Applying of GA-BP Neural Network in the Land Ecological Security Evaluation

Li Wu, Jing Zhou, Zhouhong Li*

Abstract—**The land ecological security evaluation should be a research emphasis for its key role in the sustainable development of a region. In this research, according to the PSR framework-based land status of Yuxi City, an evaluation index system has been built up to reveal the changes of the land ecological security and analyze the causes of the variations from 2001 to 2015 in Yuxi City. This system is composed of three layers--direction layer, criterion layer which further consists of pressure, status and response, and index layer with 20 indices covering the various aspects of land use, society, economy and environment. In this paper, the genetic algorithm (GA) is introduced to improve the BP neural network, with advantages in solving the problems of slow convergence and getting into local minimum easily when the BP neural network was applied alone in land ecological security evaluation. A GA-BP neural network is then established to evaluate the land ecological security from 2001 to 2015. Comparisons between the BP neural network and the GA-BP neural network are drawn in their performances and errors and the assessment results of both are further separately compared with the target results of the comprehensive index method. The results show that: (1) The land ecological security index increases steadily from 0.3696 to 0.6020 and the security grade ascends from risky (IV) to safe (II) from 2001 to 2015 in Yuxi City; (2) Compared to the traditional BP neural network, the GA-BP neural network has less errors in training and predicting, and it is faster in convergence and higher accuracy in assessing results. Therefore, the GA-BP neural network model is not only able to function as well as the BP neural network in land ecological evaluation and prediction, it can obtain more accurate results and has faster convergence ability as well.**

Index Terms—**BP neural network, genetic algorithm, land ecological security evaluation, Yuxi City**

I. Introduction

IN 1977, Constance Holden called for the redefinition of national security and mentioned that it should be related to ecology in order to change the traditional equation with military might [1]. With the rapid development of the economy, the living space of human has been unprecedentedly challenged, which arouses increasing and urgent concerns over the ecological security worldwide. The concept of ecological security was proposed in 1989 by IIASA (International Institute for Application System Analysis) [2]. Afterwards, ecological security was defined as natural, economic and social security [3, 4], or in a broad-sense, as nature-centered, human-centered and in-between security [5]. Contemporarily, some more specific or narrow-sense concepts have been put forward. For example, ecological security is viewed as an internal stable structure and positive healthy service functions in the system [4, 6]. It focuses on a sound ecosystem, sustainable exploitation of natural resources and harmonious human and nature relationships [7], or is defined as a goal of satisfying the needs of inhabitants involved in the ecosystem without diminishing its natural stock [8, 9]. Both aspects contain structural and functional security of an ecological system, and land structure and production function security are of the most importance without a doubt.

For decades, scholars have proposed many evaluation methods in land ecological security (LES) assessment. Methods that can calculate security index and grade security level varied from comprehensive evaluation [4,10] to landscape ecology [11,12] and ecological models, all of which are based on various mathematical models and algorithms, such as the hierarchical patch dynamics [7,13], the ecological footprint theory [14-16], the cellular automata model [17,18], GDHAS combined GTT and AHP [13], the catastrophe theory [19], the least-cost path (LCP) model [20], the minimum accumulative resistance (MCR) [21,22] and the logistic regression model [23] etc. In recent, a back-propagation (BP) neural network which can approximate any nonlinear function [24-26], was widely applied in predicting, optimizing, assessing and classifying data in China [27].

Land ecological system is a complex, variable, nonlinear and dynamic system, and this poses many limitations on the traditional methods for assessing and analyzing the system. The BP neural network has a strong nonlinear approximation capability to handle unclear, disordered and complex information, which overcomes the shortcomings of traditional approaches, thereby helping reach a higher accuracy of data in short time. At present, many researches have verified that the BP neural network is feasible for evaluating and predicting equality of water [28] and land resources [29]. However, the traditional BP neural network has many defaults as well as a slow learning convergence and over-fitting in algorithms [30]. Thus, an algorithm optimization is required to balance the capabilities of exploration and development [31, 32]. A BP

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neural network with prediction and assessment to improve genetic algorithm (GA)-BP network [33, 34], has been applied to many fields. Compared with the traditional BP neural network, the improved GA-BP neural network not only has better stability and global searching ability but the capacities of automatically acquiring and accumulating spatial knowledge and controlling the searching process adaptively. The performance of the network, therefore, is greatly improved.

