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Using NN Method for Regional Recognition Eco-Efficiency

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Abstract

Regional eco-efficiency could be regarded as a relative concept and adjusted for balance according to the changes of economy and environment. Which means the current optimal values of regional eco-efficiency under the energy constraints could be not the optimum compared with the values in the future. As a beneficial supplement of the eco-efficiency measurement, this paper set up a life cycle stage criterion and identified the stage of regional relative eco-efficiency by adopting DEA neural network models. Furthermore, the phenomenon of predicted value "floating up" has been restrained effectively before input into the neural network models which makes the whole models converge fast and identify accurately by improved prediction GM (1, 1) model. The empirical analysis shows that this method has fast convergence, accurate identification, and extensive application and worthy promotion in practice. Research in this paper would be a basis of policy making of local governments to identify the life cycle stage of current regional eco-efficiency.

Keywords: DEA; Neural Network; Recognition; Regional Eco-Efficiency; Energy Constraints.

1. Introduction

With the rapid development of Chinese economy, the phenomena of resource constrains, environment pollution and ecology deterioration are increasing fiercely. It has become the urgent problem that how to take preventive measures in time and effectively to keep and promote the regional eco-efficiency, and which must be based on the accurate identification of the regional eco-efficiency. The basic concept of the eco-efficiency is to reduce the impact of the economic activity on the environment and improve the ability of the economic sustainable development. At present, the definition of WBCSD and OECD is generally accepted. That is, by providing the competitive pricing goods and services which can meet the human needs and improve the life quality, so as to make the ecological influence of the whole life cycle and resource strength reduced to the level which is in accordance with the load bearing ability of the earth [1][2].

The study of the ecological efficiency in western countries is more thorough, and which is applied widely in the field of business and enterprise, but the application study in the regional level is still in exploration. Because of the support of influential institutions such as OECD and WBCSD, the ecological efficiency evaluation method has already become the decision tool of many management layers. In the calculation method, the ecological efficiency hasn't been reached the consensus all the time. The most influential calculation method of the specific value of the ecological efficiency is put forward by Verfaillie and Bidwell (2000), i.e. ecological efficiency = product or service value/environmental impact, but this formula is still controversial up to now [3]. Besides the method of the specific value, X-Y graphic method [4], data envelopment analysis (DEA), ecological cost value ratio (Eco-cost/Value Ratio, EVR) model [5], and the ecological efficiency decomposition method [6], etc. The ecological efficiency research in China is still in the introduction and application stage of studying. This stage focuses on the solving of the specific problems and improving of the industry efficiency, such as the relation between ecological efficiency and circular economy, the ecological efficiency evaluation index and the construction of the model. The ecological efficiency calculation method is divided into four methods by Wang Yan (2009) et al, a single ratio method, the priority structure method, the multi-objective programming method and the ecological topological method, and the advantages and disadvantages of each calculation methods are analyzed systematically in this paper [7]. Combining the energy analysis and the material flow analysis, the ecological efficiency expression of the regional level is constructed by Li Mingsheng [8]. Combining the material flow analysis (MFA) and DEA model, the ecological efficiency of Jiangsu Province is analyzed and evaluated by Zhang Bing [9].

The regional sustainable development is an important goal of the eco-efficiency evaluation, and which shall be taken into consideration from the level that economic and social development can’t go beyond the resource and environmental bearing capacity. On the basis of comparative analysis and reference the previous researches, this study suggests that regional eco-efficiency is a relative level value, and its relative effectiveness will be achieved if the changes of economy and environment meet certain conditions. That means the optimal value of regional eco-efficiency in a certain period may not be the optimum if it relative to the next period or longer period. We can set up an ecological efficiency benchmarking in the point of future time, the relative level value of regional eco-efficiency shall be reevaluated and the stage of life cycle location shall be determined, so as to the influencing factors of potential eco-efficiency identified. Therefore, the recognition method of the regional relative eco-efficiency under the energy constraints would become one of the basic principles to evaluate the relative period eco-efficiency of a particular area.

Based on the ideas of above, DEA neural network method in this paper is applied to make predictive analysis and judgment recognition on the relative eco-efficiency from 1987 to 2020 of Jilin Province (China), and further analyzed the relative eco-efficiency influencing factors in Jilin Province.

