BIOMEDICAL AND ENVIRONMENTAL SCIENCES 16, 379-391 (2003)

Forecasting Loss of Ecosystem Service Value Using a BP Network: A Case Study of the Impact of the South-to-north Water Transfer Project on the Ecological Environmental in Xiangfan, Hubei Province, China

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Objective To recognize and assess the impact of the South-to-north Water Transfer Project (SNWTP) on the ecological environment of Xiangfan, Hubei Province, situated in the water-out area, and develop sound scientific countermeasures. **Methods** A three-layer BP network was built to simulate topology and process of the eco-economy system of Xiangfan. Historical data of ecological environmental factors and socio-economic factors as inputs, and corresponding historical data of ecosystem service value (ESV) and GDP as target outputs, were presented to train and test the network. When predicted input data after 2001 were presented to trained network as generalization sets, ESVs and GDPs of 2002, 2003, 2004... till 2050 were simulated as output in succession. **Results** Up to 2050, the area would have suffered an accumulative total ESV loss of RMB104.9 billion, which accounted for 37.36% of the present ESV. The coinstantaneous GDP would change asynchronously with ESV, it would go through an up-to-down process and finally lose RMB89.3 billion, which accounted for 18.71% of 2001. **Conclusions** The simulation indicates that ESV loss means damage to the capability of socio-economic sustainable development, and suggests that artificial neural networks (ANNs) provide a feasible and effective method and have an important potential in ESV modeling.

Key words: Artificial neural network; BP; Ecosystem service value; South-to-north Water Transfer Project

INTRODUCTION

The distribution of water resource is out of balance throughout China. In general, South China has a runoff of >80% of country's total with the arable areas <40%. On the contrary, North China covers more arable areas with less runoff. South-to-north Water Transfer Project (SNWP) is a key project to optimize allocation of water resource in the new era, which will ease the water shortage in North China. The Project is to divert water totaling 9 billion m^3 from Hanjiang River each year. Hanjiang River flows across Xiangfan, and the basin area in Xiangfan reaches 16893 km^2, accounting for 85.6% of the total land area of the district, which is situated in the northwest part of Hubei Province, China (110°45'-113°05'E, 31°14'-32°37'N). Like a hand's two sides, the huge man-made project would inevitably bring serial negative influences to the ecological environment of Xiangfan, which is the water-out area of the project. In order to recognize and assess the impact of the

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0895-3988/2003
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Project on Xiangfan's ecological environment, and further develop sound scientific countermeasures, we undertook a research task to study the negative impact of SNWP and to design a relevant retrieval program on Xiangfan district.

The services of ecological environment are critical to socio-economy by underpinning human welfare[2]. Both ecological and socio-economic systems are undeniable complex large networks with components linked by dynamic processes[1,2]. In the past decade, the threat to the natural environment has become a key issue in policy evaluation because of the great many externalities involved. Ecological economic analysis and conflict management nowadays are major challenges to policy makers[3].

To embody the nonlinear dynamic properties of ecosystem, modelers have disposed a lot of methods, ranging from systemic dynamics models[4], multi-objective programming[5], analytic hierarchy process[6] to techniques originating from artificial intelligence[7], like expert systems[8], genetic algorithms[9] and artificial neural networks[10]. These researches have led to a rapid growth in ecosystem modeling in the last three decades.

Artificial neural networks (ANNs) have been widely applied in many fields of science and technology as a branch of artificial intelligence, such as physics[11], image recognition[12], chemistry[13], medicine and molecular biology[14]. The field of ANNs has been extremely prolific since its resurgence in the early 1980s, and especially in the last few years.

Since Colasanti found similarities between ANNs and ecosystem and recommended the utilization of this tool in ecological modeling[10], ANNs have been used successfully in an increasing number of applications in environment. In a view of computer-aided research in predicting environmental parameters, Cammarata, Cavalieri and Fichera found that ANNs could provide very accurate approximation of trend of equivalent sound pressure (L_{eq}), and they underlined that ANNs had an important potential in noise prediction[15]. Kolehmainen, Martikainen and Ruuskanen identified ANNs to be able to learn complex relationships between atmospheric components[16]. Results of other researches in environmental management showed that ANNs had many advantages over other methods[17,18]. Relevant examples are found in different fields in applied ecology, such as predicting the greenhouse effect[19], modeling the biodiversity[10], predicting grassland community change[20], modeling spatial dynamics of fish[21], modeling water and carbon fluxes above forest[22], modeling habitat distribution[23], spatially predicting of tree and shrub succession[24]. Most of these works showed that ANNs performed better than more classical modeling methods, however, few applications have been reported in ecological economics at present.

ANNs simulate a highly interconnected and parallel computational structure loosely analogous to human brains. Being nonlinear networks, ANNs provide powerful tools for system modeling, especially when the system is too complex to underlie unknown or unclear mechanisms[20,25]. They have the ability to learn patterns of relationships in data from being shown a given set of inputs and output (including combinations of descriptive and quantitative data), and to generalize or abstract results from them. With this method, input and output variables can be related without any knowledge or assumption about the underlying mathematic representation. Since the ecosystem is an incomprehensive complex system, in which many mechanisms remain outside of our present scope of knowledge, we applied an ANN to predicting ESV loss in Xiangfan after SNWTP is established.

METHODS

Back Propagation Algorithm

ANNs are composed of simple processing elements, called 'neurons', operating on their local data and communicating with other elements. In principle, ANN has the power of a universal approximator[25,26]. ANNs possess abilities of self-learning, self-organizing and self-adaptability, and show excellent characteristics of robustness and fault-tolerance. When presented with examples of the concepts to be learned, the network then organizes itself internally to be able to reconstruct similar situations, which is the so-called self-organization. It is the self-organization that gives ANNs the ability to generalize correct responses to incomplete or noisy singles.