This paper chooses the land ecological security of Yuxi City as a research object, and a PSR framework-based evaluation index system is established. Then, in virtue of the BP neural network and GA-BP neural network, an empirical analysis and evaluation of land ecological security from 2001 to 2015 in Yuxi City will be obtained. The feasibility of GA-BP neural network's application in land ecological security will be verified and explored to provide some references for future researches and applications.

II. Materials and methods

A. Regional overview

The Research site in this study, Yuxi City is in the west edge of Yungui Plateau and is a resort for leisure and recreation. Located between 101°16′E~103°09′E and 23°19′N~24°53′N, Yuxi City is high in the northwest, and low in the southeast. As a typical mountainous area with an altitude of 1800m, the topography is complicated with the mountains, canyons, plateaus and basins staggered, which brings complexity and vulnerability to the utilization of land. Due to the subtropical and sub-humid plateau climate, the annual average temperature is 17.4~23.8℃, and the annual average rainfall is 670~2412mm. There are three plateau lakes in Yuxi City, contributing to the abundant water resources and high ratio of farming. The three plateau lakes in the territory of the city, mountain stereo climate, and unique ethnic customs, are attracting more and more local and international visitors to visit and study in this city, which facilitates the development of the local society and economy. However, in the wake of rapid development and increasing human activities, the ecological environment has been greatly damaged. As a gateway to South Asia and Southeast Asia, to keep the land ecological security of Yuxi City in a good state is not only the goal of sustainable development of the city, but also an important guarantee of ensuring the land safety and ecological civilization of Central Yunnan City Group construction.

B. Data source and processing

The land use data approached in the index system of this paper are from the land use change survey data provided by Yuxi Land Resources Bureau. Human, social and economic information used for evaluation index are mainly derived from Yuxi Statistical Year Book (2001-2015) and corresponding statistical bulletins. According to the influences of the factors on land ecological security, indexes can be divided into positive index and negative index. To eliminate incompatibilities among the parameters due to their differences in dimensions, min-max normalization method [35] was applied to standardize the indexes in the evaluation index system. The formula are as follows, when the value is becoming larger, the index optimal, (1) will be applied; when the value is becoming smaller, the index optimal, (2) will be used.

$$Y_{ij} = \frac{X_{ij} - X_{j\min}}{X_{j\max} - X_{j\min}} \quad (1)$$

$$Y_{ij} = \frac{X_{j\max} - X_{ij}}{X_{j\max} - X_{j\min}} \quad (2)$$

Where Y_{ij} is the criterion standardization or normalization, X_{ij} is the jth original criterion in ith year, $X_{j\max}$ is the maximum of criterion, and j $X_{j\min}$ is the minimum of criterion j.

C. Establishing evaluation index system

With the advantages of integrity and flexibility, the PSR framework was developed into "pressure-state-response" model by OECD and UNEP in the early 1970s [36], and became the widely applied framework to establish the evaluation index system in ecology and other fields and it provides theoretical proofs for the sustainable development [37, 38]. To entirely reflect the land ecological security status and to take the accessibility of data into account, this paper builds an evaluation index system from three aspects, pressure, state and response based on the PSR framework. The Criterion layer covers seven factors that include population pressure, land pressure, socio-economic status, land use status, eco-environment status, socio-economic response and land protection response. Twenty indices are to be chosen to establish the index system in index layer (TABLE I) and also be divided into two types, positive indices (+) and negative indices (-), according to their impacts on the destination layer.

D. Comprehensive index method

According to some early researches, the comprehensive index method has been applied to a mass of land ecological security evaluation [4, 10]. Therefore, to accurately compare and verify the evaluation results obtained by the BP neural network and the GA-BP neural network, the land ecological security will be assessed firstly in virtue of comprehensive index method in this paper.

Index weight determination

There are many methods of weight determination, but generally they include subjective weight methods such as AHP method [7, 10], Delphi method [18], and objective weight methods such as entropy method [39], factor analysis method [40], variation coefficient method [41], gray correlation method [42], etc. Entropy method, as a mathematics method that can calculate comprehensive index weight by entirely taking all index-provided information into account [43], can avoid the influence of subjectivity. Compared with other objective weight methods, it is simple and easy to evaluate [44]. So, the entropy method will be used in this paper as it is more objective and direct to reflect the influence degree of every index.