2. Relative regional eco-efficiency recognition methodology

Neural network in this research is the predicted procedure of eco-efficiency recognition after DEA calculated. Before regional relative eco-efficiency predicted by neural network, the eco-efficiency influencing factors such as water, energy, etc. must be forecast in medium and long term. In order to make the models more effectively, we chose equal dimension innovation GM (1, 1) model to predict each of the above variables. Ordinary GM (1, 1) model has an effective result in short period predicted but would show a phenomenon of “floating up” values in middle-long period. The equal dimension innovation GM (1, 1) model used in this paper is the improvement of ordinary GM (1, 1) model. It first establishes GM (1, 1) model with known sequence of number, forecasts the next value, and then supplements the forecast value after the known sequence of number. And meanwhile, remove the first datum in former establishing model, maintaining the equal dimension of sequence of number for not to increasing the length of sequence of number, then reestablish GM (1, 1) model and forecast the nest value, supplement the result after the sequence of number again. Reiterating in this way, forecasting one by one and filling vacancies in the proper order, until the predicted target is completed or the certain requirement of precision is reached.

The regional relative eco-efficiency identifying network starts to form whenever completed the above analysis, taking the selected variables as the input, and the recognition result as the target output. Above these form the basis to constitute the training sample set and a repeated training network to simulate. After the network stable, the identification of regional eco-efficiency in a certain stage shall be operated accurately and repeatedly. Finally, the pre-identification results from DEA model shall be revised according to many accurate identified results, thereby the ultimate recognition results of regional relative eco-efficiency can be obtained [10].

2.1. Analysis of DEA model

Data Envelopment Analysis (DEA) is a comprehensive evaluation method by establishing a mathematical programming model based on the data of output and input objects, one of its advantages is not need to care for the function relation of input and output, and directly to envelope analysis. If having *n* decision unit, every decision unit have *m* kind of " input ", and *s* kind of " output", set the input and output index of j decision unit is $X_j = (x_{1j},\ldots,x_{mj})^T$ and $Y_j = (y_{1j},\ldots,y_{sj})^T$ (j=1,2,…,n), so the appraisement of j_0 decision unit would be decided by the optimum value from the following mathematics program .

$$(\bar{P})\begin{cases} \max h_{j_0} = \dfrac{u^T Y_{j_0}}{v^T X_{j_0}} = V_{\bar{P}} \\ \text{s.t. } h_j = \dfrac{u^T Y_j}{v^T X_j} \le 1, \quad j = 1,\ldots,n \\ v \ge 0 \\ u \ge 0 \\ \sum_{j=1}^{n} \lambda_j = 1 \end{cases} \tag{1}$$

Alternate using Charles-Cooper, it will be changed as a equivalent linear program problem.

$$(P)_{C^2R}\begin{cases} \max \mu^T Y_{j_0} = V_P \\ \text{s.t. } \omega^T X_j - \mu^T Y_j \ge 0, \quad j = 1, \ldots, n \\ \omega^T X_{j_0} = 1 \\ \omega \ge 0 \\ \mu \ge 0 \end{cases} \tag{2}$$

Its dual linear program is

$$(D_{C^2R})\begin{cases} \min \theta = V_D \\ s.t. \sum_{j=1}^{n} X_j \lambda_j + S^- = \theta X_{j_0} \\ \sum_{j=1}^{n} Y_j \lambda_j - S^+ = \theta Y_{j_0} \\ \lambda_j \ge 0, \quad j = 1, \ldots, n \\ S^+ = (S_1^+, \ldots, S_s^+)^T \ge 0 \\ S^- = (S_1^-, \ldots, S_m^-) \ge 0 \end{cases} \tag{3}$$

Linear program and dual linear program has feasible solution, and optimum value satisfies $V_P = V_D \le 1$. S^{-0} , S^{+0} is the variables of input excess and output shortage. If problem (P) optimum untie ω^0 , μ^0 satisfy $V_P = \mu^{0T}, Y_{j_0} = 1$, DMU is called as weak effective DEA ; If still have $\omega^0 > 0, \mu^0 > 0$, DMU_{j0} is called as effective DEA.

Obviously, if DMU_{j0} is effective DEA, it surely is weak effective DEA.

About dual linear program (D), it can be proved that its ample condition for DMU_{j0} as weak effective DEA is the optimum value of (D) V_D =1; its ample condition for DMU_{j0} as effective DEA is the optimum value of (D) V_D =1, and each of its optimum solution $\lambda^0 = (\lambda_1^0, \ \ldots\lambda_n^0)^T$, S^{-0}, S^{+0}, θ^0 would be satisfied with $S^{-0} = 0$, $S^{+0} = 0$, $\theta^0 = 1$.

