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Application of Genetically Optimized LVQ Neural Network in Trade Economic Forecasting

Xin Zhang

School of Business
Applied Technology College of Soochow University, Suzhou 215325, P. R. China
zfb46244880@126.com

Yan-Qiu Wei*

Fan Li Business School
Shaoxing Vocational & Technical College, Shaoxing 312000, P. R. China
weiyq@sxvtc.edu.cn

Lin Ni

School of Business
Applied Technology College of Soochow University, Suzhou 215325, P. R. China
842920253@qq.com

Zrdplwa Hashim

Faculty of Engineering, Computing and Science,
Swinburne University of Technology, Kuching 93350, Malaysia
tp5098@163.com

*Corresponding author: Yan-Qiu Wei

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Abstract. *For the purpose of enhancing the prediction accuracy of trade economic cost under increasingly complex environment, genetic optimization LVQ neural network (AGLVQ) algorithm is intended for trade economic forecast. First, this paper optimizes LVQ neural network algorithm by updating the weight vector. Then, on the ground of this, this paper further enhances the individual selection strategy in genetic algorithm to select the optimal individual and the individual with poor fitness value with a large probability and the individual with medium fitness value with a small probability, actually eluding the overfitting phenomenon of training data. The characteristic data affecting import and export costs should be fully considered in the forecasting model of trade economy to guarantee the forecasting accuracy. Finally, MATLAB R2017a is used to forecast and simulate trade economic costs. The simulation outcome signifies that when the genetic variation probability is 0.1, the optimization iteration time of test sample prediction is short and the root mean square error (RMSE) is small. The predicted cost is almost the same as the actual cost, and AGLVQ algorithm has high prediction accuracy.*

Keywords: trade economic; genetic algorithm; LVQ; neural network; prediction accuracy

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1. **Introduction.** As the trade economy and economic globalization speedily developing, trade economy forecasting is particularly significant in both scientific research and the formulation of national economic policies [1]. The operation of the economy tends to have cyclical changes, in the boom, recession, depression, recovery in four states of the cycle. In addition, the market is also affected by various factors, such as political and natural environment changes. The sudden changes in the market brought about by these

influences have caused problems for people to exactly foresee the trade economy [2, 3, 4]. Therefore, how to accurately predict the trade economy and help the country to formulate correct economic policies has become an important topic for scholars to research. In the early studies, scholars used to employ standardized government statistical indicators, namely structured information, to forecast the trade economy. These data have low noise and standard data, but often have a certain lag, which makes the accuracy of the prediction often fall short of the expected effect [5, 6, 7]. Today, with the rapid development of information technology and the Internet, the emergence of big data has brought new opportunities for trade and economic forecasting. How to foresee trade economy quickly and exactly has turned to the concentration of present study.

1.1. **Related Work.** Scholars combined econometrics and computer technology to make quantitative forecast of trade economy, so that the accuracy of trade economy forecast has been excellently enhanced.

Tibshirani [8] suggested that LASSO method, which added regression parameters to the residual sum of squares to obtain the effect of variable selection. However, the parameter estimation of LASSO method is biased. Fan and Li [9] achieved the parameter estimation of linear regression with SCAD penalty function by using the Taylor quadratic expansion of the penalty function and the iterative method. In terms of forecasting content, Konstantin et al. [10] improved the forecasting effect on the growth rate of personal consumption in the United States by combining Internet search information. Compared with the prediction result of the growth rate of personal consumption in the United States by using the traditional consumer confidence index, the prediction result obtained by using the behavioral data of Internet search is more accurate. Vosen and Schmidt [11] combined the Internet search information time series to establish a monthly forecast model of personal consumption, and found that the foresee effect of this model was better than that of the consumption forecast model on the ground of traditional sample surveys. Secondly, the use of Internet search behavior to predict the macro economy is reflected in the forecast of employment. Aaronson et al. [12] added search engine data when predicting the situation of unemployment insurance receipt, and came to the conclusion that the search data of unemployment and related benefits could improve the initial application for unemployment benefits. Askitas and Zimmermann [13], Amuri and Marcucci [14] and Webb [15] found that adding genetic algorithm to the prediction of labor market conditions in Germany, France and Israel could make the prediction of the model more accurately. Thirdly, in the aspect of trade economy, the genetic algorithm is also effective in forecasting. For example, Lehmann and Wohlrabe [16], Choi and Varian [17] found that the introduction of economic feature vectors can greatly enhance the effect of the forecasting model. By analyzing the relationship between oil price and economy, Katayama [18] came to the conclusion that the impact of rising oil price on economy would gradually weaken. Anupam Das et al. [19] used the data of 45 developing countries from 1971 to 2009 to study the dynamic relationship between electricity consumption and economic growth through the method of system moment estimation, and finally found that there was a positive relationship between electricity consumption and economy. Ashraf et al. [20] analyzed the real per capita GDP and electricity consumption data of Pakistan from 1971 to 2010, and finally concluded that there was a one-way causal relationship and a long-term relationship between electricity consumption and real per capita GDP. Serafin et al. [21] analyzed the causality and cointegration of electricity consumption and economic data, and concluded that there is a long-term equilibrium relationship between them, and there is a one-way causality between economic growth and electricity consumption. Using 60 years of trade data, the U.S. Energy Information Administration analyzed the relationship between electricity consumption and the economy.

