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*Research Article*

# Research on System Economic Operation and Management Based on Deep Learning

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It is of great significance to accurately predict the operation of the system economy, analyze the gains and losses of macrocontrol policies, evaluate the operation quality of the economic system, and correctly formulate the future development plan and strategy. This paper introduces the deep belief network, which has attracted much attention in the field of deep learning in recent years, into the research of system economic operation and management. This method solves the problems of slow training and learning speed, easy to fall into local minima and insufficient generalization of BP artificial neural network in the research of system economic operation and management. Taking the consumer price index and total import and export volume of F Province as the research object, the experiment proves that DBN has better application in system economic operation and management than BP neural network and vector autoregressive analysis. This paper analyzes and compares the modeling performance of DBN, BP neural network, and VaR method from many aspects, such as prediction accuracy, training convergence speed, and pretraining with or without samples. Relevant empirical results show that DBN has better economic prediction performance than BP neural network and ver. On the other hand, DBN can effectively use nonstandard samples to pretrain network weight parameters. Therefore, DBN is a better operation and management modeling means of economic system, with excellent practicability and application, and is expected to be popularized and applied in the field of economic forecasting.

## 1. Introduction

In order to correctly judge the trend of system economy, analyze the gains and losses of macrocontrol policies, evaluate the operation quality of economic system, and correctly formulate future development plans and strategies, it is also of guiding value to the investment plans of enterprises and individuals [1]. Especially this year is the beginning year of the "14th Five-Year Plan," and China's economy is in an important period of "climbing over the ridge" and "tackling key problems and transforming." The economic pressure is still relatively large, and the uncertain factors facing economic operation and management are increasing. In such an important period, through the establishment of scientific prediction model, the current economic development trend is quantitatively analyzed and predicted by using historical data. However, most of the traditional economic models are linear models [2]. This model has certain economic forecasting ability, but it also has obvious shortcomings that it is difficult to reflect the nonlinear relations widely existing in economic systems. Economic system is very complex, with many internal influencing factors, strong combination, time-varying, nonlinear and other characteristics, which is very challenging for modeling and forecasting of economic system. Deep learning embodies characteristic learning, and maps samples to new spaces through characteristic transformation of each layer to promote prediction. Features obtained through deep learning are more profound in the nature of data, so they can effectively improve the performance of applications, such as regression and classification or prediction. Therefore, it is of more practical significance to establish a scientific prediction model through deep learning [3] and use historical data to quantitatively predict the current economic development trend of the system, which is convenient for the operation and management research of the system economy.

Research and investment are the foundation of economic development, so it is particularly important to measure economic well-being comprehensively and accurately. There is no similar measure in many local-level regions. We use the training deep learning model to predict 20,000 African villages to investigate their asset estimates [4]. Macroeconomic forecasting can predict the future economic situation, and also play a directional role in the formulation and implementation of economic policies, so its accuracy is required. There are many prediction models in previous studies, but they are not well used because of their low accuracy and narrow application area. In order to better predict the future global economic prospects, we put forward a new GDP growth prediction model. In the experiment, we collected 70 countries as samples and adopted different methods to realize a high-precision model, that is, deep neural decision tree. The results show that this model has a potential impact on the adequacy of macroeconomic policies and creates a new method and breakthrough for GDP growth prediction [5].

Compared with the traditional machine learning model, the deep learning model has better prediction performance, and it is undergoing great changes at present. However, there are not many works using deep learning in our actual science, so we urgently need to review the research of deep learning in various fields, let researchers and actual operators know its advantages, and then encourage its use. In this process, we provide them with guidance and enlightenment on the business analysis ability of deep learning [6]. In this paper, the proposed method is described according to the corresponding theoretical requirements, and the solution of deep learning model is adopted to solve it. However, the deep learning method in the experiment has good experimental results, and all the proposed methods are based on the deep learning method to explain the theoretical model in detail.

## 2. Deep Learning

*2.1. Neural Networks.* The human brain is made up of tens of billions of nerves. The human brain does not superimpose the received information, but after the sum of the superimposed values exceeds the set threshold, neurons send their own energy to other connected neurons. Our human brains learn by regulating the number and intensity of connections between neurons. In the field of machine learning, a neural network model is developed according to the nervous system structure and working mechanism of human brain, which is suitable for multielement nonlinear fuzzy problems, such as distributed memory, parallel computing and adaptive learning ability [7]. Therefore, it is especially suitable for the research in the field of system economic operation and management.

Compared with previous methods, deep learning has been greatly improved in the fields of sound, image and pattern recognition [8]. This is an integral part of learning multiple features, and each level learns the form of feature expression. In recent years, Deep Belief Networks have been widely used and achieved very good results [9]. In order to better understand the following chapters, this chapter provides the basic principles of BP neural network and convinced network.