2.2. Analysis of RBF neural network model

Radial Basis Function (RBF) neural network is proposed by Moody J, Darken C in the end of 1980s, which is a kind of forward neural network, having strong vector classification function and fast calculation ability, and it can approach to any nonlinear functions by any precision [11]. It was soon discovered that this new architecture had a number of advantages over the well-known multilayer perception (MLP) with regard to training, locality of approximation and transparency, with the result that interest in the network has grown very rapidly and it is now widely used as an alternative to MLPs for many applications [12]. RBF network is consisted of three layers, the first layer is input layer, consisting of signal source node; the second layer is hidden layer (radial basic layer), number of implicit units is determined by the issues described; the third layer is output layer, response for the input model. The signal is transferred from input layer to radial basic layer, produce partial response by kernel function, and linear output at output layer. The output of *i* node in the hidden layer of RBF network is:

$$r_i(x) = R_i(\|(x - c_i)\| / \sigma_i) \qquad (i = 1, 2, \ldots, k) \tag{4}$$

In equation (4), x is n dimension input variable; C_i is the center of No. i primary function, having the same number of dimension with x; R_i is No.i perceptual variable, determining the width and the size of C_i that this function surrounding the center point; k is the number of perceptual unit, $\|\bullet\|$ is vector norm, and is Euclid norm generally.

Kernel function in hidden layer is radial symmetry, and there are many types. But the most common used is Gaussian function, shown as the following equation:

$$R_i(x) = \exp\left[-\|x - c_i\|^2 / (2\sigma^2)\right] \qquad (i = 1, 2, \ldots, k) \tag{5}$$

This paper takes Gaussian function as basic function, and then the output of RBF network model is:

$$y_q = \sum_{i=1}^{k} \omega_{iq} \exp\left[-\|x - c_i\|^2 / (2\sigma^2)\right], (q = 1, 2, \ldots, m) \tag{6}$$

In equation (6), q is the number of output node; ω is the weight connecting the hidden layer and the output layer. RBF network adjusts centrality parameter c_i and weight ω through input error and output error, so that reach the adjustment on network internal coefficient. [13] [14]

2.3 Analysis of BP Neural network Model

BP Neural network transmits input signals forwards to the node of implicit layer, after acting function, transmits the output signals of implicit node to output node, and finally gives to output result.[15] Excitation function acted by node usually selects S type function, as

$$f(x) = \frac{1}{1 + e^{-x/Q}} \tag{7}$$

Assuming arbitrary network with n nodes, each node's feature is *Sigmoid* type, output of designated network is y, output of any node i is O_i, and assuming that there are N samples (x_k,y_k) $(k=1,2,3,\ldots,N)$, as for any input x_k, the network output is y_k, output of node i is O_{ik}, input of node j is

$$net_{jk}^{l}=\sum_{i}W_{ij}^{l}O_{ik}^{l-1} \tag{8}$$

$\delta_{jk}=\frac{\partial E_k}{\partial net_{jk}}$ and define the error function as $E=\frac{1}{2}\sum_{k=1}^{n}(y_k-\hat{y}_k)^2$, in which $\hat{y}_k$ is virtual output of network, define $E_k=(y_k-\hat{y}_k)^2$, $\delta_{jk}=\frac{\partial E_k}{\partial net_{jk}}$, and $O_{jk}^{l}=\hat{y}_k$, so

$$\frac{\partial E_k}{\partial W_{ij}}=\frac{\partial E_k}{\partial net_{jk}}\frac{\partial net_{jk}}{\partial W_{ij}}=\frac{\partial E_k}{\partial net_{jk}}O_{jk}=\delta_{jk}O_{jk} \tag{9}$$

if j is output node, $O_{jk}=\hat{y}_k$

$$\delta_{jk}=\frac{\partial E_k}{\partial \hat{y}_k}\frac{\partial \hat{y}_k}{\partial net_{jk}}=-(y_k-\hat{y})f'(net_{jk}) \tag{10}$$

if j is not output node, then have

$$\begin{aligned}\delta_{jk}^{l}&=\frac{\partial E_k}{\partial net_{jk}^{l}}=\frac{\partial E_k}{\partial O_{jk}^{l}}\frac{\partial O_{jk}^{l}}{\partial net_{jk}^{l}}=\frac{\partial E_k}{\partial O_{jk}^{l}}f'(net_{jk}^{l})\\ \frac{\partial E_k}{\partial O_{jk}^{l}}&=\sum_{m}\frac{\partial E_k}{\partial net_{mk}^{l+1}}\frac{\partial net_{mk}}{\partial O_{jk}^{l}}\\ &=\sum_{m}\frac{\partial E_k}{\partial net_{mk}^{l+1}}\frac{\partial}{\partial O_{jk}^{l}}\sum_{i}W_{mi}^{l+1}O_{ik}^{l+1}\\ &=\sum_{m}\frac{\partial E_k}{\partial net_{mk}^{l+1}}\sum_{i}W_{mj}^{l+1}=\sum_{m}\delta_{mk}^{l+1}W_{mj}^{l+1}\end{aligned} \tag{11}$$

therefore

$$\begin{cases}\delta_{jk}^{l}=f'(net_{jk}^{l})\sum_{m}\delta_{mk}^{l+1}W_{mj}^{l+1}\\ \frac{\partial E_k}{\partial W_{ij}}=\delta_{jk}^{l}O_{jk}^{l-1}\end{cases} \tag{12}$$