TABLE I
LAND ECOLOGICAL SECURITY EVALUATION INDICATORS SYSTEM

Destination Layer	Criterion Layer		Index Layer	Weight	Remark
Land ecological security	Pressure (A1)	Population pressure (B1)	Natural population growth rate (‰) (C1)	0.0185	-
			Population density (people/km^2) (C2)	0.0002	-
		Land pressure (B2)	Farmland per capita(hm^2/people) (C3)	0.0024	+
			Fertilizer load per unit farmland (kg/hm^2) (C4)	0.0043	-
			Mulching film load per unit farmland(kg/hm^2) (C5)	0.0791	-
	State (A2)	Socio-economic status (B3)	Urbanization level (%) (C6)	0.0139	+
			Rural per capita net income(yuan)(C7)	0.1662	+
			GDP per unit area (ten thousand yuan/hm^2) (C8)	0.1769	+
		Land use status (B4)	Multi-cropping index (%) (C9)	0.0442	+
			Rural erosion rate (%) (C10)	0.0003	-
			Land reclamation rate (%) (C11)	0.0042	-
		Ecological environment status (B5)	Ecological land index (%) (C12)	0.0004	+
			Forest coverage rate (%) (C13)	0.0017	+
			Pesticide load per unit cultivated area (kg/hm^2) (C14)	0.0525	-
	Response (A3)	Socio-economic response (B6)	Per unit area grain yield of farmland (kg/hm^2) (C15)	0.0009	+
			Tertiary industry proportion of GDP (%) (C16)	0.0026	+
			GDP per capita(yuan)(C17)	0.1568	+
		Land protection response (B7)	Green investment accounts for GDP (%) (C18)	0.1365	+
			Soil erosion control rate (%) (C19)	0.0628	+
			Comprehensive utilization ratio of industrial solid wastes (%) (C20)	0.0755	+

Ecological security index calculation

According to a comprehensive index method, the land ecological security index can be calculated by the follow equation.

$$LESI = \sum_{j=1}^{n} w_j \times Y_{ij} \qquad (3)$$

Where *LESI* stands for ecological security index, w_j is the weight of *j* criterion, Y_{ij} is the normalization of *j*th criterion in *i*th year, *n* is the number of indexes.

Assessment criteria and grade

According to some related studies at home, abroad [35, 41] and the status in Yuxi City, a land ecological security grade will be divided into highly safe, safe, critically safe, risky and very risky, in total five grades (TABLE II).

TABLE II
GRADING STANDARD OF CULTIVATED LAND ECOLOGICAL SECURITY

Grade of security	LESI	Characteristic of land ecological system
I (highly safe)	0.8~1.0	complete structure; strong function; less pollution; higher forest cover
II (safe)	0.6~0.8	more complete structure; better function; low pollution; higher land use degree
III (critically safe)	0.4~0.6	deteriorating trend; basic function; emergence of ecological problems
IV (risky)	0.2-0.4	structural deterioration; insufficiency function; more ecological problems
V (very risky)	0~0.2	incomplete structure; decreased function; severe ecological disaster

E. BP neural network model

The BP neural network

Rumelhart and McClellan firstly established a BP neural network in the mid-1980s [45]. When the network is training, the BP neural network mainly relies on error back propagation and can make many nonlinear problems solved based on the continuous adjustment of weights and thresholds in back propagation process. It has stronger computing power and can master the correlations of mass data between the inputs and outputs through training in order to find the data attributes in virtue of an approximate function.

The primary structure and algorithm implementation: the BP neural network is a parallel and multilevel feed forward network, which includes the input layer, the hide layer and the output layer, three layers or more than three layers (Fig.1).

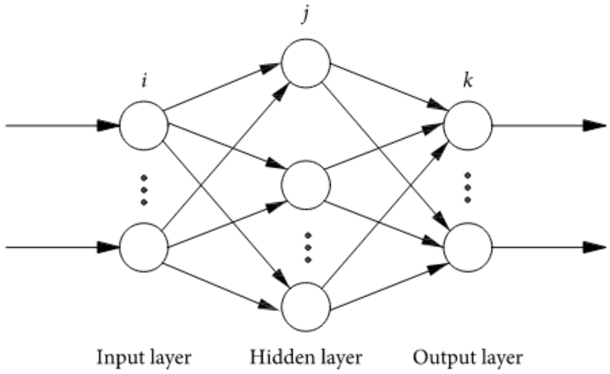

Fig.1. Three layers topological structure of the BP network model

As a nonlinear complex network model, the BP neural network has strong robustness and autonomous learning ability, so it can effectively solve the highly uncertain problems and avoid the subjective influences on results to some extent. There is at least a hidden layer in the BP neural network, but the node numbers of hidden layer are difficult to confirm, so the optimum node numbers mainly depend on the experiences and trial and error method in an actual establishment of neural network. Generally, the node numbers of the hidden layer have obvious impacts on the output results in solving actual problems. The algorithm process graph of the BP neural network is showed as Fig.2.