The outcome suggests that electricity consumption and economic growth in developing countries tend to be the same in both the long and short term. The trend of electricity consumption and economic growth in developed countries is consistent only in the short term [22]. In their trade and economic prediction on the ground of big data, Tuo et al. [23] put forward a network structure ADL model suitable for big data prediction in combination with the particularity of time series, and carry out dimensionality reduction by Lasso method. In addition to parameter estimation and model selection, network relations between variables are taken into account, but the accuracy of prediction is relatively low.

1.2. **Motivation and contribution.** In view of the fact that the current trade economic forecasting models are all quarterly models, and the research on macroeconomic forecasting models with smaller time intervals and higher forecasting accuracy is still lacking, this paper applies genetically optimized LVQ neural network (AGLVQ) algorithm to trade economic forecasting.

First of all, this paper modified the weights according to the tutor signal and optimized the LVQ neural network. Then each part selected individuals in light of the corresponding probability formula, binary coded the LVQ structure (number of network layers, number of nodes in each layer) and activation function for optimal prediction. Finally, the prediction and simulation of trade economic cost were carried out. AGLVQ algorithm has higher prediction accuracy in trade economic cost prediction, especially when the variation probability is 0.1, the prediction stability is higher.

2. **Theoretical analysis.**

2.1. **LVQ neural network.** In deep learning research, neural networks are often used to classify data. Among them, single-layer perceptron is the simplest neural network that can uniformly approximate the linear continuous function space, but it is inseparable to the nonlinear sample space. BP neural network is the most widely used, but the disadvantage of BP neural network is that it adopts the nonlinear iterative algorithm on the ground of gradient descent, which may be trapped in the local minimum problem in the process of solving, so that the global minimum cannot be guaranteed [24]. The advantage of LVQ neural network is that it does not need to normalize and orthogonalize the input vector, but only needs to directly calculate the distance between the input vector and the competing layer, so as to realize the classification. LVQ neural network, also known as Learning Vector Quantization neural network, is a learning algorithm that trains the competition layer under a teacher state (complete classification label), and is widely used in the area of pattern recognition and optimization [25, 26, 27]. LVQ neural network belongs to supervised pattern recognition, and its basic structure is basically the same as other neural networks, that is, LVQ neural network is also composed of three layers of neurons, namely input layer, hidden layer and output layer [28, 29]. LVQ neural network structure is displayed in Figure 1.

2.2. **Genetic algorithm.** Genetic algorithm (GA) has the advantages of good robustness, low computational complexity and few parameters of target function [30, 31]. The optimization of genetic algorithm mainly includes five steps: initialize population, construct fitness function, select operation, cross operation and variation operation.

(1) Initialize the population. According to the parameters set by the algorithm, the population is initialized, including the connection weight between the input layer and the

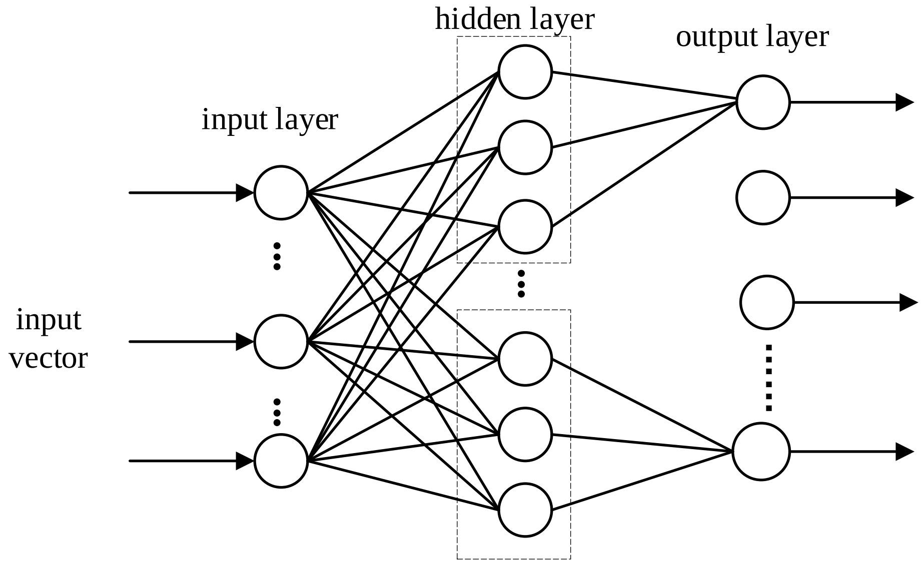

Figure 1. LVQ neural network structure

hidden layer, the connection weight between the hidden layer and the output layer, and the threshold of the hidden layer and the output layer.

(2) Construct fitness function. The wavelet neural network is constructed according to individual information in the population, and the data in the training set are used to train and predict the neural network. The absolute value of the error between the predicted output value of the neural network and the actual expected value is used as the index to evaluate the pros and cons of individuals in the population, that is, the fitness F of individuals. The calculation formula is Equation (1).

$$f = l(\sum_{j=1}^{m} cdt(x_j - p_j)) \tag{1}$$

where I is the fitness function coefficient; m is the number of network output nodes; x_j is the predicted output value of the j-th output node; p_j is the actual expected value of the j-th output node.