Up to now, various types of ANNs have been developed in order to address different problems, such as classification, optimization, pattern recognition, data reduction, control and prediction. They are adaptive linear element[27], Hopfield network[28], Kohonen network[29], Boltmann machine[7], BP[30], etc. Which type of ANNs should be chosen depends on what kind of problem is to be addressed. Nowadays, the most popular one is BP, also called multi-layer feed-forward neural networks trained by back-propagation algorithm.

Neurons are fundamental units of ANNs. The basic function of a neuron is to sum up its input and produce an output by means of transfer functions. In an ANN, the connection between the *i*th and *j*th neurons is characterized by the weight coefficient w_{ij} and the *i*th neuron by the threshold coefficient b_i (Fig.1). The weight coefficient reflects the degree of importance of the given connection in the ANN. The threshold coefficient is usually understood as a weight coefficient of the connection with formally added neuron j, where p_j=1(called bias). The output value of the *i*th neuron (a_i) is determined by Eqs.1:

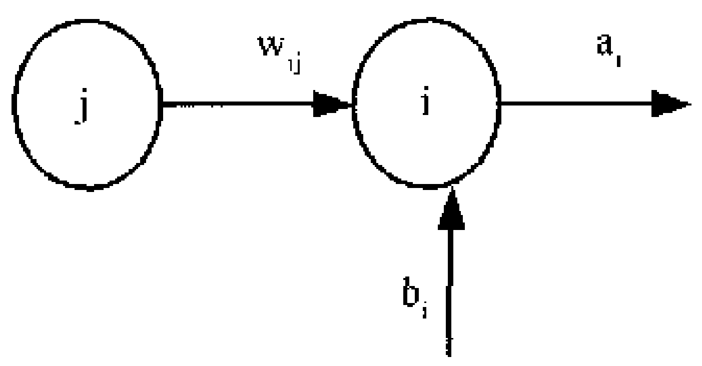

FIG. 1. Connection between two neurons *i* and *j*.

$$a_i = f(\sum(w_{ij}p_j + b_i)) \tag{1}$$

where f is transfer function, by which summation carried out over all neurons j is transferred to the *i*th neuron. Three of the most commonly used transfer functions are shown in Fig. 2, one is linear, the other two: log-sigmoid and tan-sigmoid are nonlinear. Their function expression is shown Eqs. 2, 3, 4. It is the nonlinear transfer functions that lead to the ability of universally approximating any data.

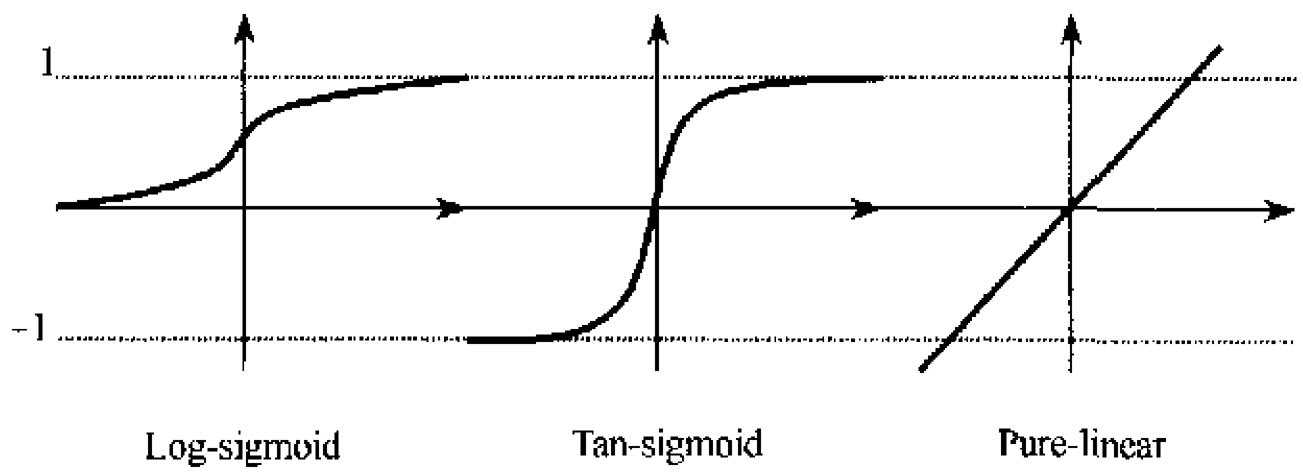

FIG. 2. Three most commonly used transfer function.

log-sigmoid transfer function: $f(a) = \dfrac{1}{1+e^{a}}$ (2)

tan-sigmoid transfer function: $f(a) = \tan(a)$ (3)

linear transfer function: $f(a) = a$ (4)

BP networks have multi-layer feed-forward topology, in which the nonlinear neurons (nodes) are arranged in successive layers: the first layer is called input layer, the last layer is called output layer, and the layers between are hidden layers (usually there is only one hidden layer in a BP network), and the information (singles) flows unidirectionally, from input layer to output layer, through the hidden layer. As can be seen in Fig. 3, nodes from one layer are connected to all nodes in the adjacent layer. However, neither lateral connections within any layer, nor feedback connections are possible. When a set of input/target vector pairs (p/t) is used to be presented to test and train a BP network, output vectors (a) of hidden layer and output layer are calculated by Eqs. 5, 6.

