD(i+1,6)- 0.01\*BCD(i,6) ...

+ 117.14\*BCD(i+2,2)- 50.66\*BCD(i+1,2)- 8.19\*BCD(i,2) ...

- 1.92e-06\*BCD(i+2,3)+4.91e-07\*BCD(i+2,3)-5.69e-07\*BCD(i,3) ...

+ 12.35\*BCD(i+2,4)- 186.68\*BCD(i+1,4)+ 195.87\*BCD(i,4) ...

- 86.57\*BCD(i+2,5)+ 328.85\*BCD(i+1,5)- 327.51\*BCD(i,5)- 3.36;

end

**code4:** **multiple** **linear** **regression**

clc

clear

X=xlsread('C:\Users\Admin\Desktop\datah.xlsx','Sheet1','Q19:S28');

X=[ones(size(X,1),1),X];

Y=xlsread('C:\Users\Admin\Desktop\datah.xlsx','Sheet1','S33:S42');

[b,bint,r,rint,stats]=regress(Y,X);

b,bint,stats

rcoplot(r,rint)

z=b(1)+b(2)\*X(1,:)+b(3)\*X(2,:)+b(4)\*X(3,:);

plot(X,Y,'k+',X,z,'r')

xlswrite('C:\Users\Admin\Desktop\datah.xlsx',b,'Sheet2,'A3')

xlswrite('C:\Users\Admin\Desktop\datah.xlsx',bint,'Sheet2','B3')

xlswrite('C:\Users\Admin\Desktop\datah.xlsx',stats,'Sheet2','D3')

**code5:AHP**

**AHP.m**

function [Q]=AHP(B)

% Q is the weight and B is the contrast matrix

[n,m]=size(B);

%The discriminant matrix has complete consistency

for i=1:n

for j=1:n

if B(i,j)\*B(j,i)~=1

fprintf('i=%d,j=%d,B(i,j)=%d,B(j,i)=%d\n',i,j,B(i,j),B(j,i))

end

end

end

%Find the eigenvector corresponding to the largest eigenvalue

[V,D]=eig(B);

tz=max(D);

tzz=max(tz);

c1=find(D(1,:)==max(tz));

tzx=V(:,c1);

quan=zeros(n,1);

for i=1:n

quan(i,1)=tzx(i,1)/sum(tzx);

end

Q=quan;

CI=(tzz-n)/(n- 1);

RI=[0,0,0.58,0.9,1.12,1.24,1.32,1.41,1.45,1.49,1.52,1.54,1.56,1.58,1.59];

CR=CI/RI(1,n);

ifCR>=0.1

fprintf('Did not pass the consistency test \n');

else

fprintf('Pass the consistency test \n');

end