In the formula, Q is sigmoid parameter form of adjusting excitation function. The learning course of its algorithm is formed by forward transmission and reversed transmission. In the course of forward transmission, the input information is transmitted from input layer, after disposed by implicit layer, into output layer. Neuron states in each layer merely affect the neuron state in next layer. If the output layer can't receive the expecting output, then it returns to reversed transmission, lets the error signals go along the original interface channel. Through revising weight values in different layer, get the error signals minimal. [16]

If there are M layers, and the M^{th} layer merely involves output node, the first layer is input node, the steps of BP algorithm is:

(1) Select initial weight value W

(2) Repeat the following course until convergence:

a. As to $k=1$ until N, first calculate the values of O_{ik}, net j_k and $\hat{y}_k$ (forward course), then reversed calculate from M to 2 in each layer (reversed course).

b. As to the same node $j\in M$, calculate δ_{jk} with formula (10) and (12).

(3) Revise weight value $\frac{\partial E}{\partial W_{ij}}$, $W_{ij}=W_{ij}-\mu$, $\mu>0$, in which $\frac{\partial E}{\partial W_{ij}}=\sum_{k=1}^{n}\frac{\partial E_k}{\partial W_{ij}}$.

2.4 The identification criterion of regional relative eco-efficiency

According to the above model, the efficiency θ of the relative eco-efficiency, corresponding slack variables of excess s^- and shortage s^+ need to be calculated. The slack variables calculated by DEA model are shown in Table 1. The redundancy rate α_{j_0} of the total input and insufficient rate β_{j_0} of the total output need be further calculated:

$$\alpha_{j_0}=\frac{x_{j_0}-\hat{x}_{j_0}}{x_{j_0}}=\frac{x_{j_0}-(\theta x_{j_0}-s^-)}{x_{j_0}}=(1-\theta)+\frac{s^-}{x_{j_0}} \tag{13}$$

$$\beta_{j_0}=\frac{\hat{y}_{j_0}-y_{j_0}}{y_{j_0}}=\frac{y_{j_0}+s^+-y_{j_0}}{y_{j_0}}=\frac{s^+}{y_{j_0}} \tag{14}$$

The total input redundancy rate $\alpha_{j_0}=\sum_{i=1}^{m}\alpha_{ij_0}$ of the period j_0, the insufficient rate of the total output $\hat{\beta}_{j_0}=\sum_{i=1}^{s}\beta_{ij_0}$. In the process of regional economic development, ***the recognition criteria*** of life cycle stages where the relative eco-efficiency locates are as follows [17]:

1) The eco-efficiency recognition locates in the formation (F) stage. When $\theta<1$, and $\hat{\alpha}_{j_0}>\hat{\beta}_{j_0}$ or $\hat{\alpha}_{j_0}-\hat{\beta}_{j_0}>0$, in the period j_0, DEA is ineffective. The environment is affected by the excess investment caused by the economic development. The cooperation between the eco-efficiency factors is not coordinate, the economic development potential need to be improved, we need to pay attention to the environment protection. The reasons of relative inefficiency and whether the ineffectiveness is in technology or in scale need to be found by the system located in this phase. By changing the mode of unreasonable production management and environment management, to optimize the configuration of elements, so as to make the regional eco-efficiency improved.

2) The eco-efficiency recognition in the improving (I) stage. When $\theta=1$, and $\hat{\alpha}_{j_0}-\hat{\beta}_{j_0}\neq 0$, DEA is effective in the period j_0. The economic development is good, but the eco-efficiency of each element does not achieve optimization, and it needs to be further optimized. The economy and environment in this region are in the improving stage. The good conditions shall be created to improve the regional economy development. The economic development mode influencing the ecological environment needs to be improved. The regional ecological environment and economic competitiveness shall be enhanced.

3) The eco-efficiency recognition in the balance (B) stage. When $\theta=1$, and $\hat{\alpha}_{j_0}-\hat{\beta}_{j_0}=0$, DEA is effective in the period j_0. And the configuration of the ecological environment and economic development is relatively optimized in this period. The eco-efficiency development is in a relatively balanced stage in this period. The regional economic development is in a relatively optimal state. At this time we need to pay close attention to the development of regional environment. The adverse effect of the regional ecological environment need to be eliminated, the best regional competition status shall be maintained.