$$a_i^1 = f(\sum_j (w_{ij}^1 p_j + b_i^1)) = f(net_i^1) \tag{5}$$

$$a_i^2 = f(\sum_i (w_{li}^2 a_i^1 + b_i^2)) = f(net_i^2) \tag{6}$$

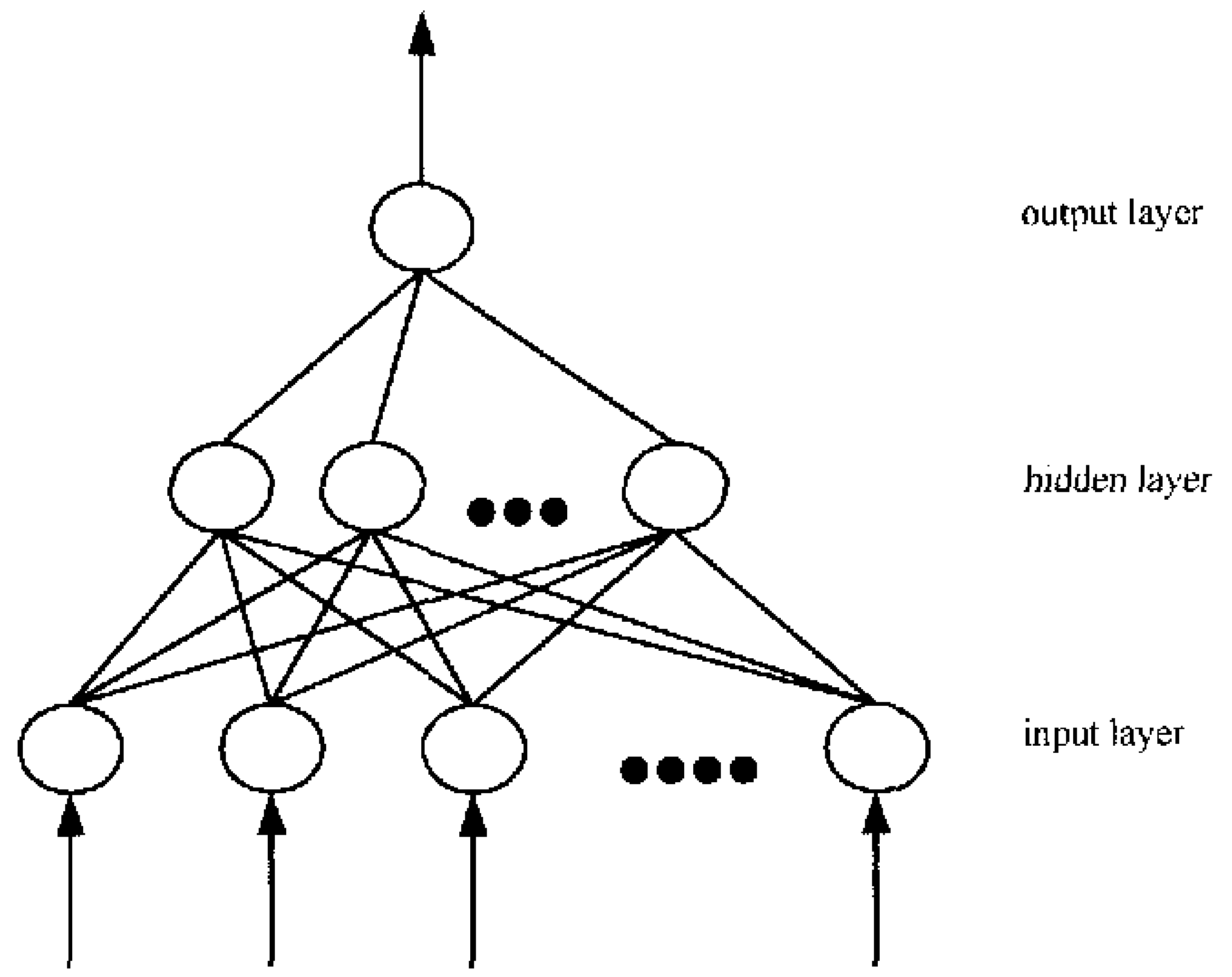

FIG. 3. Typical three-layers BP network.

BP networks are based on a supervised procedure, and trained with a gradient-descent technique. Actually, this is a relatively simple concept: if the network gives an wrong answer after an epoch of training, then the weights w_{ij} and bias b_i are corrected, so future responses of the network are more likely to be correct. After the successful completion of training, the sum of square errors is minimum for all the training samples, and can be defined as Eqs. 7.

$$E = \sum_i \frac{(t_i - a_i^2)^2}{2} = \min(E) \tag{7}$$

By modifying the learning parameters w_{ij} and b_i, the network can meet the above objectives of this investigation. Usually, we define an error goal for the network. If E>e, the output error propagates backward from the output layer through the hidden layer to the input layer, and weight and bias values are updated synchronously (see Eqs. 8, 9, 10, and Eqs.11, 12, 13).

$$w_{li}^2(k+1) = w_{li}^2(k) + \Delta w_{li}^2 = w_{li}^2 + \eta \delta_l a_i^1 \tag{8}$$

$$b_l^2(k+1) = b_l^2(k) + \eta \delta_l \tag{9}$$

where
$$\delta_l = (t_l - a_l^2) f'(net_l^2) \tag{10}$$

$$w_{ij}^1(k+1) = w_{ij}^1(k) + \Delta w_{ij}^1 = w_{ij}^1(k) + \eta' \delta_i' p_i \tag{11}$$

$$b_i^1(k+1) = b_i^1(k) + \eta' \delta_i' \tag{12}$$

where
$$\delta_i = f'(net_i^1) \sum_l \delta_l w_{li}^2 \tag{13}$$

BP algorithm involves a forward-propagation step followed by a backward-propagation step. It requires enough samples to be presented to a network and train it, calculate the computed outputs and compare with target output iteratively, adjust weights and biases recurrently, until it can associate inputs with specific target outputs defined. Based on the above given approach, as the adjustment recurrently continues, weights and biases gradually converge to the global optimal values. When E<e, the network finishes training and is ready for generalization.

