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Assessment Analysis and Forecasting for Security Early Warning of Energy Consumption Carbon Emissions in Hebei Province, China

Yi Liang *, Dongxiao Niu, Haichao Wang and Hanyu Chen

School of Economics and Management, North China Electric Power University, Beijing 102206, China; niudx@126.com (D.N.); ncepuwhc@163.com (H.W.); hbdxlhr@163.com (H.C.)
* Correspondence: lianglouis@126.com; Tel.: +86-10-61773079

Academic Editor: S. Kent Hoekman
Received: 9 February 2017; Accepted: 17 March 2017; Published: 19 March 2017

Abstract: Against the backdrop of increasingly serious global climate change and the development of the low-carbon economy, the coordination between energy consumption carbon emissions (ECCE) and regional population, resources, environment, economy and society has become an important subject. In this paper, the research focuses on the security early warning of ECCE in Hebei Province, China. First, an assessment index system of the security early warning of ECCE is constructed based on the pressure-state-response (P-S-R) model. Then, the variance method and linearity weighted method are used to calculate the security early warning index of ECCE. From the two dimensions of time series and spatial pattern, the security early warning conditions of ECCE are analyzed in depth. Finally, with the assessment analysis of the data from 2000 to 2014, the prediction of the security early warning of carbon emissions from 2015 to 2020 is given, using a back propagation neural network based on a kidney-inspired algorithm (KA-BPNN) model. The results indicate that: (1) from 2000 to 2014, the security comprehensive index of ECCE demonstrates a fluctuating upward trend in general and the trend of the alarm level is "Severe warning"–"Moderate warning"–"Slight warning"; (2) there is a big spatial difference in the security of ECCE, with relatively high-security alarm level in the north while it is relatively low in the other areas; (3) the security index shows the trend of continuing improvement from 2015 to 2020, however the security level will remain in the state of "Semi-secure" for a long time and the corresponding alarm is still in the state of "Slight warning", reflecting that the situation is still not optimistic.

Keywords: energy consumption carbon emissions (ECCE); security early warning; pressure-state-response (P-S-R) model; time and space analysis; back propagation neural network based on kidney-inspired algorithm (KA-BPNN)

1. Introduction

Emissions of carbon dioxide have become a global issue of the World's common concerns nowadays, not only because this issue has a significant impact on the global ecological environment, but also because it is closely related to humans' work and life through its influence on the global economy [1]. By decomposing the carbon productivity, it can be found that due to the energy consumption growth, increased carbon emissions have become an increasingly important factor which threatens the success of countries all over the world to achieve sustainable development goals due to the energy consumption growth [2]. At present, energy consumption carbon emissions (ECCE) are a practical issue which runs through the political, economy, social and other fields more than a scientific problem. In this context, carrying out systematic studies on ECCE has become a priority research areas and research hotspot disciplines for domestic and overseas scholars in the fields of geography, environmental science, economy and others [3].

In recent years, research on ECCE has mainly focused on the following aspects: the relationship between carbon emissions and economic development, efficiency assessment of carbon emissions, analysis of carbon emissions influencing factors, carbon emissions and urban planning, and the calculation and assessment of carbon emissions. Bekhet et al. [4] studied the dynamic causal the relationship among carbon emissions, financial development, economic growth, and energy consumption for Gulf Cooperation Council countries from 1980 to 2011. Liu et al. [5] discussed the issues concerning Chinese provincial carbon dioxide emission efficiency by using a slacks-based measure model. In order to analyze the impacts of population, affluence and technology were applied on the carbon emission of 125 countries at different income levels during the period 1990–2011. Shuai et al. [6] combined the STIRPAT model and used the panel and time-series data. Zubelzu and Álvarez [7] calculated the carbon footprint of the industrial sector during the urban planning stage for clearly developing and implementing preventive measures. Chang et al. [8] investigated the performance estimation of energy consumption and carbon dioxide emissions for sustainable development in the Baltic Sea countries. These studies have formed a systematic research framework of ECCE, and their research methods have been relatively enriched and completed to a certain extent, which provide a strong theoretical support towards promoting the construction of low-carbon city and the regulation of ECCE in practice.