4) The eco-efficiency recognition at the recession (R) stage. When $\theta < 1$, and $\hat{\alpha}_{j_0} < \hat{\beta}_{j_0}$ or $\hat{\alpha}_{j_0} - \hat{\beta}_{j_0} < 0$, DEA is ineffective in the period j0. And the inadequate investment is caused by the whole external economic and environmental degradation, which causes that the overall performance is economic recession and environmental degradation in this region. At this time, with the development of production and the change of outside environment, the configuration of all elements is changed from the best to unreasonable. The potential of invested elements has already run out of steam, the economic development ability is not enough, and the ecological environment is destroyed. The economic development and ecological environment are at the recession stage in this period. The reasons of the recession of eco-efficiency need to be found. By optimizing the configuration of all elements, adjusting the proportion of elements or increasing new elements, we shall strive for the optimization of eco-efficiency at the next stage.

3. The Empirical Analysis

On the basis of referencing the related researches, water（10000cu.m） and energy（10000tn of SCE） are acted as the input indicators of DEA regional eco-efficiency recognition model. The output index is divided into two parts, one part is the unexpected output, such as waste water(10000tn）, waste gas (100000000cu.m), industrial dust (10000tn）, SO_2 (10000tn）, and the other part is the expected output, for example GDP(100million Yuan）. [18] The data of *Jilin Province(China) Statistics Yearbook* from 1987 to 2009 is chosen to construct the DEA predicted recognition model. Then according to the identification standard of ***the recognition criteria***, the total investment redundancy rate $\hat{\alpha}_{j_0}$ and the output value $\hat{\beta}_{j_0}$ of insufficient rate need to be calculated, the regional relative eco-efficiency needs to be pre-recognized at this stage.

Before Neural network forecasts regional relative eco-efficiency, each value could be predicted by gray equal dimension innovation model. On the basis of the above analysis, the data from 1987 to 2006 are chosen as the training sample of RBF network model. After the data are standardized, the seven above index values are chosen as the input variables, $\hat{\alpha}_{j_0}$ and $\hat{\beta}_{j_0}$ are the expected output variables. The network parameters are set as followings: input node number is 7, output node number is 2, the implicit node number is 10, the training rate is 0.015, the weighted seed number is 2, the sigma parameter is 0.5, and the weight is 0.2. The error is 0.149926 and within the allowed accuracy range after 10000 iteration training. When the network training is stable, input the test values from 2007 to 2009 and the predicted values from 2010 to 2020 into the network. The accuracy of model identification can be tested by the output values from 2007 to 2009, and the output values from 2010-2020 are the identification results of the model. In addition, the author has values of identification got with BP neural network model as comparison. Take minimal training speed as 0.1, dynamic parameter as 0.6, Sigmoid parameter as 0.9, allowable error as 0.00001, maximum iterative frequency as 2000, and convert the input values standardization, attain the request after 1186 times' training, fitting residual error is 0.002987. The analysis and identified results is as Table 2.

It can be seen from the calculation and identified results that:

(1) The recognition accuracy of RBF neural network model is better than BP neural network model. The results show that two neural network models all can achieve recognition accuracy, but the RBF neural network model is more precise. Except the year of 1994, the RBF neural network identification at other stages is in accordance with the analyzed results of DEA, which indicates that this model has the better applied value. The applied numerical examples show that, RBF neural network model analysis and

identification of the effectiveness of regional relative eco-efficiency can become a supplement of the eco-efficiency measured method. The structure of RBF neural network analysis model is shown as Figure 1 and the residuals of prediction are shown in Figure 2.

(2) The stepwise balance of regional relative eco-efficiency is realized in the process of adjustment. Relative to the optimal year of 2020, the years from 1987 to 1989, 1995 and 2009 are in the optimal stage of relative eco-efficiency. When the economic development level is not high, its influence on the environment is limited. At this time the low level of the relative balance of eco-efficiency is achieved, such as years from 1987 to 1989. This equilibrium is easily broken by the rapid development of economy, and the 3-year decline stage of relative eco-efficiency appears. In the new level, the situation which the economic adapts to the environment is formed (from 1993 to 1994), and eventually the new equilibrium point is reached (1995). Since then, the rapid development of economy breaks the equilibrium once again, the insufficient input elements not only make the economic development obstructed, but also intensify the environmental impact, which cause a longer period of recession (from 1996 to 2008), until a new point of equilibrium appears (2009). After experiencing a long adjustment, this equilibrium is the high level of the relative balance of eco-efficiency.