(3) Select operation. In this paper, the roulette strategy is adopted to select individuals in the population, that is, the individual selection probability is determined based on the fitness of individuals in the population, and the calculation formula is as follows: $f_j = \frac{I}{U_j}$, where U_j is the fitness of the j-th individual in the population; I is the coefficient; Since the smaller the fitness value, the better, f_j replaces U_j, and p_j is the probability of the individual being selected.

(4) Cross operation. In this paper, the crossover strategy adopts the real number crossover method. It is assumed that individual c_m and individual c_n cross at the j-th position, and its operation process is displayed in Equation (2).

$$\begin{cases} c_{mi} = c_{mi}(1-d) - c_{mi}d \\ c_{mi} = c_{mi}d - c_{mi}(1-d) \end{cases} \tag{2}$$

where d is the uniformly distributed random number between 0 and 1.

(5) Variation operation. Suppose that the j-th part c_{ij} of the i-th individual is mutated, and its operation process is displayed in Equation (3).

$$c_{ji} = \begin{cases} c_{ji} + (c_{ji} - c_{\max}) \cdot f(v) & \text{if } s \geq 0.5 \\ c_{ji} - (c_{\min} - c_{ji}) \cdot f(v) & \text{if } s < 0.5 \end{cases} \tag{3}$$

where $c_{\max}, c_{\min}$ are the upper and lower bounds of c_{ji}, s is a uniformly distributed random number between 0 and 1. Among them, the algorithm variation operation is adopted $f(v) = s_1(1 - \frac{v}{V_{\max}})$, where s_1 is the random number between $[0, 1]$, h and $V_{\max}$ are the current and maximum iterations, respectively.

3. **Improved LVQ network model.** LVQ neural network is a supervised neural network. In this paper, the weight of LVQ neural network is modified according to the tutor signal, so as to achieve the goal of training the learning process.

From the classification point of view, the tutor signal belongs to the target classification. In order to better achieve the learning goal, adding the tutor signal to the training sample of the network has become the top priority of LVQ neural network learning. All right. The competitive learning method based on LVQ neural network means that in the classification process of the network, only one neuron can become the "lucky one" in each classification, and only this one neuron can adjust the weight vector. So, which neuron can be the lucky one, that needs to be a competition. Specifically, the competitive learning process of an improved LVQ neural network can be divided into the following steps.

(1) Set the initial value of the weight vector and network parameters. There are two ways to set the initial value. One way is to set the initial weight vector $H_i^{(j)}$ $(i = 1, 2, \ldots, k)$ of the competing layer neurons to a smaller value, and the other way is to set the sample vector as the initial value. Finally, the training number M and learning rate $\varphi(k)$ should be set to ensure that the whole learning and training process can proceed smoothly.

$$h_{ji}^2 = \begin{cases} 1, \text{the competition layer neuron } j \text{ is classified as class } i \\ 0, \text{otherwise} \end{cases} \tag{4}$$

(2) Weight vector update. Through the above rules, the weight of the winning neuron and similar neurons contained in its neighborhood are adjusted together. The corresponding learning rule is displayed in Equation (5).

$$h_j(l+1) = \begin{cases} \phi_j(l) + \rho(l) \dfrac{y^T(l)\phi_j(l)[y(l) - \phi_j(l)]}{||y(l)||_2 ||Q_j(l)||_2} \; j \in M_p \\ \phi_j(l) \; j \notin M_p \end{cases} \tag{5}$$

(3) Input the training sample vector Y accurately.

(4) Calculate to find the winning neuron "lucky". The winning neuron refers to the neuron closest to the input sample. The calculation method is based on Equation (6), which calculates the distance between the weight vector of each neuron in the competition layer and the input sample vector, then compares the distance, and finally finds the nearest neuron among these neurons. In the whole LVQ neural network competitive learning mechanism, the winning neuron is labeled as $j*$, and its output is defined as "1".

$$Y - V_f^j = \min Y - V_i^j, i = 1, 2, ..., k \tag{6}$$

(5) Modify the weight vector of the winning neuron. Modifying the weight vector of winning neurons is the core and purpose of LVQ neural network's competitive learning mechanism. The method of modifying is to judge whether the output classification result is correct according to the target classification. If the target classification result of the output layer is correct, the weight of the winning neuron will continue to be corrected in the direction close to the input sample, that is Equation (7).

$$V_{i'}^{1}(m+1) = V_{i'}^{1}(m) + \mu(m)(Y - V_{i'}^{1}(m)) \tag{7}$$

If the target classification result of the output layer is not correct, it will be corrected away from the input sample, that is the Equation (8). In particular, the weights of the other neurons remained constant throughout the correction.

$$V_i^j(m+1) = V_i^j(m) - \mu(m)\left(Y - V_i^j(m)\right) \tag{8}$$

(6) Update the learning rate, i.e., $\mu(m) = \mu(1)(1 - \frac{m}{M})$.

