Agricultural Economy Prediction Method based on Improved BP Neural Network

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***Abstract* — This paper deals with the problem of agricultural economy prediction method, which is a crucial problem in modern rural economy management. The main innovations here is an improved Back Propagation (BP) neural network which is exploited to solve the agricultural economy prediction problem. The BP neural network utilizes the algorithm of multilayer neural network model. As the BP algorithm cannot effectively search the global optimum solution of the prediction application, in this paper we develop an improved BP neural network based on genetic algorithm to promote the accuracy of state prediction. The genetic algorithm refers to a policy to solve both constrained and unconstrained optimization problems using a natural selection process. Additionally, the proposed algorithm repeatedly modifies a population of individual solutions, and then suitable individuals are chosen by the genetic algorithm from the current population. To demonstrate the effectiveness of the proposed algorithm, we choose the agricultural economy data from China's statistical yearbook to construct two datasets, which are corresponding to grain yield and index of gross agricultural output value respectively. Experimental results verify that compared with other methods, the proposed algorithm can achieve higher prediction accuracy and more stable prediction ability.**

Keywords -- Agricultural economy prediction; BP neural network; Genetic algorithm; Fitness value, Statistical yearbook.

I. INTRODUCTION

In recent years, rural development greatly influences the overall process of future social and economic development of China[1]. In the past few years, with the great pressure of both population growth and the reduction of cultivated area, China's agriculture has obtained an obvious shift from a shortage of agricultural products to the balance of supply and requirement[2][3]. The above achievements highly relied on modern agricultural science and technology. Additionally, in the modern agricultural development, both the agricultural science and technology human capital play important role in agricultural management and development[4].

In particularly, three rural issues greatly influence Chinese modernization process. In the year of 2004 and 2009, two No. 1 Documents both concentrate on the problem of farmers' income. However, it is difficult to enhance farmers' income, because the prices on agricultural products are fairly low and the jobs are difficult to find for farmers as well[5][6]. Therefore, the local government promotes incomes through the preferential agricultural policies, e.g. the exemption of agricultural tax and agricultural subsidies, and agricultural economic policy. Although many scholars have focused on Chinese agricultural economic growth, the quantitative analysis is far from satisfaction[7][8].

From the all the above analysis, this paper aims to develop an effective agricultural economy prediction method. Particularly, in this work we introduce an improved BP neural network to solve the proposed method. As is well known that the BP neural network is belonged to a typical feedforward network. Moreover, utilizing the network structure positive transfer approach and the training function reverse revision network weight matrix, the BP neural network implements samples training model of the structure, and then it exploits the built training model to complete the treatment of the sample to be estimated[9][10].

The rest of the paper is organized as follows. Section 2 analyzes the related works about applications of BP neural network. In section 3, we introduce some concepts of BP neural network, and then we propose the improved BP neural network. Next, we discuss how to apply it to solve the agricultural economy prediction problem. To verify the effectiveness of the proposed algorithm, in section 4, experiments are designed and implemented. Finally, the conclusions are drawn in section 5.

II. RELATED WORKS

In this section, we will discuss the utilization of BP neural network in several different domains. In the past few years, as a powerful computing tool, BP neural network has been successfully used to solve many different problems, and in the following section, related works are listed and analyzed as well.

Li et al. used the block matching algorithm to eliminate the occlusion-disturbance and proposed the back-propagation neural network algorithm to compensate for the low-resolution image. In particular, a computational integral imaging pickup technology is exploited to save the multiple-image to construct an elemental image array at the same time[9].

Xu et al. developed a novel back propagation (BP) neural network model to map the complex non-linear relationship between microstructural parameters and elastic modulus of the composite. Afterwards, the proposed method is used to forecast elastic modulus of 3-D multi-phase and multi-layer braided composite[10].

Xia et al. proposed a new silicon microgyroscope (SMG) temperature forecast and control system in a narrow space. Considering the temperature of SMG is corresponding to its drive mode frequency and driving voltage, a temperature prediction model is constructed using the BP neural network[11].