Table 1 Data of Input Excess and Output Shortage

Year	Excess water S-(1)	Excess energy S-(2)	Shortage waste water S+(1)	Shortage waste gas S+(2)	Shortage industry dust S+(3)	Shortage SO2 S+(4)	Shortage GDP S+(5)
1987	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1988	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1989	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1990	0.00	0.00	8370.57	0.00	4.22	0.00	217.99
1991	88030.62	0.00	0.00	0.00	7.22	6.01	38.98
1992	0.00	0.00	8805.41	0.00	4.39	0.00	536.76
1993	0.00	0.00	0.00	0.00	2.95	0.31	211.10
1994	0.00	0.00	0.00	61.62	0.00	0.71	0.00
1995	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1996	0.00	0.00	23812.34	0.00	0.67	0.00	125.98
1997	0.00	0.00	35097.29	349.54	0.00	0.00	0.00
1998	19308.62	0.00	35704.15	689.52	0.00	0.00	0.00
1999	27952.04	0.00	30154.97	631.01	0.00	0.00	0.00
2000	29813.88	0.00	27836.03	767.19	0.00	0.00	0.00
2001	39420.42	0.00	21481.30	697.81	0.00	0.00	0.00
2002	20468.97	0.00	19946.10	557.00	0.00	0.00	0.00
2003	60862.56	0.00	13707.78	548.44	0.00	0.00	0.00
2004	13015.04	0.00	23093.06	747.64	0.00	0.00	0.00
2005	67934.31	0.00	30362.28	1211.88	1.43	0.00	0.00
2006	58645.12	0.00	35940.51	1673.29	3.09	0.00	0.00
2007	1955.97	0.00	27182.97	2276.62	2.90	0.00	0.00
2008	0.00	76.37	12321.59	2903.33	5.21	0.00	0.00
2009	0.00	0.00	0.00	0.00	0.00	0.00	0.00

(3) The adjustment period of regional relative eco-efficiency is influenced by the external economic environment. From 1995 to 2009, during the equilibrium emergence, the external environment changes rapidly, the economic recession caused by the global financial crisis spreads, when a new equilibrium appears, it is broken soon. If the external environment cannot get improved continuously, the optimal equilibrium of 2020 may not appear, and the recession will still continue.

4. Conclusion

Regional ecological efficiency is a relative concept and the optimum at the current stage may not be the best in the longer period. In order to achieve the optimal target of medium and long term ecological efficiency, DEA neural network models and the criteria of life cycle are used in this paper for constructing the recognition model of the regional relative ecological efficiency, and which is applied in predicting and identifying the stages of ecological efficiency from empirical analysis. It can be seen from the evaluation results that this method has fast convergence, accurate identification, and extensive application and worthy promotion in practice. It would be a supplement method of ecological efficiency evaluation. The unique advantage of this method is well combined the DEA model, neural network model and equal dimension innovation GM (1, 1) model which makes the phenomenon of “floating up” values in middle-long period predicted values restrained effectively, and the results of whole model converged fast and identified accurately. The research in this paper would be a management tool for local governments to evaluate the regional ecological status, and adopt the corresponding policy to guarantee the regional economic and environmental strategy realization.