Establishing land ecological security evaluating model based on BP neural network

(1) Mode building steps

Firstly, three layers including input, hidden and output layer will be chosen to set up the BP neural network structure.

Secondly, 20 node numbers will be set in the input layer according to the study contents which cover the evaluation of land ecological security in virtue of 20 indexes.

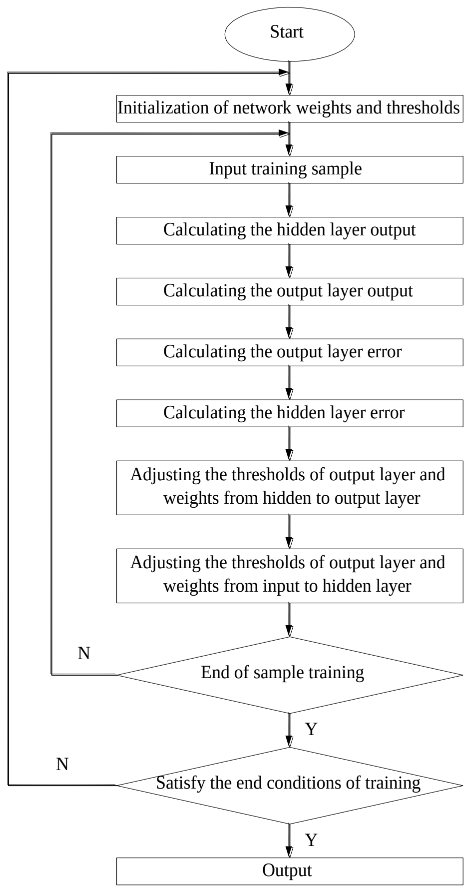

Fig.2. Process of BP neural network

Thirdly, the node numbers of the hidden layer concerning the precision and volatility of the approximation function is with the BP neural network. If the node numbers are too many, the training process will be longer and the results errors are not always optimal. So the scope of node numbers can be firstly determined according to the experience formula $M=\sqrt{m+n}+a$ (m , n respectively stands for the node number s of input and output layer, $a\in(1,10)$), then the least error node numbers will be found in the network training through trial and error method. In the process of training the sample data, the least error node numbers are 6, so the node numbers of hidden layer are 6.

Finally, because the results of land ecological security are the only output of the mode, so the node number of output layer is 1. Then, the assessment level can be determined through the matching between the output results and grading standard in TABLE II.

(2) Algorithm implementation of neural network

Initial data can be read, set and normalized through mapminmax function in virtue of Matlab2016a. Then a function will be passed and begin to train, the default trainlm will be chosen for the training function and when the learning rate chooses 1, the stop condition of training is $E_1 \leq 0.00001$, and the maximum training frequency is 30000.

After making an evaluation index be the expected output value, 9 groups data of initial data of the training sample, 6 groups data as the testing samples in virtue of the evaluating grade and index will be acquired from the comprehensive index method, and the land ecological security evaluation index from 2001 to 2015 can be obtained in the following TABLE III.

Since the algorithm training of the BP neural network is based on the weight modification principle that is from error gradient descent, it’s problematic that the network doesn’t converge or get into local extremum when different initial weight values are chosen inevitably. In recent years, as a new kind of artificial intelligence optimization algorithms, the genetic algorithms simulated by Darwin's genetic choice and natural elimination biology evolution process, is applied [40]. The GA method follows the rules that only the fittest will survive and can choose the evolution individually to be the optimum solution. It is mainly applied in the fields of functions and combination optimization, so the BP neural network embedded genetic algorithm can guide the weight optimum and topology choice. This method has the characteristics of global optimum, which can remedy the defaults of local optimum and optimize the initial weights and thresholds of the BP neural network so as to enhance the stability and efficiency [46-50].

F. GA-BP neural network model

The GA-BP neural network

The optimizing in connection weights optimization of network with genetic algorithm is described as follows:

$$minY(x)=f(\omega_1,\omega_2,\cdots,\omega_n)$$

Where $\omega_1,\omega_2,\cdots,\omega_n$ stand for the connection weights with unified code, n stands for the numbers of connection weights, and the constraint condition is $-1<\omega_i<1(i=1,2,\cdots,n)$.

Network initially weights optimization with genetic algorithm

Step1: An initial population is randomly generated. One chromosome corresponds to a set of network weights. The chromosomes all are coded with real number, population number is set as N_1, Gen is generations, P_i is crossover probability, P_x is the mutation probability.