Model

Ecological environment is closely connected with and interact with socio-economy, which are subsystems of an even larger regional human system. A fundamental precept of research into systems is that complex systems are not reducible, i.e. the essence of systems is integration. If we separate them into parts, a lot of important information will be lost[1,2]. In order to grasp the inherent essential relationship between ecological environment and socio-economy as a whole, we put ecological environmental factors and socio-economic factors in a same BP model, when the ESV loss of Xiangfan after SNWFP was assessed.

Historical data of ecological environmental factors and socio-economic factors as inputs, and corresponding historical data of ESV and GDP (gross domestic product) as target outputs, through training and iteratively adjusting weights and biases, calculated outputs gradually inclined to target outputs, and the BP network would finally grasp the inherent essential relationships between inputs and outputs. Such a trained network tended to give reasonable answers, when presented with inputs that it had never seen. That is to say, when conditions of ecological environmental factors and socio-economic factors after SNWTP were presented to the trained BP network, it could have the capability to predict the trend of ESV accordingly.

Topology

We used Toolbox in MATLAB6.1 to create a three-layer BP network for forecasting ESV loss. Fig. 4 shows its topology. We defined 'tansig' as the transfer function in hidden layer and 'purlin' in output layer.

Output layer including two neurons represent ESV and coinstantaneous GDP of Xiangfan respectively. Through test network's convergence, the number of neurons in hidden layer was defined to 4. In input layer factors group on ecological environment and factors group on socio-economy were considered to be correlative with the ESV loss and socio-economic loss (GDP loss) after SNWTP. Factors group on ecological environment included flow, flow velocity, water level, COD and hydrobios of Hanjiang River, groundwater level and ecological investment (including investment in fading cropland and returning forest, grass or wetland) in Xiangfan. Factors group on socio-economy involved fishery, river-beach, shipping, farm-irrigation, annual decrease of ESV (⊿E) and new investment in industry and agriculture. However, we found that some of these factors were highly correlated by principle component analyses, and their details were presented as follows:

a. Groundwater level was linearly correlated with water level of Hanjiang River;

b. Hydrobios were highly correlated with flow and COD of Hanjiang River;

c. Fishing products were highly correlated with flow of Hanjiang River;

d. River-beach resources were highly correlated with water level of Hanjiang River;

e. Shipping products were highly correlated with flow of Hanjiang River;

f. Farm-irrigation was highly correlated with flow of Hanjiang River.

So we filtered out redundancies, and got 7 actual input parameters: flow, flow velocity, water level ad COD of Hanjiang River, ecological investment, ⊿E and new investment in industry and agriculture in Xiangfan.