Table 2 The Result of DEA neural network evaluation and recognition

	Year	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
DEA eval	θ	1	1	1	0.9292	0.887	0.9142	0.7436	0.7213	1	0.7705	0.7946	0.8649
	$\hat{\alpha}_{j_0}^D$	0	0	0	0.1416	0.7425	0.1716	0.5128	0.5575	0	0.4589	0.4107	0.5523
	$\hat{\beta}_{j_0}^D$	0	0	0	0.8129	0.8796	1.2055	0.3175	0.0167	0	0.6318	0.8417	0.8674
	Result	B	B	B	R	R	R	F	F	B	R	R	R
RBF recog	$\hat{\alpha}_{j_0}^R$	-0.0014	0.0007	0.0005	0.2223	0.2229	0.2228	0.5128	0.2053	0	0.4794	0.2652	0.4656
	$\hat{\beta}_{j_0}^R$	-0.0060	0.0034	0.0023	0.9569	0.9595	0.9593	0.3175	0.8837	0	0.8669	0.9442	0.8718
	Recog	B	B	B	R	R	R	F	R	B	R	R	R
BP recog	$\hat{\alpha}_{j_0}^B$	0.0004	0.0004	0.0093	0.1325	0.6727	0.1591	0.5361	0.5241	0.0257	0.4127	0.4450	0.4829
	$\hat{\beta}_{j_0}^B$	0.0017	0.0023	0.0360	0.7481	0.7453	1.1455	0.4993	0.0810	0.1200	0.5338	0.6829	0.8930
	Recog	B	B	B	R	R	R	F	F	I	R	R	R
	Year	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	
DEA eval	θ	0.8396	0.8799	0.829	0.764	0.7255	0.7513	0.8334	0.8259	0.7965	0.7456	1	
	$\hat{\alpha}_{j_0}^D$	0.5427	0.4581	0.3426	0.472	0.6311	0.4973	0.3332	0.3483	0.4069	0.5088	0	
	$\hat{\beta}_{j_0}^D$	0.8759	0.9064	0.9611	0.889	0.8055	0.9862	1.6056	1.9889	1.6021	1.5157	0	
	Result	R	R	R	R	R	R	R	R	R	R	B	
RBF recog	$\hat{\alpha}_{j_0}^R$	0.4949	0.4968	0.4980	0.4954	0.4997	0.4921	0.2878	0.3352	0.3378	0.3392	0	
	$\hat{\beta}_{j_0}^R$	0.8613	0.8606	0.8602	0.8611	0.8595	0.8644	1.4277	1.7710	1.7895	1.7996	0	
	Recog	R	R	R	R	R	R	R	R	R	R	B	
BP recog	$\hat{\alpha}_{j_0}^B$	0.4960	0.4158	0.3938	0.4665	0.5496	0.5198	0.3337	0.3372	0.4059	0.5102	0.0014	
	$\hat{\beta}_{j_0}^B$	0.9481	0.9575	0.8202	0.8404	0.8785	0.9377	1.6804	1.8344	1.7065	1.4600	0.0675	
	Recog	R	R	R	R	R	R	R	R	R	R	I	
	Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	
DEA eval	θ	0.8279	0.8496	0.8673	0.8828	0.8904	0.9069	0.9184	0.9306	0.9570	0.9780	1	
	$\hat{\alpha}_{j_0}^D$	0.3443	0.3007	0.2655	0.2343	0.2193	0.1862	0.1632	0.1389	0.0860	0.0440	0	
	$\hat{\beta}_{j_0}^D$	1.8118	1.8664	1.9726	2.1744	2.0459	2.0088	1.8254	1.4571	0.9532	0.5491	0	
	Result	R	R	R	R	R	R	R	R	R	R	B	
RBF recog	$\hat{\alpha}_{j_0}^R$	0.3394	0.3394	0.3394	0.3388	0.2083	0.1962	0.1579	0.1125	0.1125	0.0308	0	

	$\hat{\beta}_{j_0}^{R}$	1.8012	1.8013	1.8013	1.8023	2.0162	2.0360	1.3921	1.2052	1.2052	0.3301	0
	Recog	R	R	R	R	R	R	R	R	R	R	B
BP recog	$\hat{\alpha}_{j_0}^{B}$	0.3390	0.3006	0.2724	0.2443	0.2162	0.1911	0.1624	0.1295	0.0827	0.0470	0.0216
	$\hat{\beta}_{j_0}^{B}$	1.8546	1.9531	2.0155	2.0333	2.0031	1.9528	1.7872	1.4906	0.9554	0.5193	0.0513
	Recog	R	R	R	R	R	R	R	R	R	R	B