Step2: If Gen reaches maximum genetic algebra, it will go directly to Step8.

Step3: Calculate the adaptation of every chromosome. The adaptation value F_i of i chromosome can be measured by the reciprocal of its relevant network error E_i , $F_i = 1/E_i$

Step4: A pair of chromatids will be chosen through roulette method and interlace operation can be fulfilled with crossover probability P_i , and then mutation operation with the probability P_x will be applied in the intersected chromatids. Random value that varies from -1 to 1 can be added to the weights of mutant gene.

Step5: Progeny chromosome can be put in a new population.

Step6: Step4 and Step5 will be redone to make the new chromosome population is N_1.

Step7: Parents chromosome population can be replaced by new chromosome population, then go to Step2.

Step8: An initial weight and threshold with the least network error will be obtained by decoding the highest adaptability chromosome through genetic algorithms.

Lastly, the optimal individuals through genetic algorithms will be decomposed into connection weight and threshold, which can be the initial weight and threshold of the BP neural network model. When trained, the BP neural network model can output the optimal solution. The algorithm flow chart of the GA-BP neural network is as the Fig. 3.

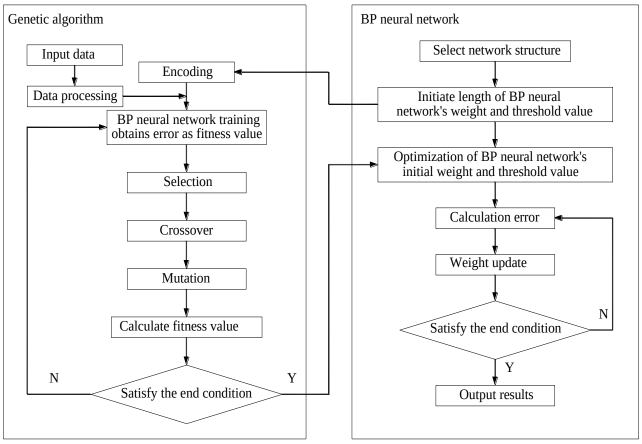

Fig.3. Process of GA-BP neural network

To establish the land ecological security evaluation model based on GA-BP neural network

When the accuracy is satisfied, the program can be determined in training the BP neural network which is improved in the initial weight and threshold by genetic algorithm in "*Network initial weights optimization with genetic algorithm*". Then, the BP neural network program with self-adaption genetic algorithm was written to evaluate the land ecological security with the help of Matlab2016a. The main parameters of the BP neural network are the same as above. The parameters of genetic algorithm: the input layer is 20, the output layer is 1, so the numbers of weight value are 126 (20*6+6*1=126), the numbers of the threshold value are 7(6+1=7), that is to say, the length of chromosome is 133 (126+7=133). The Selective probability is 0.09, the crossover probability is 0.1, and the mutation probability is 0.006. The set parameters of training data and testing data are the same. As in BP neural network model, 9 groups data are chosen as training samples and 6 groups data as testing samples, the land ecological security value from 2001 to 2015 can be obtained as TABLE III.

III. Results and Analysis

A. *Performance comparison between BP neural network model and GA-BP neural network model*

The predicting errors would be rather big for the large random cities in optimizing process of weights and thresholds because the node numbers of the hidden layer cannot be easily determined in the BP neural network. Based on those defaults, genetic algorithm can be used to optimize the initial weights and thresholds of the BP neural network and show better predicting outputs in the improved the BP neural network.

In fact, the training of the BP neural network and GA-BP neural network are showed as Fig. 4 and Fig. 5 respectively, and the training errors of the BP neural network and the GA-BP neural network are expressed as Fig. 6 and Fig. 7. Network stopped the training when the network is trained to Step3 from the BP neural network training chart (Fig. 4) but GA-BP neural network stops in Step1 for the faster convergence speed.

The results show that GA-BP neural network has much less iteration steps when the fitting data reaches the target and it is faster compared to BP neural network. Therefore, the initial weights and thresholds can better fitting data through the improved BP neural network with genetic algorithm to conquer the defect of slow convergence speed and easy to put into local optimum.