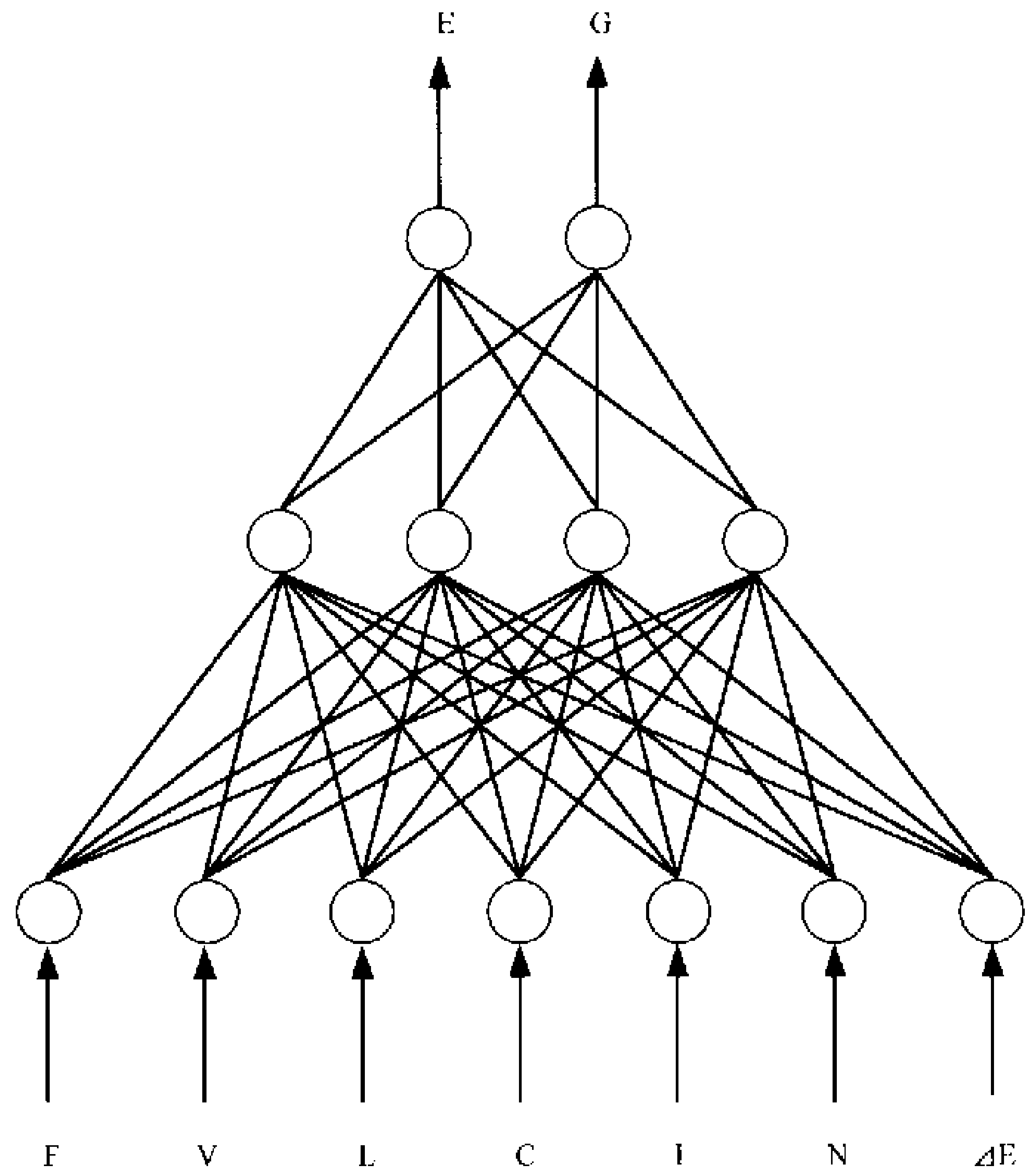

FIG. 4. Topology of the BP network used to simulate the loss of ESV of Xiangfan after SNWT project. Inputs include flow, flow velocity, water level, COD, ecological investment, new investment in industry and agriculture, ⊿E representing annual decrease of ESV; Outputs include ESV and GDP.

Data

Data presented to BP network included training sets, test sets and generalization sets.

1) Training sets were pairs of input vectors and corresponding target output vectors. Annual average data from 1960 to 2001 (except 1975, 1985, 1995, 1999) of above 7 input parameters (offered by Xingfan monitoring station) were used as training input vectors,

while annual average data from 1960 to 2001 (except 1975, 1985, 1995, 1999) of ESV and GDP were used as training vectors. Data of annual GDP were obtained from the Bureau of Statistics of Xiangfan. We used coefficients of Costanza and his co-workers published in 1997[2] to estimate annual ESV. ⊿E, see Eqs.14:

$$\varDelta E = E_i - E_{i-1} \tag{14}$$

where E_i and E_{i-1} represent ESVs of adjacent two years respectively.

2) Test sets were divided into validation set in training and test set after training. Validation set was used to monitor the training process, while the validation error was computed periodically during and after training when validation error started to go up. Test sets were used after training to compare design parameters of different models (error, speed of convergence, time of calculation, etc.) and to choose the best of them.

a. Annual average data of 1975, 1985 and 1995 of above 7 input parameters and 2 output parameters were used as validation sets;

b. Average data of 1999 of above 7 input parameters and 2 output parameters were used as test set.

3) Predicted data of above 7 input parameters after 2001 were used as generalization sets:

a. Flow, flow velocity and water level: from 2002 on, predicted data after SNWTP were used;

b. COD: maximum charging COD of predicted water environment capacity of Hanjiang River after SNWTP was used.

c. Ecological investment: in order to objectively reflect the ESV loss of Xiangfan after SNWTP, from 2002 on, annual ecological investment was evaluated with 0;

d. New investment in industry and agriculture: the level of 2001.

e. ⊿E: see Eqs.14.

Training

Training sets were presented to the network to train it, and Levenberg-Marquardt algorithm was applied in training to ensure the network converge quickly. By trying and comparing iteratively, parameters of training function were finally defined as:

max_epoch=9000;

err_goal=0.5;

lr=0.05

Result of training showed: trainlm: 8098/9000; sse=0.4999891, i.e. the network had approached quick convergence, see Fig. 5.

Test

Test set of 1999 to was used to check how accurately the network performanced. Calculated outputs showed: the ESV of 1999 of Xiangfan was RMB282.5 billion, and the actual ESV was RMB282.1 billion. The error was RMB0.4 billion; the error rate was controlled in 1.4%. So the network had been trained, and was ready for generalization with such a high accuracy.

Model Improvement

Just like any new methods or technologies, ANNs still have some restrictions and disadvantages to overcome, and they will take a long time to improve these models. The excellent nonlinear approximation ability of a BP network is ensured by determining the topology and structural parameters properly, learning efficient training sets with good typical characters, searching for the global minimum solutions, especially escaping 'multimodal', 'overfitting' and 'overlearn'[31].