*2.2. Principle of BP Neural Network.* In 1989, Robert proved that the continuous function existing in the closed interval can be approximately represented by BP neural network including hidden layer [10,11], so BP neural network including three layers allows the construction from arbitrary input (m-dimension) to output (n-dimension) as shown in Figure 1.

BP algorithm is the most commonly used algorithm in neural network model learning. BP algorithm is based on supervised learning algorithm [12, 13].

The specific process is as follows:

It is assumed that the neural network is an $I$ input unit and a $K$ output unit, the implicit layer is a layer, and the $J$ unit is shared. The formula for the sum of squared errors is as follows.

$$E = \frac{1}{2} \sum_{k=1}^{k} \left(\mathrm{d}_k - o_k\right)^2. \tag{1}$$

Here, $o_k = f\ (\mathrm{net}_k)$ is the actual output value of neuron $k$ in the output layer; $d_k$ is the expected output value of neuron $k$ in the output layer; and $y_j$ is the output value of hidden layer neuron $j$.

For the $E$ value, in order to achieve the goal of the ideal value, it is necessary to change the weight value of the network. First, adjust the connection weights between the implicit layer and the output layer.

$$w_{kj}(t+1) = w_{kj}(t) + \Delta w_{kj}. \tag{2}$$

In the above formula, the value obtained by the gradient method is the adjusted value of the connection weight between the implicit layer and the output layer.

$$\Delta w_{kj} = -\eta \frac{\partial E}{\partial w_{kj}} = \eta \left(d_k - o_k\right) f'\left(net_k\right) y_j. \tag{3}$$

In the above formula $\eta$ is the normal value, which is expressed as the iteration step.

In a similar manner, you can adjust the join weights between the input layer and the implicit layer. Formula adjustment:

$$v_{ji}(t+1) = v_{ji}(t) + \Delta v_{ji}. \tag{4}$$

In the above formula, $\Delta v_{ji}$ is the adjustment amount for determining the connection weight between the input layer

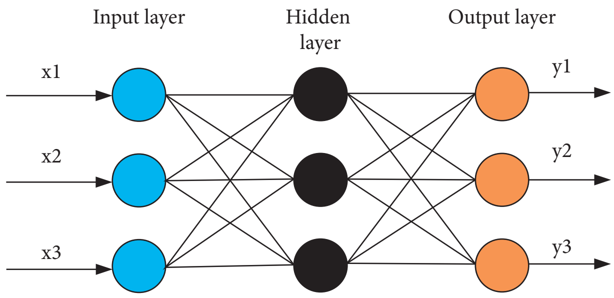


Figure 1: Structure diagram of BP neural network.

and the implicit layer by the gradient method. It can be obtained from the following formula:

$$\Delta v_{ji} = -\eta \frac{\partial E}{\partial v_{ji}} = \eta \sum_{k=1}^{k} (d_k - o_k) f' (\text{net}_k) w_{kj} f' (\text{net}_j) x_i. \quad (5)$$

When there are samples, if there are $P$ training samples, the total error sum form of the above calculation method is defined as

$$E_p = \frac{1}{2} \sum_{p=1}^{P} \sum_{k=1}^{K} (d_k - o_k)^2. \quad (6)$$

As long as the operation is repeated for $P$ samples as described above, $Ep$ reaches the minimum requested value, and the algorithm ends.

The following introduces the principle derivation of the two processes of BP neural network [14,15].

*2.2.1. Forward Propagation of BP Neural Network.* The connection weight between the two nodes is $w_{ij}$ the offset of the nodes is $b_j$ the output value of each node is $x_j$ and the output value of the node is calculated based on all the nodes in the previous layer and the offset of the current layer. The calculation is as follows:

$$S_j = \sum_{i=0}^{m-1} w_{ij} x_i + b_j, \quad (7)$$

$$x_j = f(S_j). \quad (8)$$

where $f$ is the activation function, which is usually the sigmoid function:

$$f(x) = \frac{1}{1 + \exp(-x)}. \quad (9)$$

In BP neural network, only the input layer of the network has no bias term.

*2.2.2. Error back Propagation.* Compared with forward propagation, the back propagation of error is complex and is based on Widrow-Hoff rule. If the output result of the output layer is defined as $d$, the following error function is defined:

$$E(w, b) = \frac{1}{2} \sum_{j=0}^{n-1} (d_j - y_j)^2. \quad (10)$$

By continuously modifying the weight matrix and offset, the BP neural network is gradually reduced to reduce the error function.

*2.2.3. Disadvantages of Neural Network.* BP neural network is widely used, but it also has some shortcomings [16]:

(1) It is easy to fall into local minimum, and the global minimum cannot be obtained. Because there are many minimums in the network, it is easy to enter local minimum. For this problem, better initialization is needed, but it is difficult to get a good initial value.