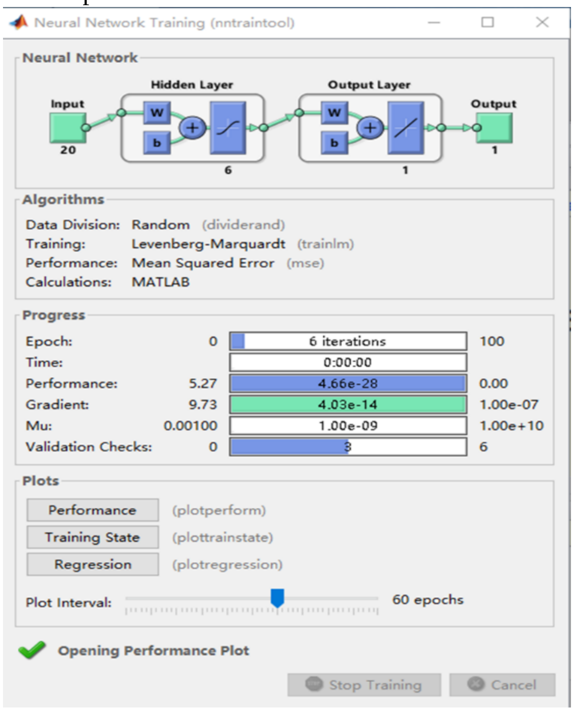

Fig.4. Training of BP network

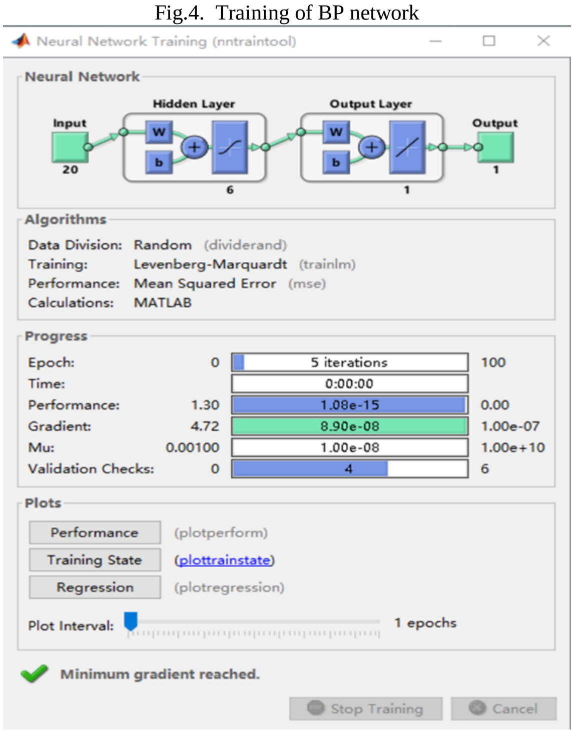

Fig.5. Training of GA-BP network

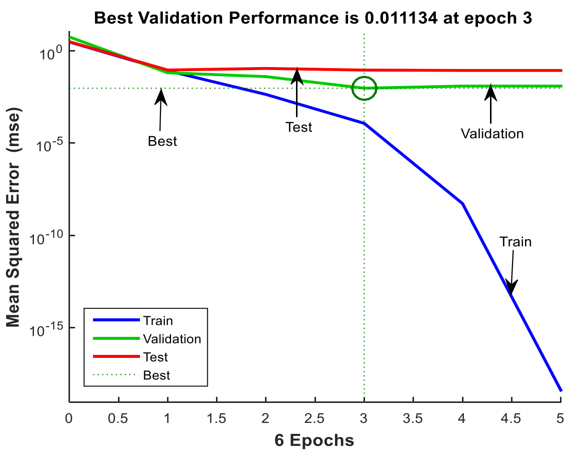

Fig.6. Training mean squared error of GA-BP

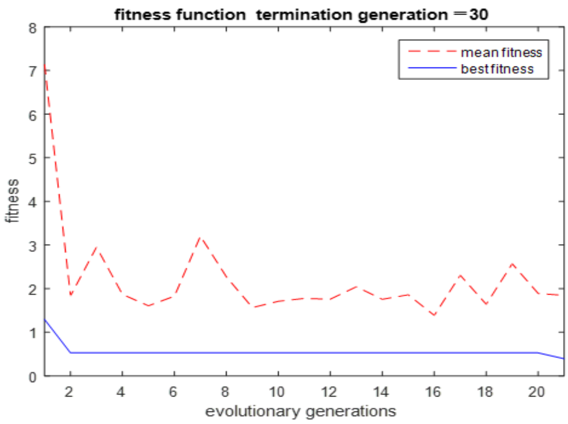

Fig.7. Optimized curve of best fitness

Therefore, the results which are obtained from training and testing on the built network in virtue of the BP neural network weights and thresholds optimized with genetic algorithm, were compared with the results that are obtained from the traditional prediction methods without genetic algorithm optimization. It can be found that the GA-BP neural network can decrease the average relative errors and enhance the accuracy of the evaluation results (Fig.8 and Fig.9). The BP neural network model improved with genetic algorithm is meaningful when applying it in land ecological security assessment based on taking the comprehensive evaluation index as the expectation index and the performance of GA-BP neural network is better than that of the BP neural network.