(7) When $m < M$, set $m = m + 1$ and go to step (2) again to train the learning process for the next sample. Repeat the above steps until $m = M$ or all input patterns are correctly classified, at which point the network training is finished.

4. Trade economic forecasting based on genetically optimized LVQ neural network model.

4.1. Improved genetic algorithm combined with LVQ neural network algorithm.

On the ground of the above enhanced LVQ neural network algorithm, this chapter further improves the individual selection strategy in the genetic algorithm. Instead of setting a fixed number of optimal retained individuals, the optimal individuals are selected with a greater probability, and individuals with poor fitness values are selected with a greater probability and individuals with medium fitness values with a small probability.

In this way, the speed of searching solutions can be ensured. At the same time, it can maintain good population diversity and effectively avoid overfitting of training data. Random cutting of edges and nodes may cut some important edges and nodes. Therefore, a genetic algorithm optimization LVQ neural network (AGLVQ) algorithm is designed in this paper to preserve important edges and nodes for the purpose of obtaining better trade economic forecasting results. The algorithm flow is displayed in Figure 2.

Parents and children are first merged, sorted by fit value, and evenly divided into two parts. Then the LVQ structure (the amount of network layers, the amount of nodes in each layer) and the activation function are binary coded, the learning rate and the network weight are real coded, and the individual objective function value is the prediction error of the feedforward neural network. Each generation of the algorithm is run by improving the selection strategy and cross-mutation operator to find the optimal individual, that is, the optimal amount of layers of the feedforward neural network, the amount of nodes in each layer, the learning rate, the weight and the activation function. Then the LVQ strategy cuts the edge, and the algorithm runs iteratively until the maximum amount of set times is met.

(1) Population initialization, build a neural network model in terms of each individual, $s = 0$.

(2) In generation s, parent $p(s)$ performs crossover and mutation operations to produce a new child $P'(s)$.

(3) Implement sparse network strategy for individuals in child $P'(s)$ according to a certain probability to generate child $P''(s)$;

(4) Among *2m* individuals, according to the probability formula designed in this paper, m individuals are selected for the next step. The selection is based on the fact that the individuals with extreme fitness values are more likely to be selected.

$$p(i) = 1 - \left[\frac{s(i)}{s(2m) - s(0)}\right]^{\frac{b}{n}}, (1 \leq i \leq m) \tag{9}$$

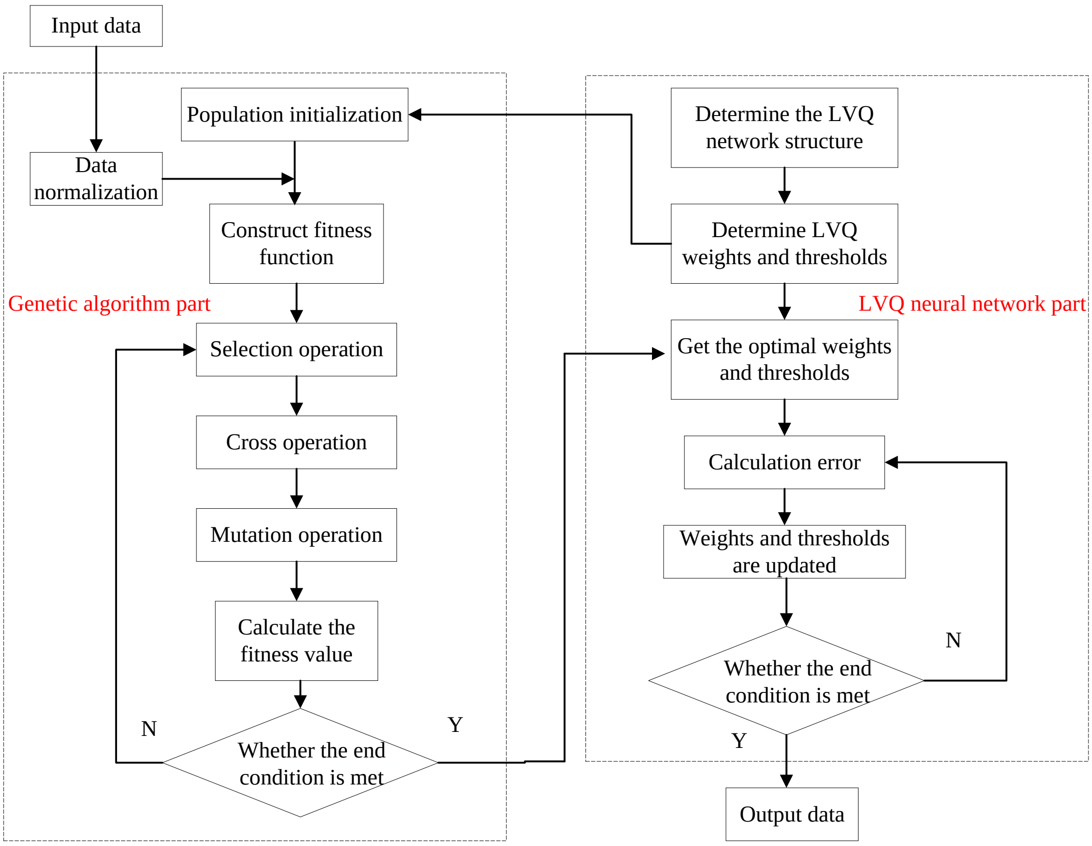

Figure 2. The algorithm flow of AGLVQ

$$p(i) = \frac{s(i)}{s(2m) - s(0)}, (m + 1 \leq i \leq 2m) \tag{10}$$

where $p(i)$ represents the probability that the i-th individual is selected, and $s(i)$ represents the ranking value of the i-th individual in the whole according to the value of the objective function from small to large. Individuals with small objective function values have small ranking values, and individuals with large objective function values have large ranking values. b represents a constant that controls the range of probabilities, s represents the algebra that is currently running, and n represents the maximum algebra that the program set is running.