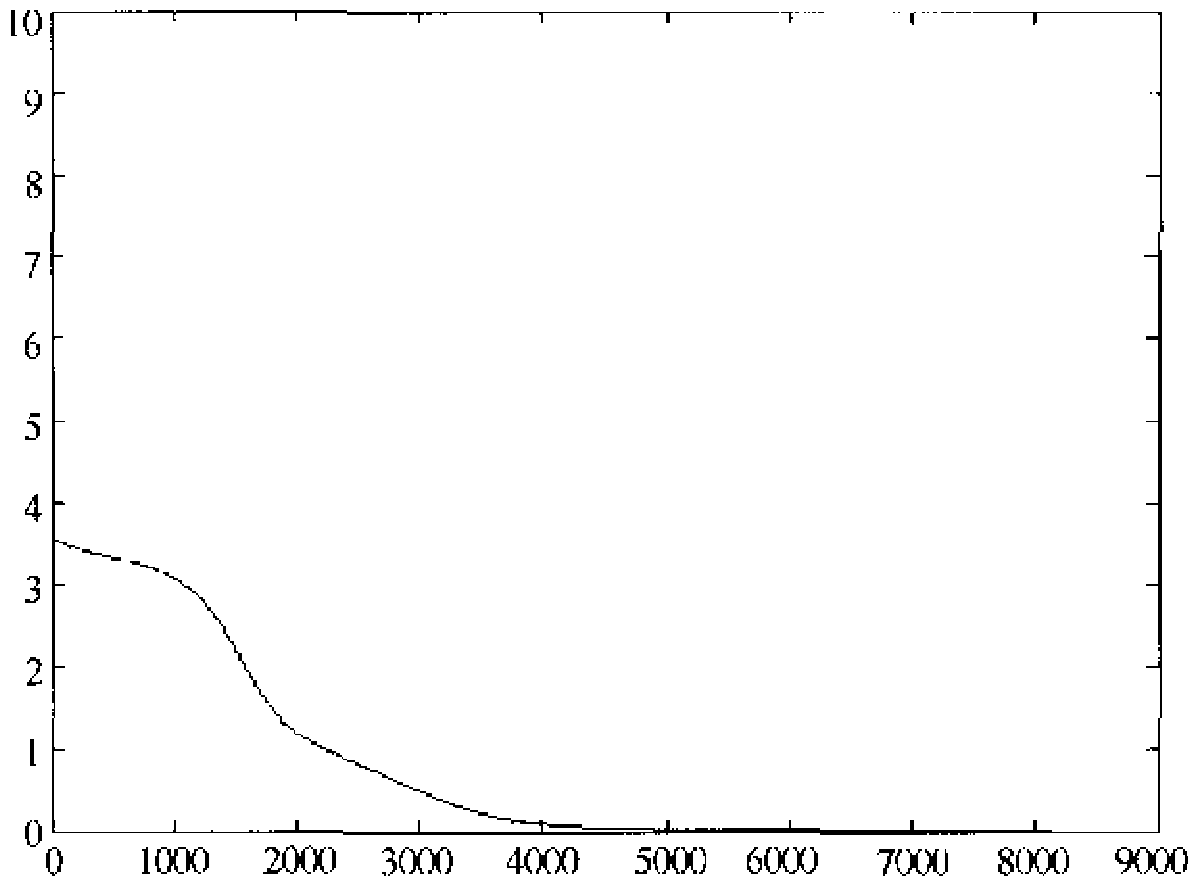

FIG. 5. Curve of error in network training.

Multimodal

The most important task of creating an ANN is how to ensure and enhance its capability of generalization and prediction, namely how to make the network give reasonable answers when presented with vectors that it has never seen. 'Multimodal' in training process will cause the network poor generalization. The ultimate reason to 'multimodal' is inadequate or poor typical training data. As we know, it's necessary to present a BP network with sufficient training sets to be trained to learn to grasp the inherent essential relationships within factors. If training sets are of striking few or poor typicality, the network will be insufficient to grasp the intrinsic essential relationships. The essence of 'multimodal' is that network gets variable weights and biases when presented with the same training sample. Actually, 'multimodal' indicates that several local minimums occur in training process, and the network loses part or even all of its capability of generalization.

In order to avoid 'multimodal', the more training sets presented to a BP the better the network. At least, the quantity of training sets should not be less than that of weights between neurons; the best is 3 times or more. The BP network in this paper including 7, 4 and 2 neurons belonged to input, hidden and output layers respectively, so there were 36 weights between neurons. On the other hand, there were 37 training sets covering 1960-2001 (except 1975, 1985, 1995 and 1999), which just meet the above rule.

Overfitting

Though a network converges rapidly and the error on training sets is driven to a very small value, when new set is presented to the network the error is large, it's so-called 'overfitting'. Too large topology is the direct reason to 'overfitting' of a network. Although the network has memorized the training examples, it has gone far away from the essential relationships within training examples, and has not learned to generalize new situations.

The key to avoid 'overfitting' is to use a network that is just large enough to provide an adequate fit. Especially for input vectors, those vectors with close correlation should be filtered out to reduce the dimension of the network; it's the so-called principle component analysis. Principle component analysis was conducted to filter out redundancies in our BP network design, by using prepca and trapca in MATLAB6.1 Toolbox, and 15 input parameters considered initially were reduced to 7.

Overlearn

Early stopping is the most commonly used method to avoid 'overlearning'; it's also an alternative method for avoiding 'overfitting'. In this technique, validation sets are divided from test sets, and then compute the validation error periodically during training, and training is stopped when the validation error rate starts to go up. In our BP network, we chose data of 1975, 1985 and 1995 as validation sets, and 'overlearning' was not found in training.

RESULT

By presenting generalization sets after 2001 to the trained network, we could dynamically simulate the trend of ESV loss of Xiangfan after SNWTP. When the network with generalization set of 2002 was presented, we got the ESV and GDP of 2002 as the network output. The network with generalization data of 2003 was continuously presented, and then we got the ESV and GDP of 2003 as the network output. The procession was repeated again and again, and we could in succession get ESVs and GDPs of 2004, 2005, and 2006… till 2050 (Table 1).

TABLE 1

Ecosystem Service Value and GDP of Xiangfan After South-to-north Water Transfer Project

Year	Ecosystem Service Value (RMB10^8)	Annual Decrease (RMB10^8)	Total Loss (RMB10^8)	GDP (RMB10^8)	Annual Increase (RMB10^8)	Total Increase (RMB10^8)
2001	280.8			477.2		
2002	279.1	-1.7	-1.7	501.1	23.9	23.9
2003	277.4	-1.7	-3.4	521.1	20.0	43.9
2004	275.6	-1.8	-5.2	536.7	15.6	59.5
2005	273.6	-2.0	-7.2	550.9	14.2	73.7
2006	271.3	-2.3	-9.5	563.9	13.0	86.7
2007	268.4	-2.9	-12.4	569.5	5.6	92.3
2008	264.7	-3.8	-16.2	575.2	5.7	98.0
2009	260.2	-4.5	-20.7	578.1	2.9	100.9
2030	198.1		-82.7	487.6		10.4
2050	175.9		-104.9	387.9		-89.3

And then we got the curve of ESV of Xiangfan after SNWTP by using cubic spline interpolation function (Fig. 6). The trend of ESV of Xiangfan after SNWTP was delineated in Fig. 6, and was compared with that of GDP in Fig. 7. According to Fig. 6, SNWTP would cause remarkable damage to ecosystem services of Xiangfan. The curve inclined slowly in the first 10 years after the project, which indicated that the impact on ecosystem service would be slowly released and the loss of service value would gradually cumulate in the period. However, the curve inclined steeply in the following 20 years, which revealed that ecosystem services might have been destroyed badly due to the cumulative effect of damage to ecology. After 2030 the curve tended to be horizontal, perhaps because ecosystem services of a special area, restricted by surrounding areas, could not unboundedly attenuate too far. So the figure shows that ecosystem services finally got steady.