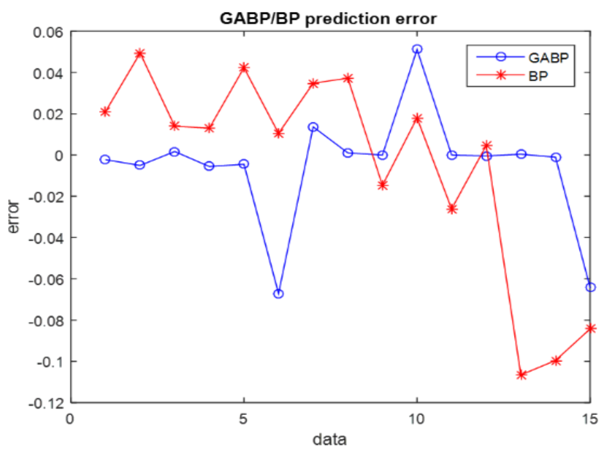

Fig.8. Prediction error comparison

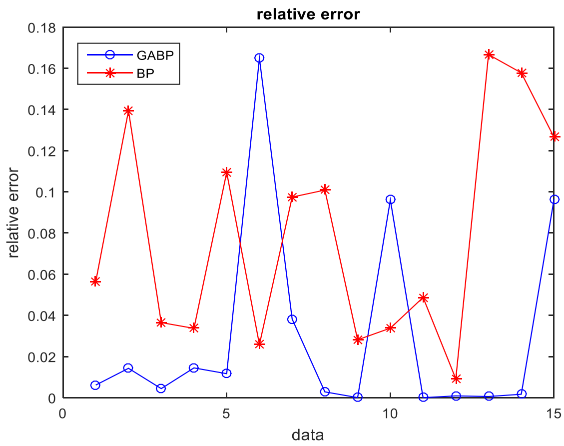

Fig.9. Relative error comparison

B. *Comparative analysis of land ecological security evaluation results*

The land ecological security evaluation results based on the BP neural and the GA-BP neural network can be acquired through the operation of Matalab2016a program as showed in TABLE III.

TABLE III
COMPARE OF EVALUATION RESULTS

Year	BP neural network model		GA-BP neural network model		Comprehensive index method	
	LESI	Grade	LESI	Grade	LESI	Grade
2001	0.3929	IV	0.3696	IV	0.3719	IV
2002	0.4037	IV	0.3492	IV	0.3543	IV
2003	0.3960	IV	0.3838	IV	0.3821	IV
2004	0.3990	IV	0.3804	IV	0.3860	IV
2005	0.4286	III	0.3818	IV	0.3863	IV
2006	0.4173	III	0.3397	IV	0.4068	III
2007	0.3919	IV	0.3707	IV	0.3571	IV
2008	0.4063	III	0.3701	IV	0.3691	IV
2009	0.5086	III	0.5233	III	0.5233	III
2010	0.5500	III	0.5831	III	0.5320	III
2011	0.5100	III	0.5360	III	0.5360	III
2012	0.5087	III	0.5037	III	0.5041	III
2013	0.5329	III	0.6398	II	0.6394	II
2014	0.5314	III	0.6300	II	0.6310	II
2015	0.5818	III	0.6020	II	0.6661	II
Average relative error	0.0780		0.0302		–	

As can be seen from TABLE III, land ecological security index keeps rising from 2001 to 2015, and the rising speed is more obvious for the average increase of 5.27% a year in Yuxi City. One of the reasons is that the continual improvement of urbanization level, with the urbanization rate ascending from 30.7% in 2001 to 47.07% in 2015, rural per capita net income going up more than four times from 2385 RMB in 2001 to 10977 RMB in 2015, and per land area GDP rising up more than four times from 18421 RMB in 2001 to 83290 RMB in 2015. People's living standards and quality had been greatly improved in the past 15 years in Yuxi City. The second main reason is that the continuous increasing efforts in forest coverage rate through ecological construction, for example, implementing the grain for green policy and the construction of eco-civilized city. However, under the influence of global economic environment, the land ecological security index showed an obvious decline in 2006, 2007 and 2008. The main reason is the rapid dropping of green investment accounts for GDP and tertiary industry proportion of GDP. Since 2009, the land ecological security grade has kept ascending for the development of society and economy and the vigorous implement of ecological livable city policy in Yuxi City, rising from IV to III, then up to II from 2013.