(5) Calculate the objective function value of the child $P(s)$ individual.

(6) Merge the parent $p(s)$ with the child $P(s)$ individual and select the individual as the new parent $P(s+1)$.

(7) When the maximum number of iterations of the population is reached, the optimization will stop and enter step (7); otherwise, $s = s + 1$, it will return to step (2).

(8) Population individuals predict the test data and obtain the LVQ neural network with the smallest test error.

4.2. **Trade economic forecasting based on genetically optimized LVQ neural network.** Trade economic calculation involves the holding cost of goods b_1, export cost b_2, import cost b_3, and shipment volume b_4, etc., and the cost is closely related to the real-time price relationship of the market.

Therefore, in order to realize trade economic forecast, it is necessary to consider the fixed factors such as demand orders, warehouse capacity and management default cost. It is also necessary to fully consider the price, demand and supply factors that change with the market. Therefore, the characteristic data affecting inventory cost should be fully considered when modeling trade economic forecast. In summary, the objective function of inventory cost is Equation (11).

$$cost = b_1 + b_2 + b_3 + b_4 - P \tag{11}$$

Collect and organize historical export data, inventory data and other relevant variables, such as supply chain information, market demand, etc., to ensure data quality and integrity. After obtaining the inventory cost characteristics, the objective function of cost prediction was established, and then a trade prediction model based on genetically optimized LVQ neural network was constructed according to Section 4.1. The probability of genetic variation and the number of weak classifiers were set, and strong classification results were obtained by weighting multiple weak classifiers. Finally, the performance of trade economic prediction was evaluated. The prediction process is displayed in Figure 3.