Liu et al. applied the real-coded quantum-inspired genetic algorithm to optimize the weights and threshold of BP neural network, the aim of this paper is to solve the defect that the gradient descent method makes the algorithm easily fall into local optimal value in the learning process. In particular, the proposed algorithm is used to search the whole space[12].

Huang et al. forecasted wind power via chaos and BP artificial neural networks approach based on genetic algorithm, and then to evaluate feasibility of the approach of forecasting wind power[13]. Safarvand aims to use exergy analysis of natural gas liquid (NGL) process more understandable by coupling it with the use of an artificial neural network modeling[14]. Apart from the above works, BP neural network is also used in other types of applications, such as Weld appearance prediction[15], Ensemble detection model for profile injection attacks[16], Rapid Assessment of Populations with Difficulties Accessing Drinking Water[17].

Inspired by the above works, in this paper, we attempt to utilize a modified version of BP neural network to provide a solution scheme to forecast agricultural economy development.

III. THE PROPOSED ALGORITHM BASED ON THE IMPROVED BP NEURAL NETWORK

Exploiting the Back Propagation algorithm of multilayer neural network model is denoted as BP neural network. Particularly, BP artificial neural network means to the most widely used neural network. The traditional BP neural network is made up of three modules, that is, a) input layer, b) hidden layer and c) output layer. To describe BP neural network more clearly, its structure is given as follows.

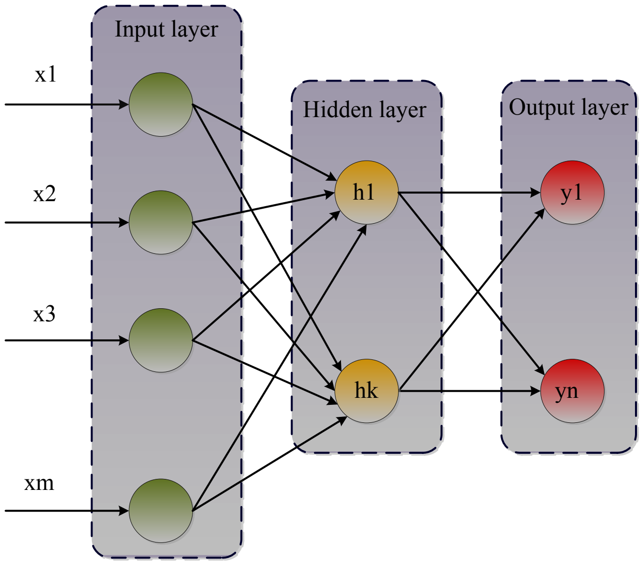

Fig. 1 Architecture of the BP neural network

The BP neural network requires some continuous non-linear excitation functions, which are represented as follows.

$$F\left(net_{jk}\right)=\frac{1}{\left(1+e^{-Net_{kj}}\right)} \quad (1)$$

where the symbol net_{jk} can be calculated as follows.

$$net_{jk}=\sum_{i=N} w_{ji}\cdot OT_{ki}+\delta_j \quad (2)$$

$$OT_{ki}=\left(1+\exp\left(-\sum_{i=1}^{N} w_{ji}\cdot OT_{ki}-\delta_j\right)\right)^{-1} \quad (3)$$

Afterwards, for a given output layer, parameters are illustrated in Eq. 4.

$$\omega_{kj}=\left(t_{kj}-OT_{kj}\right)\cdot OT_{kj}\cdot\left(1-OT_{kj}\right) \quad (4)$$

Next, for a given hidden layer, its parameters can be given in Eq. 5.

$$\omega_{kj}=OT_{kj}\cdot\left(1-OT_{kj}\right)\cdot\sum_{m=1}^{M}\omega_{km}\cdot\nu_{uj} \quad (5)$$

Based on the above formal definitions, process flow of the BP neural network is proposed in Fig.2.