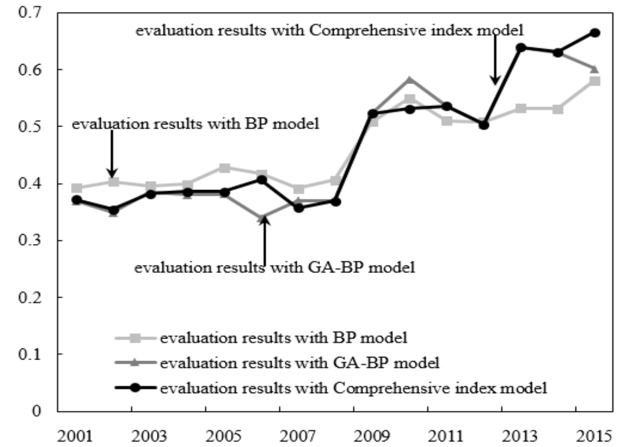

Fig.10. Comparison of evaluation results

It is showed in Fig.10 that the evaluation results of both the BP neural network and the GA-BP neural network are consistent with the results from the comprehensive index method, which can illustrate that although both models can be applied in land ecological security evaluating, it is obvious that the GA-BP neural network is superior to the BP neural network. The average related errors of the BP model are two times more than the average related errors of the GA-BP model. It is also evident that the evaluation results changing the curve of the GA-BP model is more consistent with that of comprehensive index model than that of the BP model.

IV. Conclusions and discussions

Firstly, the land ecological security evaluation index system of Yuxi City was established based on the PSR framework. Secondly, the land eco-security dynamic variations of Yuxi City from 2001 to 2015 were evaluated by three assessment methods, the comprehensive index method, the BP neural network and the improved the GA-BP neural network. Then, comparisons of advantages and disadvantages between two mathematics evaluation models were analyzed. The conclusions are as follows:

(1) The defects of the BP algorithm can be found through the analysis of problems and final training. First, in the process of modeling, to ensure the character of approximate sample, numbers of neurons in hidden layer should be suitably chosen to decrease the network error and accuracy, however, the optimal numbers neurons are not easy to determine. Secondly, the weights and thresholds are randomly chosen and short of evidence, but the overall distribution of connection weights and thresholds can influence the results of data fitting. Thirdly, there exists problems of local optimum in the BP algorithm based on gradient descent, and different initial weights would lead to network non-convergence or get into local optimum. So, corresponding algorithm should be introduced to improve the optimizing of weights and thresholds in the BP neural network. It can be concluded from the comparative analysis that the GA-BP neural network has higher stability in modelling and the evaluation results are more realistic and stable under the circumstance of the same network structure and training parameters. The BP neural network improved with genetic algorithm has good reliability for less iteration steps in data fitting and more quickly in achieving the expected targets when compared to the BP neural network.

(2) The optimization of initial weights and thresholds in the BP neural network is from the applying of genetic algorithm in function optimization to improve the insufficiency of the BP neural network. The results showed that the improved genetic algorithm can greatly solve the nonlinear objective function optimization. According to the comparative analysis with comprehensive index method, in comparison with the GA-BP neural network improved with genetic algorithm, the training error of the BP neural network is obviously higher than the former. It is indicated that the GA-BP neural network can be applied in evaluating land ecological security and the accuracy of assessment results can be evidently enhanced.

(3) The evaluation results showed that land ecological security would be rising, with the security grade of level moving from IV to II, from risky to safe. The main reasons are that the efforts to improve the ecological environment have been intensified, the awareness of environmental protection has been increased and the construction policy of ecological livable city has been vigorously promoted and implemented for 15 years in Yuxi City.

(4) Land ecological security system is a complex and dynamically varied ecological system, its satisfaction level to mankind can be reflected by the stable structure and healthy function. The establishing of evaluation index system should be scientific and reasonable for the intricate influencing factors on the land structure and function. However, the evaluation index system needs to be adjusted and improved in this paper for the reasons that some data cannot be acquired and differences exist in unifying statement. Moreover, not only the spatial-temporal variations should be considered but also the research should put emphasis on pre-warning and regulatory mechanism of the land ecological security.

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