(2) The learning efficiency during training is very low, and it is still very long until the end of the network.

(3) The number of hidden layers and the number of neurons in each hidden layer are lack of effective theoretical guidance.

BP neural network including hidden layer can approximate any function in theory, but it has no good effect in practical application.

*2.3. Principle of Deep Belief Network (DBN).* Deep Belief Network (DBN) is different from the neural network belonging to the previous discriminant model, which is a probability generation model. The probability generation model calculates P (observation label) and P (label observation) while modeling the cooperative distribution between samples and labels, and the discriminant mode only calculates (label observation).

*2.3.1. Principle of 1 Deep Belief Network (DBN).* Deep Belief network (DBN) can obtain the connection weights between neurons by iterative optimization, and can generate the trained network according to the benchmark of maximum probability as shown in Figure 2:

DBN is composed of restricted Boltzmann machines (RBM). DBN is trained for each layer. During training, the input layer is the input layer of the first RBM in units of RBM, and the output layer of the first RBM is the input layer of the second RBM. Inference is made for each layer.

The structure of RBM is shown in Figure 3.

*2.3.2. DBN Training Process.* The training process of RBM is basically to find the most possible distribution form of generating training samples [17].

The training method of Deep Belief Network is as follows: firstly, the initialization weight of the network is obtained by the training method of each nonmonitoring layer, and then the subsequent network optimization is realized by error inverse adjustment.

(1) Training the first RBM until the error converges

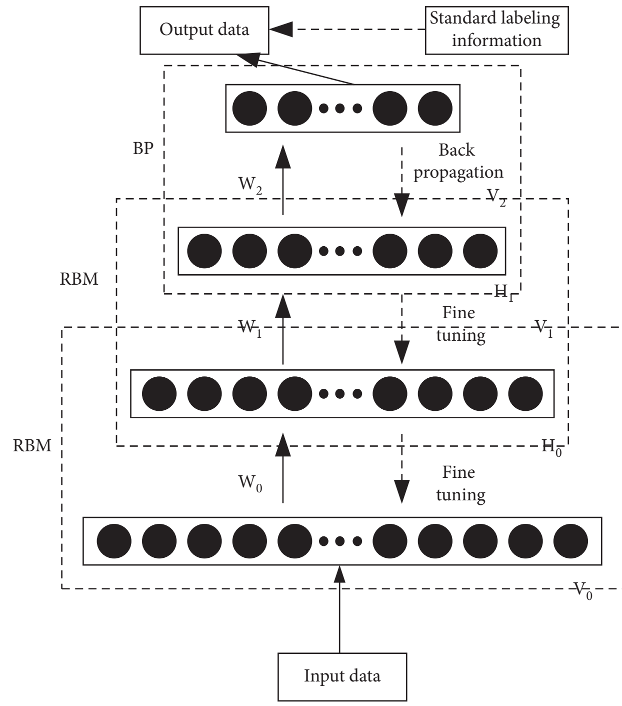


Figure 2: Schematic diagram of Deep Belief Network structure.

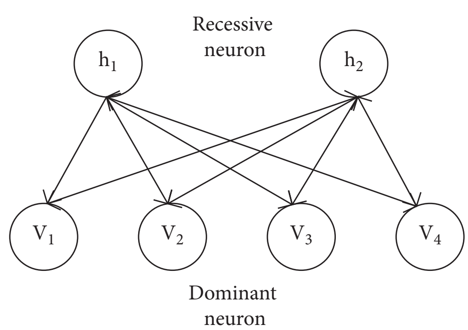


Figure 3: Schematic diagram of RBM structure.

(2) Fixing weights and offsets of the RBM trained in the previous step, and calculating an output of the RBM as an input vector of the second RBM
(3) Before error convergence, the output layer of the second RBM is trained as the output layer of the whole network, and the output layer of the first network is operated as the hidden layer of the whole network
(4) repeat the above steps until all layers are trained
(5) If the whole network is a supervised network with labels, the weight method used to train the last layer network initializes all connections, and the number of neurons in the last output layer is 5 neurons, which is gradually optimized by using the error inverse adjustment algorithm until the error converges

The model proposed in this paper has good forecasting effect and practical application. From the experiment, DBN is a better modeling method for economic system operation and management, which has excellent practicability and applicability, and is expected to be popularized and applied in the field of economic forecasting.