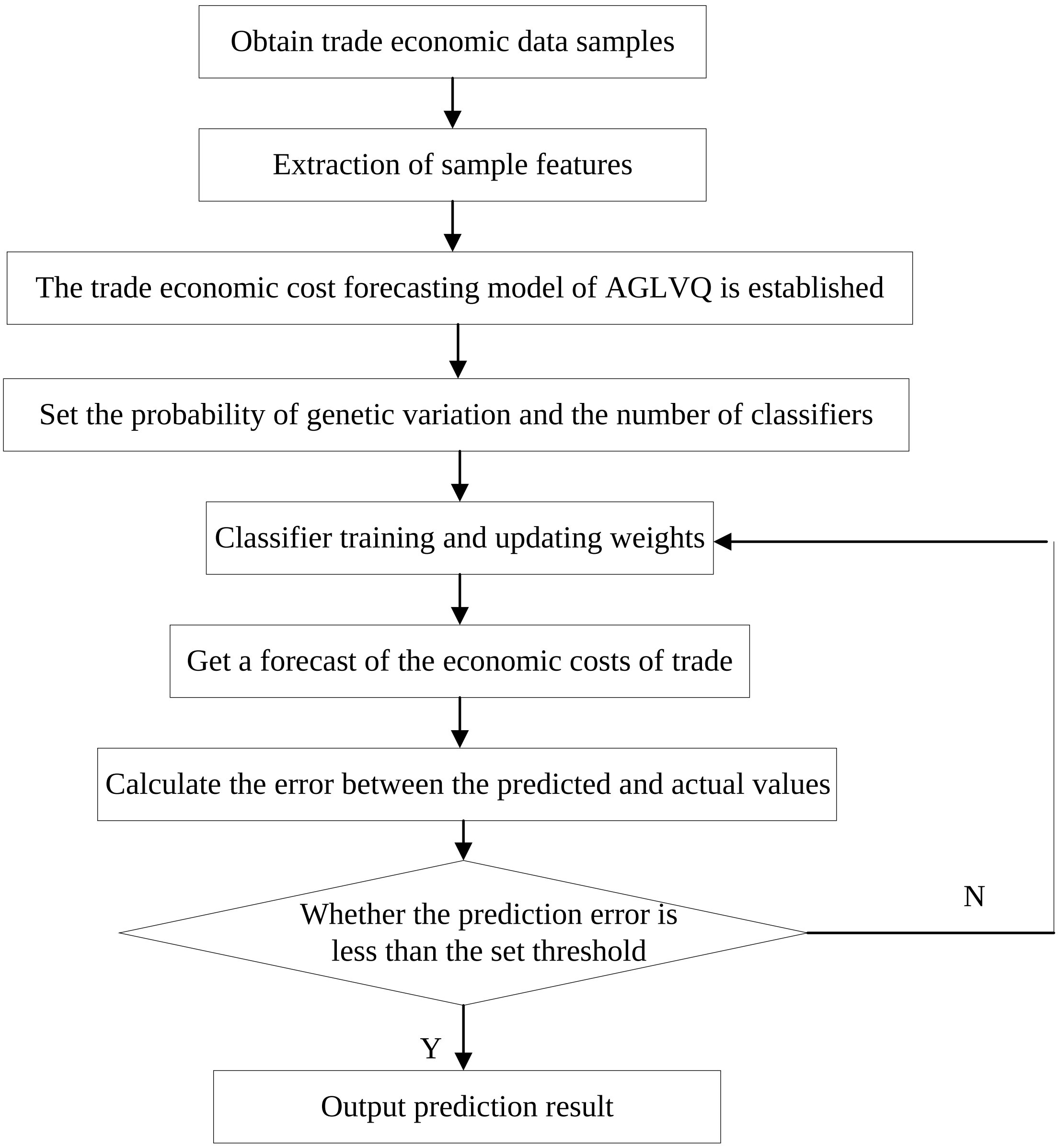

Figure 3. Forecasting process of economic cost of trade

5. Algorithm performance test and analysis.

5.1. LVQ's Economic Cost projections for trade. This paper verifies the performance of genetically optimized LVQ neural network algorithm (AGLVQ) in trade economic forecasting, and performs cost pre-measurement simulation on 1000 data of 10 trade warehouses in 2023 of a large e-commerce platform.

Firstly, MATLAB R2017a is used to predict the economic cost of trade, and the prediction error of each sample is calculated. Secondly, LVQ algorithm with different genetic variation probability is used to simulate inventory cost prediction, and the influence of variation probability on trade cost prediction performance is analyzed. Then, the prediction stability and efficiency of the algorithm are analyzed. Finally, the cost optimization simulation is carried out. In this paper, a single-step rolling prediction mode is adopted, that is, every four kind of input data is predicted the fifth output data, the target error is set to 0.0001, and the maximum training times is 1000. In the genetic algorithm, the number of population is set to 50, the maximum number of iterations is 500, and the crossover probability is 0.5.

AGLVQ algorithm is used to predict the trade cost of 50 test samples, and the result is displayed in Figure 4.

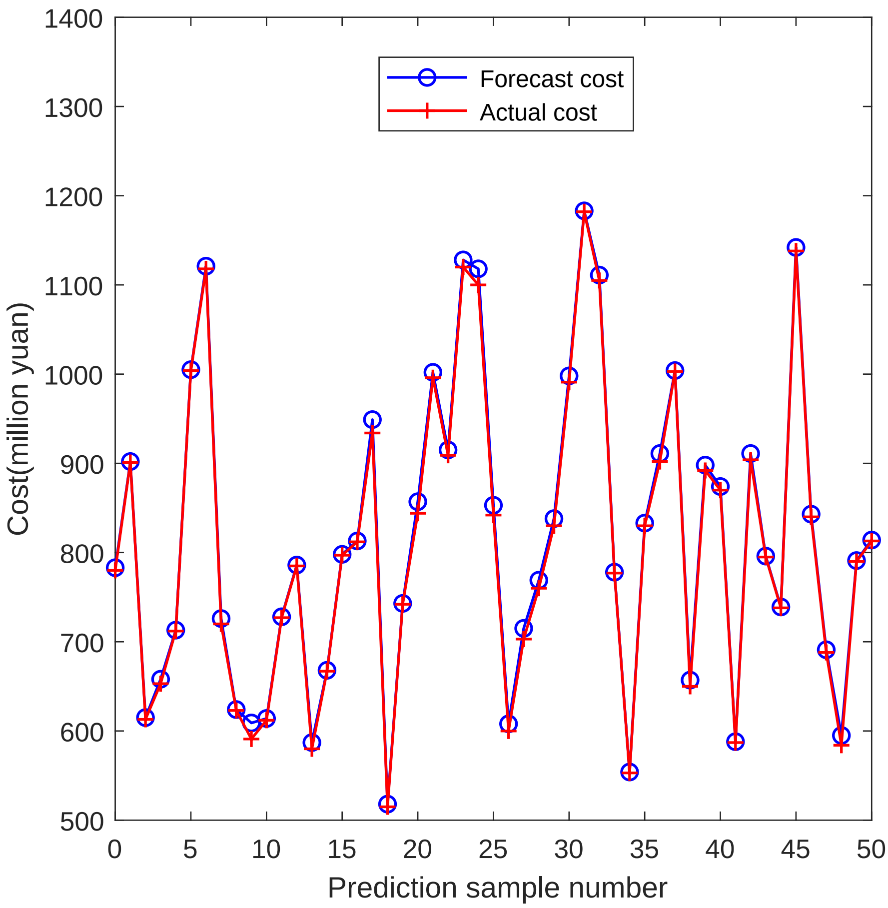

Figure 4. Actual cost and forecast cost

It can be seen from Figure 4 that among the predictions of 50 test samples, the predicted cost of trade economy of AGLVQ algorithm has a high coincidence degree with the actual cost, and even if there are some non-coincidence points, the gap between the two is not large. The sample number is in the 20-30 segment, and there is a certain cost forecast deviation, which may be because this period is just in the annual promotion period of trade e-commerce, and its supply quantity fluctuates greatly compared with the previous months, so it causes a certain shock to the performance of trade economic forecast. For the purpose of more directly reflecting the forecast error of trade cost, the absolute forecast error is displayed in Figure 5.