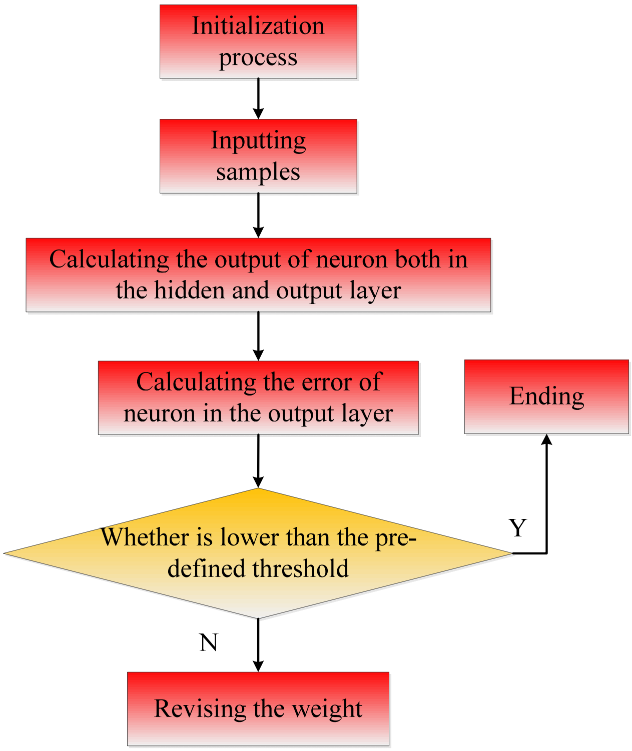

Fig.2 Process flow of the BP neural network

As is shown in Fig.2, The outputs of each layer are transmitted to its neuron of the next layer. Furthermore, BP neural network holds a bias neuron to generate constant outputs with no receiving inputs. Additionally, similar to neural network, BP neural network is constructed through minimizing errors in neural networks as well.

Considering the BP algorithm is not suitable to search the global optimum solution of the prediction application, the BP neural network has limitations when solving the state prediction problem. Therefore, in this work, we proposed an improved BP neural network to enhance the accuracy of state prediction. The main innovations of this paper lie in that we introduce the genetic algorithm (GA) refers to an approach to tackle both constrained and unconstrained optimization problems via a natural choosing process which mimics biological evolution process. Particular, our proposed algorithm repeatedly revises a population of individual solutions, and then the genetic algorithm is utilized to choose suitable individuals from the current population.

Our proposed improved BP neural network aims to find the most suitable connection weights and thresholds of neural network, and then to optimize the initial weights of neural network via the genetic policy. The implementation of the proposed algorithm is described as follows.

In the first step, populations are initialized, and real number coding algorithm is exploited to code each individual in the population. In the second step, each individual is corresponding to several initial weights and the threshold of the BP neural network. In particular, the fitness value is calculated as follows.

$$F = \lambda \cdot \sum_{i=1}^{N} \sum_{j=1}^{M} abs\left(Y_{j,i} - O_{j,i}\right) \tag{6}$$

where the symbol j denotes the number of output nodes, $Y_{j,i}$ means the i^{th} wanted output of the BP neural network, and $O_{j,i}$ refers to the i^{th} computed output of BP neural network, N represents the number of the training samples, and λ is a constant.

In the third step, genetic algorithm is used as a selection strategy of the fitness proportion. The probability to be chosen as its next generation of individual i is computed as follows.

$$pi = \frac{f_i}{\sum_{i=1}^{n} f_i} \tag{7}$$

where f_i is equal to λ / F_i.