## 3. Research on System Economic Operation and Management Based on Deep Belief Network

Economic system is a relatively complex nonlinear system. There are many influencing factors in the system, such as resources, consumption, investment, industrial structure. These factors also influence and restrict each other. The characteristics of high nonlinearity and time-varying bring great obstacles to economic operation and management. It can be seen from the explanation in the previous chapter that artificial neural network has strong nonlinear approximation ability. Theoretical research shows that artificial neural network can approximate any nonlinear function and can deal with difficult problems such as economic prediction. In recent years, the deep learning method proposed by the academic circles provides a good initial value for the neural network through the hierarchical pretraining method [18, 19], which overcomes the existing shortcomings and activates new vitality to a certain extent.

This chapter focuses on several variables reflecting the macroeconomic development of F province, such as consumer price index, fiscal expenditure, tax revenue, total exports and total imports, as the forecast of consumer price index and total imports. The error propagation neural network, deep belief network, and vector self-regression (VAR) are verified [20], and the prediction accuracy of DBN deep learning method, the limitation of target sample size and the performance of training and learning speed are studied.

*3.1. Construction and Selection of Economic Forecast Index System.* Use neural network or deep learning method to predict the actual economy, In essence, the highly nonlinear function between dependent variable economic indicators and independent variable economic indicators is learned through training samples, and introduce new independent variable economic indicators, use nonlinear function to forecast the corresponding variable economic indicators. Because of the highly nonlinear characteristics of economic development, the relationship between economic indicators is very different. Therefore, for different variable economic indicators, appropriate independent variable economic indicators should be selected as input. Choosing different index variables for forecasting will have a great impact on the forecasting results. If the selected variable forecasting indicators cannot reflect the economic goals we want to predict and cannot achieve the best algorithm, we can only evaluate enough independent variable economic indicators according to experience and experimental results.

*3.1.1. Selection of Indicators.* Accord to that basic principles of construct the above indicators, This paper selects several indicators, which can reflect the local macroeconomic development of F province, analyzes their correlation, predicts their time correlation, and selects some economic indicators closely related to the local economic development trend. The economic indicators proposed in this paper include public finance, foreign trade and residents' life. This paper studies the application of DBN deep learning model in the field of economic forecasting [21,22]. Specific indicators are tax expenditure, tax revenue, total imports, total exports and consumer price index.

*3.2. Selection and Preprocessing of Data Samples.* Based on the abovementioned index construction principles, this paper collects relevant source data and establishes relevant economic forecasting index system. The source data used in this paper comes from China Economic Database. The time span of data collection is the economic data of F province from January 2005 to February 2015. The collected index source data mainly include important index data of regional economic development, such as fiscal revenue, total import, total export and consumer price index. Selecting the source data of the above indicators is mainly considering that the data of relevant indicators during this period is relatively complete, which can basically meet the training and testing needs of sample quantity. Please refer to Table 1 for specific source data.

The absolute quantity of the abovementioned economic indicators and the overall trend changing with time are similar to linear monotone curves. If the absolute value of the abovementioned indicators is directly taken as the index quantity of economic prediction, it is rare for them to reappear in the past numerical position because of their monotony, that is to say, history will not repeat itself. - Therefore, this paper takes the growth rate of each economic index as the input and output of the economic prediction function, and the absolute quantity prediction of specific economic indicators is converted from the predicted growth rate. In this paper, the calculation formula of the corresponding growth rate obtained from the absolute quantity of economic indicators is as follows:

$$y^t = \frac{x^t - x^{t-1}}{x^{t-1}} \tag{11}$$

where $t$ is time value; $x^t$ and $x^{t-1}$ are the absolute quantity of a certain economic index at the current moment and the previous moment; $y^t$ is the growth rate of this economic indicator at the current time.

Using this formula, we can obtain the growth rate of each economic index in Table 1.

In addition, because different economic indicators or their growth rates have different acquisition ranges, the numerical range of input quantities of neural networks or deep networks is usually required between [0, 1] or [1,1]. Therefore, this paper normalizes the growth rate of economic indicators obtained in (11). In this paper, the maximum and minimum value normalization method is adopted, and the growth rate of all indexes is normalized to [0, 1]. The maximum value corresponds to 1 and the minimum value corresponds to 0. The specific normalization formula is as follows.

$$y\_nor = \frac{y - \min(y)}{\max(y) - \min(y)} \tag{12}$$

where $y\_nor$ is the normalized index growth rate data; $\max(y)$ is the maximum value of the index growth rate; and $\min(y)$ is the minimum of the index growth rate.

*3.3. Model Parameter Setting and Model Training and Learning.* In this study, DBN deep learning method, BP neural network and VAR method are used to predict the consumer price index of F province, but DBN deep learning method adopts single hidden layer network [23]. The number of neurons in the input layer is 30, the number of neurons in the hidden layer is 15, and the number of neurons in the output layer is 1. The network structure is shown in Figure 4.

*3.3.1. Sample Set.* In this thesis, we use two training groups: standard sample training group and nonstandard sample training group. The standard sample set includes variable and parameter pairs. In order to distinguish between labeled samples and unlabeled sample sets, capital letters A and B are used here, respectively, and $T1$ and $T2$ are the number of samples in the sample set.