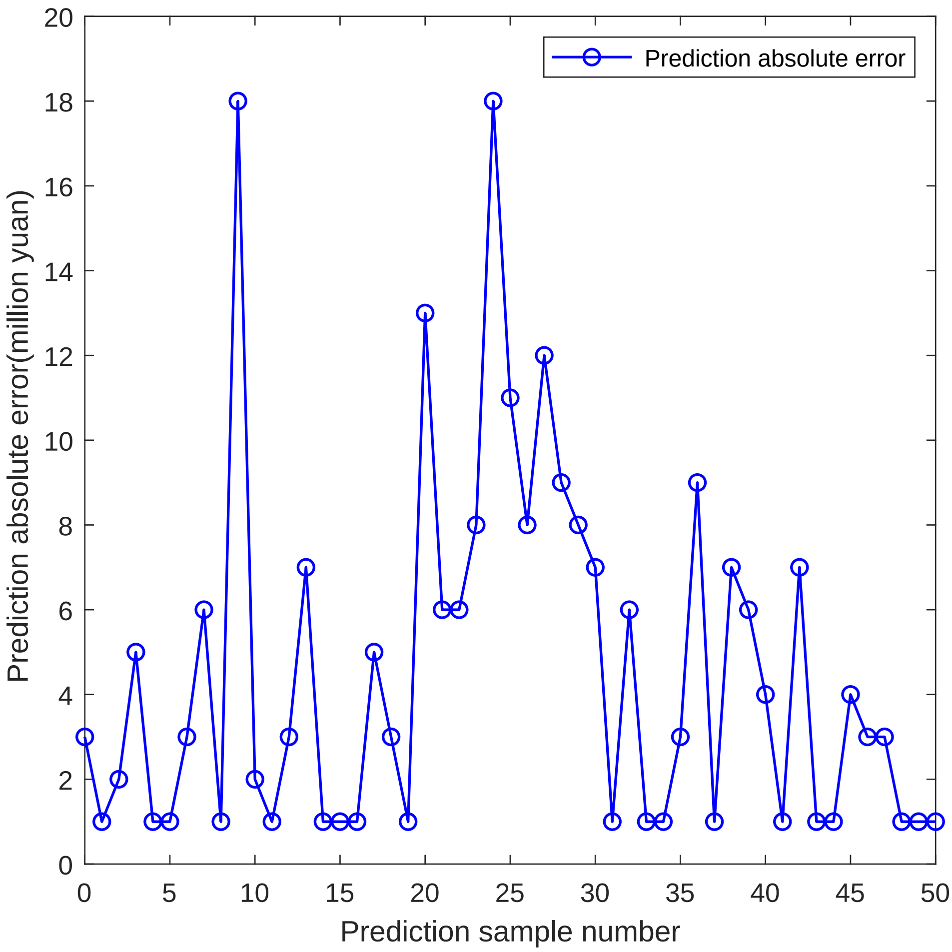

Figure 5. Absolute error of predicition

In Figure 5, the absolute error of most samples is within the range of 100,000 yuan, and the absolute error of 54% of the samples is close to 0, while the error of more than 100,000 yuan is about 1%, and the maximum value of prediction error is about 200,000 yuan. Compared with the real cost, the error value is not large, which indicates that the AGLVQ algorithm has a high prediction accuracy in the forecast of trade economic cost.

5.2. **Prediction of economic cost of trade with different probability of genetic variation.** In the prediction process of AGLVQ algorithm, its genetic probability (ϑ) has a certain influence on both training speed and training accuracy. The difference settings are different, and the prediction performance of trade economic cost under different values is verified. It can be seen from Figure 6 that compared with the actual cost of trade, the value of AGLVQ algorithm has a significant impact on the predictive performance of actual cost. When $\vartheta = 0.1$, the predicted cost of AGLVQ algorithm is infrequently close to the actual cost; when $\vartheta = 0.05$, the predicted cost of AGLVQ algorithm has the lowest fitting degree with the actual cost. As ϑ increases from 0.1 to 0.3, its predictive performance decreases.

Next, this paper will select different ϑ values respectively to test the root mean square error (RMSE) prediction performance of the sample samples. Table 1 lists the RMSE values of some samples. It can be seen from Table 1 that for the predicted RMSE of AGLVQ with three different ϑ values, the performance difference is obvious. When $\vartheta = 0.05$, the RMSE performance is the best, all within 1.6×10^{-2}. When $\vartheta = 0.3$, the performance of RMSE is the worst, and all of them are above 4.6×10^{-2}. When $\vartheta = 0.05$, sample 40 obtained the optimal performance. RMSE value of 1.512×10^{-2}. When $\vartheta = 0.1$, the RMSE value basically stays around 2.3×10^{-2}, which may be because the smaller the value, the smaller the weight update granularity of the weak classifier and the smaller the predicted vibration, so the prediction stability is higher.