In the fourth step, the crossover operation exploits the real number crossover approach, because there are several real coding individuals in the whole population. The individual h_p and h_q construct crossover operation at the k^{th} position via the following equations.

$$\hat{h}_{pk} = h_{pk} \cdot (1-b) + h_{qk} \cdot b \tag{8}$$

$$\hat{h}_{qk} = h_{qk} \cdot (1-b) + h_{pk} \cdot b \tag{9}$$

where parameter b refers to a random number in the range $[0,1]$, symbols $\hat{h}_{pk}$ and $\hat{h}_{qk}$ refer to the individual obtained by the crossover operation. In the next step, the whole evolution process ends if the fitness value is higher than the termination criteria or converges to a value.

IV. EXPERIMENT

We construct three datasets (denoted as dataset I, dataset II) from China's yearbooks in recent years to test the effectiveness of the proposed algorithm. Dataset I collects grain yield and its influencing factors (from the year 1985 to 2013), and Dataset II is made up of index of gross output value of farming and its influencing factors (from the year 1952 to 2013). In particularly, the index system used in Dataset I is illustrated as follows.

TABLE.1 THE INDEX SYSTEM USED IN DATASET I

Symbol	Index name
Y	Total grain yield (million tons)
X_1	Rural employees (million people)
X_2	total power of agricultural machinery (million kw)
X_3	Effective irrigation area (Thousand km)
X_4	Sown area of grain crops (Thousand km)
X_5	The amount of fertilizer use (million tons)
X_6	Rural electricity consumption (Billion kwh)
X_7	The affected area (Thousand km)

Afterwards, the index system used in Dataset II is described in Table. 2 as follows.

TABLE.2 THE INDEX SYSTEM USED IN DATASET II

Symbol	Index name
Y	index of gross output value of farming
X_1	Agricultural labor (million people)
X_2	Grain yield (million tons)
X_3	Agricultural tax (100 million yuan)

The measurement criteria used in this experiment is 1) Mean squared error (MSE), 2) Mean absolute percentage error (MAPE), 3) Absolute percentage error (APE). To test the prediction accuracy of the proposed algorithm, when forecasting the $j+1^{th}$ sample, samples $1\ to\ j$ are used as training samples.

$$MSE = \frac{1}{N} \cdot \sum_{i=1}^{n} \left(r_i - o_i\right)^2 \qquad (10)$$

$$MAPE = \frac{1}{N} \cdot \sum_{i=1}^{n} \left(\frac{\left|r_i - o_i\right|}{r_i} \right) \qquad (11)$$

$$APE_i = \frac{\left|r_i - o_i\right|}{r_i} \times 100 \qquad (12)$$

where $i \in \{1, 2, \cdots, N\}$ is satisfied and r_i, o_i refer to the real value and the prediction value respectively, and N is the total number of sample utilized in the validation set. MSE denotes the average of the prediction error squares, it is able to evaluate the variation of the predict values of the neural network: the smaller of MSE value, the better prediction of the model. On the other hand, MAPE refers to the measure of the accuracy of prediction approach, and it illustrates the errors according to percentage.

To make performance comparison, Support vector regression model (SVR)[18] and the standard BP-neural network[19] are used to forecast agricultural economy as well. Support vector regression (SVR) reveals superior nonlinear modeling capabilities by applying the structural risk minimization principle to minimize an upper bound of the generalization errors, it is quite different with ANNs model that minimizing the training errors[18]. There are at least three layers in BP neural network: a) an input layer is designed to receive and allocate inputs, b) a middle or hidden layer is developed to model the nonlinear relationships of inputs and outputs, and c) an output layer issues the results[19].

Firstly, for the dataset I, the data from the year 1985 to 2003 are used as training dataset, and the data from the year 2004 to 2013 are regarded as the testing dataset. Prediction results of grain yield in China from the year 2004 to 2013 are given in Table. 3 as follows.