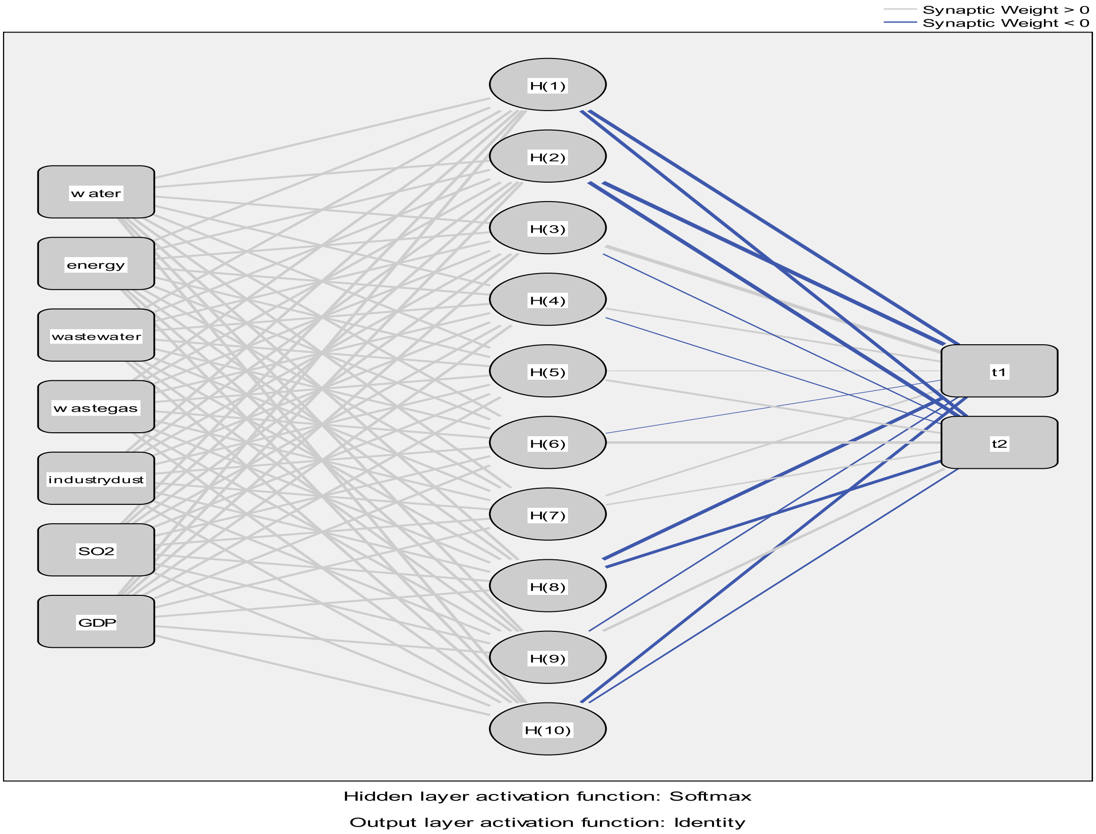
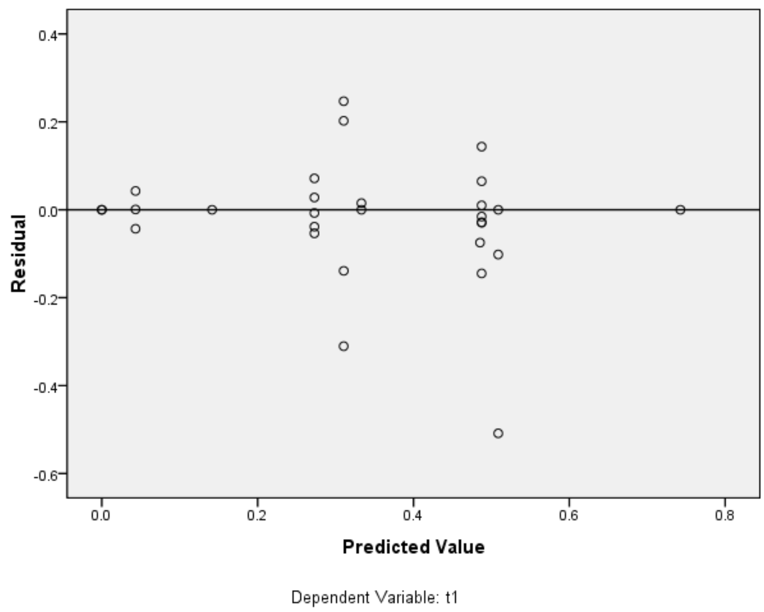
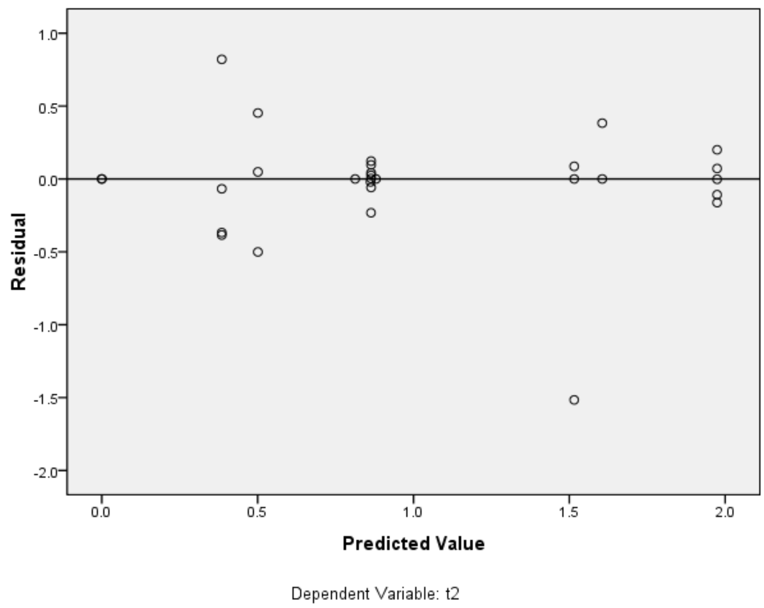


Fig. 1 DEA-RBF neural network structure





(a) $\hat{\alpha}_{j_0}^{R}$ (t1) (b) $\hat{\beta}_{j_0}^{R}$ (t2)

Fig.2 (a), (b) DEA-RBF predicted residuals

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