*3.3.2. DBN Network Weight Initialization.* A contrast divergence algorithm is used to pretrain weights between input layer and implicit layer elements to obtain initial weights. The pretraining process of CD algorithm does not need to add variable samples to output, that is, the unsampled set is selected as the pretraining samples. Because only input variables are provided, no output variables are provided.

*3.3.3. Weight Learning of DBN Network.* After initialization, the DBN network can update the weights by BP algorithm and constant sample set training, and the corresponding parameters can be optimized by intelligent optimization algorithm [24,25]. The research on the forecast of consumer price index in F province is still in its initial stage. Unlike the startup phase, there is no need to output variables at startup. BP algorithm needs to participate in output variables. The weights in the pretraining stage only provide the best initial value for BP training. The parameters of BP weight updating stage are 0.001 steps, 1000 repetitions, and 50 batches.

*3.3.4. Weight Learning of BP Neural Network.* In this study, BP neural network adopts the same training samples and network structure as DBN. The weights of BP neural network are initialized randomly in the guiding stage, and the weights are updated by error reappearance algorithm.

## 4. Experiment

*4.1. Performance Comparison between DBN Deep Learning Model and BP Neural Network.* Parameters such as network

Table 1: Economic data of F Province (Millions of RMB).

| Consumer price index | Export | Import | Fiscal revenue | Fiscal expenditure |
|---|---|---|---|---|
| 102.5 | 2433.29 | 1465.92 | 4274.00 | 3741.00 |
| 104.2 | 1956.58 | 1197.10 | 2566 | 3031 |
| 103.1 | 2953.14 | 1731.80 | 3158 | 4566 |
| 101.9 | 2894.11 | 1776.27 | 3945 | 3982 |
| 102.7 | 2590.99 | 1523.70 | 3110 | 3587 |
| 103.3 | 3161.81 | 1707.53 | 3066 | 5963 |
| 102.9 | 2942.86 | 1613.87 | 3467 | 3753 |
| 102.2 | 3355.52 | 1815.29 | 2788 | 4261 |
| 100.8 | 2965.89 | 1695.66 | 6107 | 5548 |
| 101.2 | 2971.69 | 1530.81 | 3994 | 4337 |
| 101 | 3116.78 | 1723.01 | 2898 | 5319 |
| 100.9 | 3524.29 | 1761.69 | 3887.03 | 11254.33 |
| 101 | 3063.88 | 1603.51 | 5885.00 | 4360.00 |
| 99.4 | 2184.00 | 1494.82 | 3525 | 3244 |
| 99.2 | 3344.93 | 1876.25 | 3891 | 5596 |
| 100.4 | 3566.12 | 1869.71 | 5754 | 5842 |
| 100.4 | 3346.03 | 1610.96 | 4118 | 3746 |
| 101 | 3413.19 | 1753.50 | 4560 | 5699 |
| 100.9 | 3442.79 | 1733.58 | 4989 | 4914 |
| 101 | 3739.88 | 1907.23 | 3884 | 5387 |
| 100.9 | 3538.27 | 2035.81 | 4127 | 6339 |
| 100.4 | 3702.18 | 1654.73 | 5124 | 4521 |
| 101.5 | 3765.89 | 1895.45 | 3357 | 7359 |
| 103.5 | 4236.04 | 1965.64 | 4903.07 | 15862.73 |
| 103.3 | 3684.97 | 1722.87 | 7659.00 | 4360.00 |
| 105.2 | 3336.26 | 1393.18 | 4896 | 4748 |
| 104.9 | 3187.52 | 1962.44 | 5128 | 6261 |
| 103.6 | 3973.39 | 2006.85 | 7490 | 6239 |
| 103.7 | 3946.61 | 1868.55 | 5127 | 5628 |
| 104.6 | 4835.46 | 2002.00 | 5718 | 7248 |
| 105.8 | 4154.41 | 2171.71 | 6583 | 6034 |
| 106.6 | 4271.86 | 2173.26 | 4966 | 6325 |
| 106.4 | 4519.39 | 2335.19 | 5420 | 8617 |
| 106.6 | 4332.73 | 2109.07 | 6443 | 7501 |
| 106.8 | 4690.83 | 2376.98 | 4160 | 8828 |
| 105.1 | 5020.48 | 2361.34 | 6355.77 | 19275.46 |
| 105.3 | 4634.58 | 2343.48 | 10104 | 7374.00 |
| 106.8 | 3498.13 | 2017.10 | 5902 | 4378 |
| 106.9 | 4393.20 | 2614.80 | 6322 | 7417 |
| 107.2 | 5090.21 | 2595.59 | 8767 | 8498 |
| 106.6 | 4915.64 | 2548.41 | 6608 | 8309 |
| 105.5 | 4817.22 | 2364.93 | 7445 | 8260 |
| 104.8 | 5266.06 | 2678.15 | 7850 | 9479 |
| 103.6 | 5389.98 | 2539.06 | 5377 | 6784 |
| 103.4 | 5171.11 | 2466.40 | 5964 | 8349 |
| 103.1 | 4932.37 | 2204.93 | 7754 | 7631 |
| ... | ... | ... | ... | ... |