TABLE. 3 PREDICTION RESULTS OF GRAIN YIELD

Year	Real value	Prediction results		
		BPNN	SVR	The proposed method
2004	46947	48895	39421	47229
2005	48402	45895	55632	48357
2006	49804	54801	52718	49529
2007	50160	52173	51434	48253
2008	52871	57708	53967	50683
2009	53082	53589	54616	52834
2010	54648	52807	54290	54575
2011	57121	52433	67213	56981
2012	59638	63507	65219	59295
2013	61247	61258	69566	58519

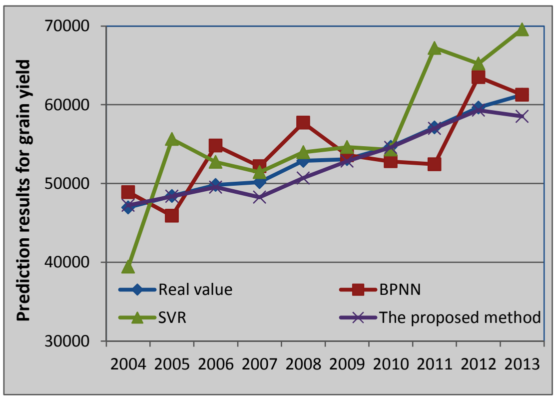

Fig.3 Changing trend of grain yield

Secondly, for the dataset II, the data from the year 1952 to 2003 are used as training dataset, and the data from the year 2004 to 2013 are regarded as the testing dataset. Prediction results of index of gross agricultural output value in China from the year 2004 to 2013 are given in Table. 4 as follows.

TABLE. 4 PREDICTION RESULTS OF INDEX OF GROSS AGRICULTURAL OUTPUT VALUE

Year	Real value	Prediction results		
		BPNN	SVR	The proposed method
2004	641.9	702.1	721.6	620.8
2005	668.2	685.4	730.5	664
2006	704.2	730.2	674.2	690.3
2007	731.7	690.6	789.6	715.8
2008	766.7	775.3	665.8	760.7
2009	798.9	763.2	857.7	811.9
2010	814.6	780.9	940.1	811.5
2011	837.4	835.2	725.8	857.7
2012	859.1	950	917	836.8
2013	878.3	874.4	875.5	910

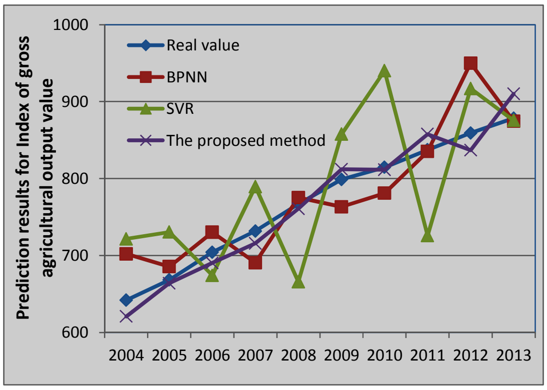

Fig.4 Changing trend of Index of gross agricultural output value

Afterwards, MSE and MAPE for the proposed two datasets are described in Table. 5

TABLE. 5 MSE AND MAPE FOR DIFFERENT METHODS

Method	**Dataset I**		**Dataset II**	
	MSE	**MAPE (%)**	**MSE**	**MAPE (%)**
BPNN	10308264	5.16	1705	4.23
SVR	32491991	8.56	5969	9.02
The proposed method	1622769	1.51	304	1.95

Integrating the experimental results together, it can be see that for the given two datasets the proposed method outperforms the SVR and the BPNN model under both MSE and MAPE criteria.

Additionally, we also can conclude that using the given datasets collected from China, higher prediction accuracy and more stable prediction ability can obtained by our method in the problem of agricultural economy prediction.

V. CONCLUSION

In this paper, we study on how to forecast the agricultural economy development with high accuracy. We develop an improved BP neural network to solve the agricultural economy prediction problem. Furthermore, we improve the standard BP neural network using genetic algorithm. Our proposed algorithm repeatedly revises a population of individual solutions, and then suitable individuals are selected by the genetic algorithm from the current population. Finally, experimental shows that our proposed algorithm is able to achieve higher prediction accuracy and more stable prediction ability.

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CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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