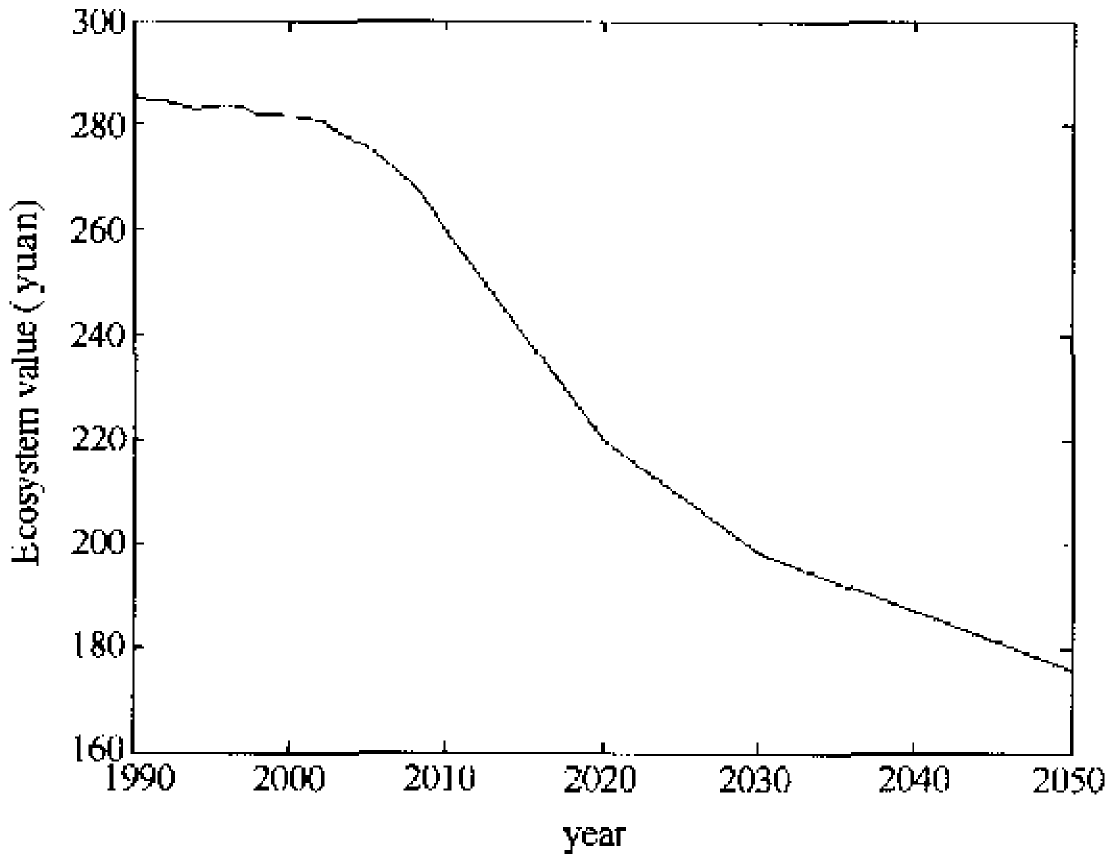

FIG. 6. Trend of ecosystem service value of Xiangfan after south-to-north water transfer project.

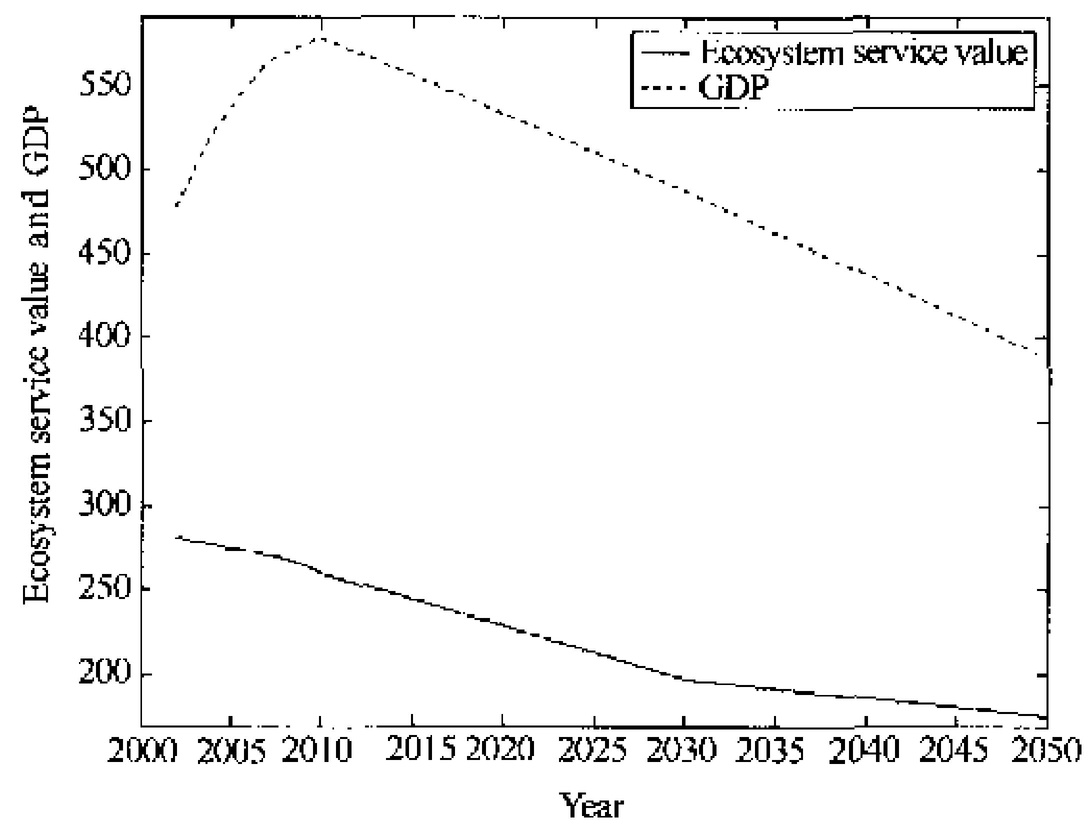

FIG. 7. Contrast of ecosystem service value and GDP of Xiangfan after south-to-north water transfer project.