weights are determined, that is, a fixed prediction model is obtained. In order to compare the modeling performance of the two models, the above two models are used for training in this experiment. The network output is the normalized growth rate $y\_nor$, and the formula for transforming $y\_nor$ into growth rate is as follows:

$$y = y\_nor \times \max(y) + \min(y) \tag{13}$$

Here, $y\_nor$ is normalized growth rate; $y$ is growth rate; max ($y$) is maximum growth rate of the indicator; min ($y$) is the minimum value of the index growth rate.

*4.1.1. Comparison of Prediction Results.* DBN deep learning model is better than BP neural network model, that is, DBN is a better modeling method than BP. Compared with VAR model, DBN deep learning model can predict the change of growth rate more effectively, and VAR tends to learn slower linear mapping in Figure 5.

Figure 5 shows that, The predicted DBN and BP values deviate from the actual growth rate to a certain extent in the local high frequency oscillation part, but in the overall growth rate change trend, the predicted values can effectively track the change behavior of the actual value, which reflects that both DBN deep learning model and BP neural network

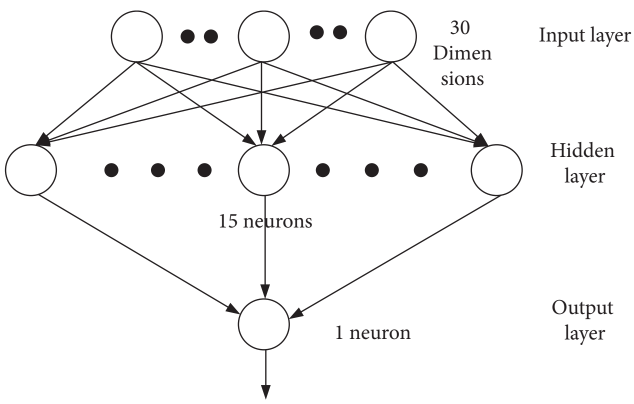


FIGURE 4: Network structure diagram adopted by DBN and BP.

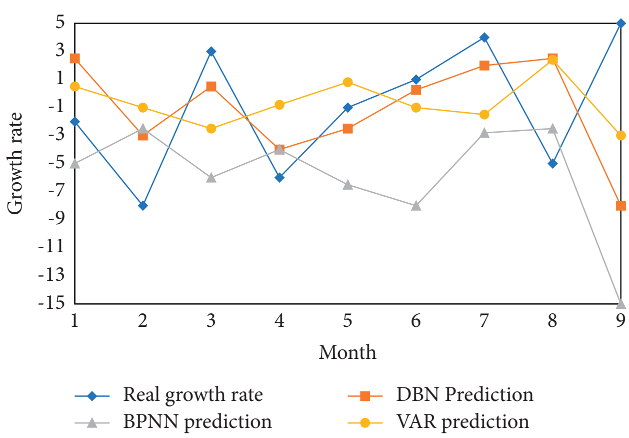


FIGURE 5: Forecast comparison of growth rate of consumer price index in F province.

model can effectively establish nonlinear problem models about economic prediction.

Using the predicted growth rate of the consumer price index of F province, the predicted value of the consumer price index of F province next month can be calculated from (13).

$$x^t = x_{true}^{t-1} \times \left(1 + y^t\right) \tag{14}$$

Here, $x^t$ is current projected indicator values; $x_{true}^{t-1}$ is the actual index value at the previous moment; and $y^t$ is current projected indicator growth rate.

The results of the consumer price index of F province from June 2014 to February 2015 predicted by formula (13) are shown in Figure 6:

Figures 6 and 7 show that compared with BP neural network model and VER model, DBN deep learning model can more accurately predict the consumer price index and import growth rate of F province.

The expected import growth rate can be used to calculate the total import volume next month. Figure 8 shows a comparison between the projected total imports and the actual value of total imports from June 2014 to February 2015, based on different methodologies.