As can be seen from Table 2, under the same training and test sample size, the cost prediction time of AGLVQ algorithms with different ϑ value is quite different. When ϑ =0.05, the prediction time is the most time-consuming, and the prediction time decreases with the increase of ϑ value. This is mainly because the smaller the probability of genetic variation, the smaller the weight update pace, and the longer the optimization iteration time. This reduces cost efficiency. By comprehensive comparison, when $\vartheta = 0.05$, the forecast stability of trade economic cost is the highest, but the prediction accuracy is not high and the time is longest; Therefore, $\vartheta = 0.1$ is chosen as a compromise to ensure both high prediction accuracy and high prediction stability.

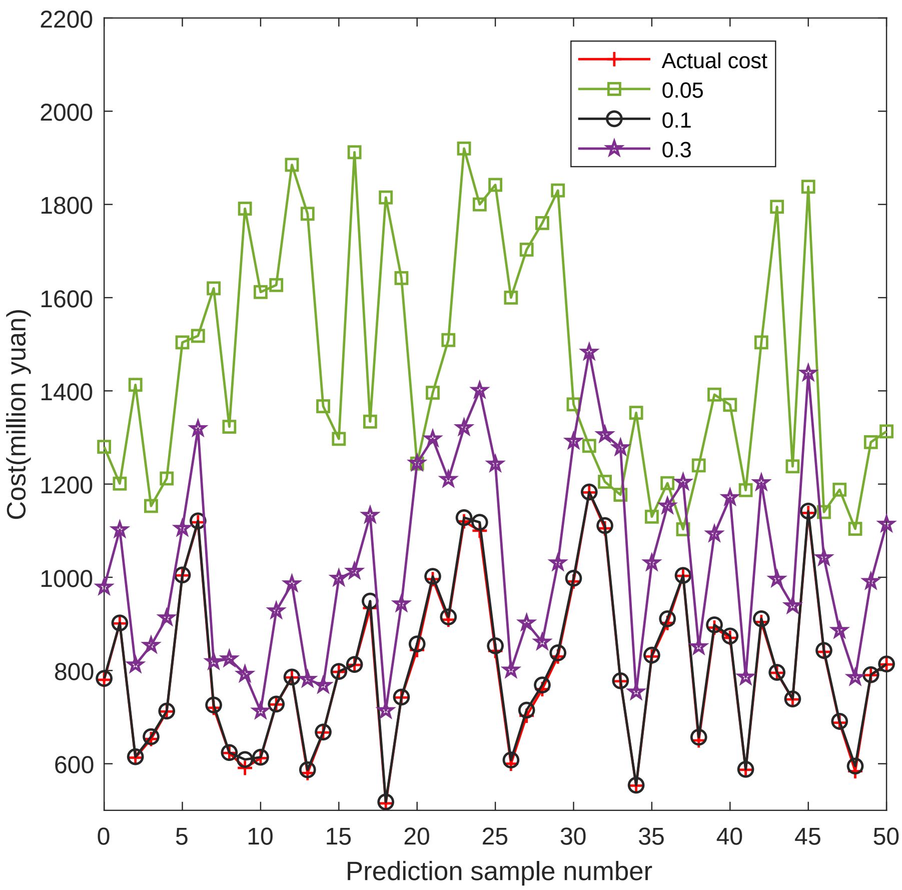

Figure 6. Forecast cost of trade economy with different ϑ values

Table 1. Trade economic forecast RMSE under different ϑ-values.

Sample number	**RMSE**		
	$\vartheta = 0.05$	$\vartheta = 0.1$	$\vartheta = 0.3$
1	1.374e-2	2.212e-2	4.261e-2
5	1.265e-2	2.154e-2	4.127e-2
10	1.318e-2	2.236e-2	4.516e-2
15	1.415e-2	2.287e-2	4.324e-2
20	1.289e-2	2.362e-2	4.381e-2
25	1.329e-2	2.315e-2	4.295e-2
30	1.264e-2	2.183e-2	4.428e-2
35	1.386e-2	2.292e-2	4.434e-2
40	1.512e-2	2.019e-2	4.167e-2
45	1.427e-2	2.371e-2	4.284e-2
50	1.351e-2	2.253e-2	4.491e-2

Table 2. Trade economic forecast RMSE under different ϑ-values.

Sample set	**Forecast time(s)**		
	$\vartheta = 0.05$	$\vartheta = 0.1$	$\vartheta = 0.3$
Training set	45.681	34.149	27.542
Test set	9.418	6.567	4.183

6. **Conclusion.** Aiming at the low forecasting accuracy of existing trade economic forecasting methods, this paper proposes a trade economic forecasting method based on Bayesian genetic optimization LVQ neural network (AGLVQ). This method first adds the tutor signal to the training sample of LVQ network to improve the competition process, then finds the optimal individual by improving the selection strategy of genetic algorithm and cross mutation operator, and uses LVQ strategy to cut edges to obtain the LVQ neural network with the smallest test error. Secondly, strong classification results are obtained by weighting and combining multiple weak classifiers. Finally, the performance of trade economic forecasting is evaluated. The simulation results show that AGLVQ algorithm has high prediction accuracy in trade economic cost forecasting and can be applied to trade economic forecasting well.

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