On the contrary, when ESV declined, Fig. 7 shows that the coinstantaneous GDP changed asynchronously with it. In the first 10 years, while the ESV curse inclined slowly, the GDP curse kept an inertial ascending. Until the following 20 years, the GDP curse stopped ascending and then began to incline, suggesting that the socio-economy might have lost its capability of sustainable development because of the release of cumulated ESV loss. After 2030, although the ESV curse tended to be horizontal, the GDP curse continued to incline, perhaps because ecosystem service of low level could only underpin low level GDP. Fig. 7 proves that, it was by providing the capability of sustainable development that ecosystem served socio-economy[32, 33]. Ecosystem service loss could result in damage to the capability of socio-economic sustainable development, and socio-economic loss would emerge behind ecosystem service loss.

DISCUSSION

As mentioned before, in order to reflect the integration, which is the fundamental feature of ecosystem, more and more ecologists are inclined to apply systemic methods in ecosystem modeling. The most popular systemic methods in ecosystem modeling from the 1990s, except for ANNs, include system dynamics, multi-objective programming, analytical hierarchy process and expert system etc. In this paper, we'd like to discuss whether their theoretical frameworks are very suitable to solve eco-economic issues.

Firstly, if we use system dynamics, multi-objective programming, analytical hierarchy process or expert system to build an ecosystem model, we would begin with some special processes of the system. It is well known that ecological environment is a highly complex system, which is closely related with socio-economic system. Factors in ecosystem are connected with and interact with each other to form a multi-input and multi-output system by energy flow, material circulation and information transmission[1,34]. We should model ecosystem as a whole, due to the multi-hierarchy construction of the system and complexity of relationships between interior factors. It seems difficult to grasp its interior essential characteristics, and to investigate it on special hierarchies or processes in analyzing such a multi-input and multi-output system[1,2,35]. What's more, many mechanisms of these processes remain unclear.

Secondly, how to solute higher-order formulas is a severe challenge, with which any dynamic method has to face, due to many higher-order non-linear relationships between factors of ecosystem. Almost all methods to solute higher-order nonlinear equations are so far in lack of theoretical support up to now[36,37]. Modelers have to apply reduce-order or line-transfer algorithm in using system dynamics or multi-objective programming methods [38,39], at the cost of system information losing and solution accuracy degrading. Besides, because it is subjective to value weights according to modellers' experiences or experts' opinions, neither analytical hierarchy process nor expert system, to which multi-layer structure and factors summed by weights are introduced, could reflect the objective relationships between ecosystem factors[40].

On the contrary, trained ANNs could grasp the nature of a system by learning sufficient historical data, and give objective answers. In the mean time, parallel algorithm and nonlinear transfer function ensure its excellent capability to treat higher-order nonlinear problems. In addition, ANNs select minimal but most representative sets of input to establish models, without using detailed mechanisms or sitting special information. Furthermore, the rules of ANNs' algorithm, such as error propagation, systemic energy minimum, competition between factors, correspond to those of nature evolution, so it seems a more harmonious way to use neural networks in ecosystem modeling.

CONCLUSION

We used a BP network to forecast ESV loss in Xiangfan, Hubei Province after SNWTP in China. From the present investigation, the following conclusions can be obtained:

SNWTP would bring serial negative influences to Xiangfan's ecological environment. According to the above simulation results, up to 2050, the area would have suffered an accumulative ESV loss of RMB104.9 billion, which accounts for 37.36% of the present ESV. For socio-economy, the ESV loss means damage to the capability of sustainable socio-economic development. Although GDP might gain a temporal increase at the sacrifice of ESV, socio-economy would finally pay for the loss of its capability of sustainable development. That is to say, socio-economic loss might regularly emerge behind ecosystem service loss. GDP of Xiangfan after SNWTP would experience an up-to-down process, in which the GDP growth gradually slows down in the first 10 years, and then begins to decline and keep a continuous decrease over more than 40 years. To avoid loss of socio-economy, relevant countermeasures and retrieval plan to ecosystem should be taken into account and put into practice.

Many other studies showed: ANNs perform better than other modeling methods[15,20,25]; this paper further proves it in theory. Someone argues that ANNs are essentially a "black-box" approach to solution, failing to provide explicit explanation of the underlying causes and mechanisms of phenomena under study. Yet the most important point is precisely that ANNs afford such an approach to complex systems or processes. Especially, ANNs appear to be an appropriate technique for qualitative analysis and non-mechanistic forecasting. Furthermore, due to its topology and parallel algorithm, ANNs always perform better than other systemic methods in complex system modeling. On account of it, ecosystem modeling is a new multidisciplinary field, and it is necessary to use advanced systemic methods like ANNs. To combine with other advanced algorithms or technologies, e.g. genetic algorithm, ANNs can overcome its shortcomings and broaden its application. This represents the next logic step in deriving better dynamic models of ecosystem service value.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the support of the Xiangfan Municipal Government, Hubei Province of China.

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(*Received December* 21, 2002 *Accepted June* 16, 2003)