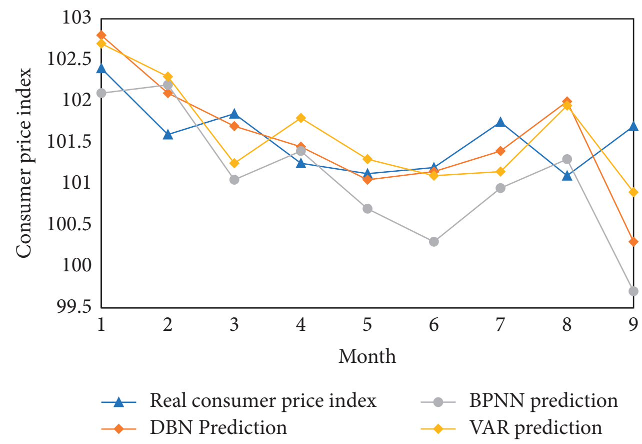


FIGURE 6: Comparison of consumer price index forecasts in F province.

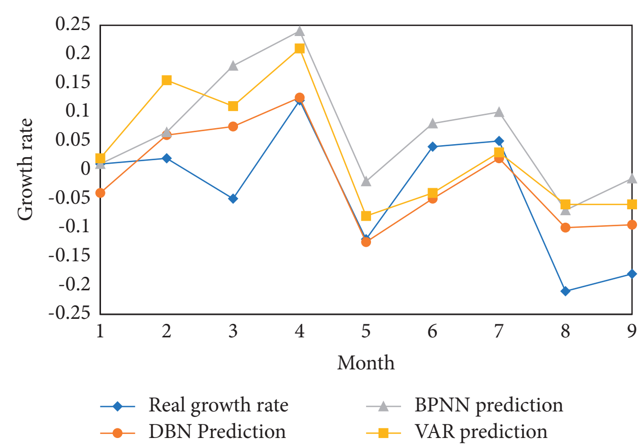


FIGURE 7: Forecast comparison of total import growth rate in F province.

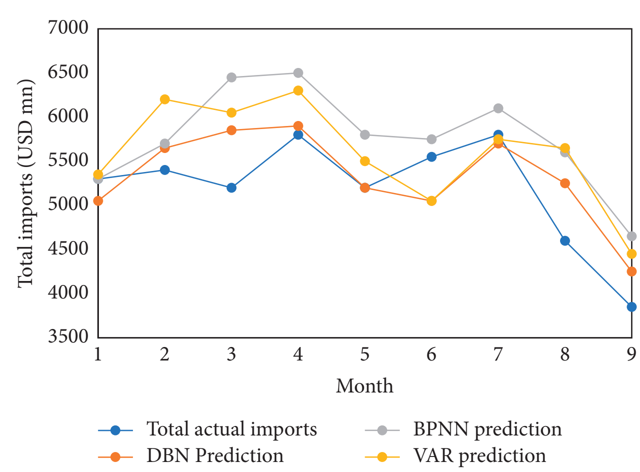


FIGURE 8: Comparison of forecast of total import in F province.

*4.1.2. Comparison of Quantitative Prediction Accuracy.* In order to quantitatively compare the prediction performance of DBN, BP and VAR, the following three indexes are used to determine the prediction accuracy. The definition formula is as follows.

$$MAE = \frac{\sum_{t=1}^{N} \left| y^t - y^t_{true} \right|}{N}, \tag{15}$$

$$MSE = \frac{\sum_{t=1}^{N} \left( y^t - y^t_{true} \right)^2}{N}, \tag{16}$$

$$\text{average relative error} = \frac{\sum_{i=1}^{N} \left| y^t - y^t_E \right| / y^t_{\text{true}}}{N}. \tag{17}$$

The comparison results of prediction accuracy of DBN, BP, and VAR models are shown in Table 2. Bold numbers indicate the metrics corresponding to the most suitable method.

The three methods in Table 2 have little error and can predict the consumer price index of F province with certain accuracy, reflecting the change behavior of the price index. Among them, DBN performs best in absolute error (MAE) and average relative error, reflecting the excellent prediction accuracy of DBN.

According to Figure 6, the forecast period is from June 2014 to February 2015, and the actual consumer price index of F Province decreases slightly and tends to be stable. The forecast results of DBN model can be followed up more closely according to the downward trend of consumer price index of F Province in the first six months, which is consistent with the actual situation. Both BP and VAR forecasts show that in the first seven months, the consumer price index of F province will follow a downward trend, which is different from the actual situation. The former is beneficial for the government to prevent inflation immediately, while the latter may lose control of inflation.

From Table 3, we can see that the absolute mean error (MAE), mean square error (MSE) and average relative error of DBN are smaller than the other two methods. DBN not only has a relatively correct average prediction level, but also has a small error range. The reason why all indicators are lower than the consumer price index is that the total import base is large and the prediction error is large. In addition, the change of total imports is very large, which is difficult to predict. Therefore, the relative error is also very large.

*4.1.3. Convergence Rate Comparison.* Figure 9 shows the error convergence curves of DBN deep learning model and BP neural network in training and learning stages. As far as convergence speed is concerned, DBN is faster than BP neural network and has less fluctuation. This is mainly because the pretraining and learning methods adopted by DBN provide a good initial value of the network. On the other hand, because BP neural network uses random parameters to initialize the network, the starting point of error curve becomes higher, the convergence time becomes longer, and fluctuation may occur, which is also one of the reasons for the degradation of BP prediction performance. VAR does not need repeated training and learning, so there is no convergence speed problem.

Table 2: Comparison of forecast accuracy of consumer price index in F province.

| Method | MAE | MSE | Average relative error (%) |
|---|---|---|---|
| DBN | **0.425** | 0.323 | **0.418** |
| BPNN | 0.690 | 0.752 | 0.679 |
| VAR | 0.492 | **0.291** | 0.484 |

Table 3: Comparison of forecast accuracy of total import volume in F province.

| Method | MAE | MSE | Average relative error (%) |
|---|---|---|---|
| DBN | **314.14** | 145569.09 | **6.303** |
| BP | 529.78 | 413963.91 | 10.626 |
| VAR | 466.64 | 303774.48 | 9.313 |

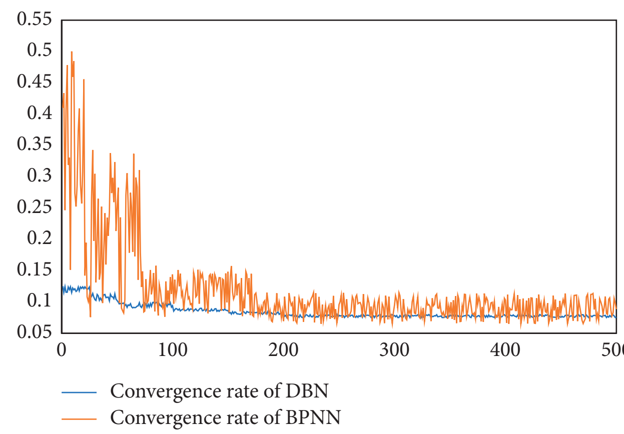


Figure 9: Convergence curves of DBN and BP.

Figure 10 shows the convergence curve of DBN and BP training of F province's total import prediction model. DBN has faster convergence speed, higher convergence accuracy and better practicability.

The prediction results of this paper show that the model can more accurately predict the phenomenon that the consumer price index of F province has a slight decline in the second half of 2014, and predict the stable fluctuation state after the decrease. By predicting this downward trend in advance, the government can estimate the effect of current policy adjustment in advance, so as to maintain or adjust the current monetary policy and keep the consumer price index at a stable level.

From the experimental results of this paper, the results obtained by using different deep learning models have obvious advantages. The simulation results of several models are analyzed and compared from the aspects of prediction accuracy, training convergence speed, pretraining with or without samples, etc. The results show that DBN has certain advantages. The scientific significance of this paper is to introduce deep learning model to predict the efficiency of economic operation and management. Therefore, scientific research is of great significance, which can find out the problems in the process of economic development and reflect the changes of residents' consumption and living index.

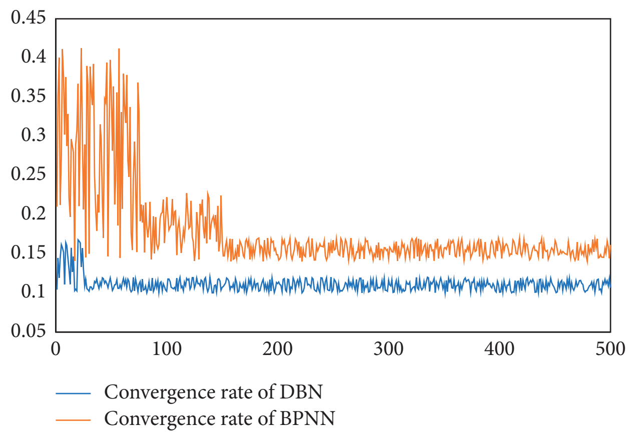


FIGURE 10: Training convergence curve of DBN and BP total import prediction model.

## 5. Conclusion

The model in this paper can predict the decline of total imports more accurately, so the relevant management departments can study the countermeasures in advance. While enterprise managers prevent the impact of the reduction of import volume on enterprise operation, enterprises relying on imports must plan in advance in order to maintain the normal production operation and market supply of enterprises. On the other hand, in order to prevent the decline of imported goods from affecting the prices and economic variables in the local market, government managers should take countermeasures as soon as possible. Actively take countermeasures to protect enterprises and consumers from the impact of import reduction. Specifically, for enterprises, the total import volume is expected to decrease. Through further analysis, we can investigate the reasons for the possible decrease in the total import volume.

## Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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