From the perspective of sustainable development, studying the security of ECCE conforms to historical background that humankind together pursues the coordinated development of regional population, resources, environment, economy and society complex system. The security of ECCE can be understood that under the premise of human's necessary needs being met, ECCE should be coordinated with the regional population, resources, economy and social system. However, at present, there are few studies on the security of ECCE. Carbon emissions, which are considered an important environmental problem, can be regarded as an important component of the ecological environment. Thus, results of ecological security research can be borrowed to study the issue of ECCE security. Han et al. [9] undertook an urban ecological security assessment for cities in the Beijing-Tianjin-Hebei metropolitan region based on the pressure-state-response (P-S-R) conceptual model. Pei et al. [10] constructed Beijing's ecological security assessment index system based on P-S-R model and used comprehensive index method to evaluate Beijing's ecological security condition. Neri et al. [11] applied P-S-R model to establish Bai Autonomous Prefecture of Dali's land ecological security assessment index system, then they used entropy method to evaluate Dali Prefecture's land ecological security comprehensive index. Therefore, the P-S-R model is widely applied in the ecological security assessment. The P-S-R model, which is proposed by the OECD and the UNEP, uses the thinking logic of the P-S-R and reflects the interaction relationship between humans and environment. Human beings acquire the necessary resources from the natural environment for their survival and development through various activities and discharge waste into the environment. Therefore, it changes the reserves of natural resources and environmental quality. Conversely, due to the changes in the state of nature and the environment that affect human society-economic activities and welfare, society responds to changes in the state of nature and the environment through environmental policy, economic policy and sectoral policy, and changes in consciousness and behavior. In such a circulation, the P-S-R relationship between humans and the environment is formed [11–13]. Thus, in the assessment of security early warning of ECCE, the evaluation index system of the security early warning can be built through the framework of the P-S-R model.

In the study of the security early warning assessment of ECCE, carbon emissions security early warning forecasting, as another focus, can change the lag of carbon emission safety control policy and carry out dynamic and advanced management of carbon emissions security. Furthermore, it can propose a new idea of carbon emissions security control to provide scientific basis for carbon emissions control and reduction decisions. Forewarning and forecasting, which is more applied in ecological environment, natural disaster and so on, such as river drought and pollution [14,15], air quality [16], earthquake [17] and floods [18], mainly include the following methods: Markov model [19], Gray model (GM) [20], support vector machine [21], neural networks [22] and so forth. Among these methods, the back propagation neural network (BPNN) which was proposed based on a neural network put forward by Rumelhart and McClelland [22], has better performance in forecasting with its strong non-linear mapping ability, high self-learning and self-adaptability [23,24]. Because the BPNN connection weights structure and threshold are randomly set during initialization, it is undeniable that the BPNN has the potential to fall into local optima, has slow convergence and other shortcomings. The kidney-inspired algorithm (KA), which is a kind of population theory proposed by Jaddi et al. in 2016, is a new heuristic algorithm that mimics the functioning of the kidneys' biological systems [25]. Through the test function operation, KA's optimization ability is superior to that of the genetic algorithm (GA) [26], particle swarm optimization (PSO) [27], bat algorithm (BA) [28] and other optimization algorithms. Therefore, KA can be used to optimize the connection weights and thresholds of BPNN, in order to improve the convergence rate of BPNN and avoid it from falling into a local optimum.

China is one of the countries with the highest CO_2 emissions in the world [29]. From the CO_2 emissions structure, due to China's coal-dominated energy structure, CO_2 emissions mainly come from the energy sector at present [30]. Hebei Province, abbreviated as HB, which is located in the north of China, near the capital of Beijing, with iron and steel, equipment manufacturing, petroleum and chemical industries as pillar industries, has a large quantity of ECCE. Large population base, low forest coverage, and the more serious environmental pollution in HB hinder the coordinated development between ECCE and population, resources, economy and social system. In recent years, the central government has focused on the environment governance of HB and set a goal summarized as "two insurances, two declines and two promotions". Two insurances are to ensure obvious and decisive progress in air quality improvement and excess capacity dissolution. Two declines mean that the total discharges of major pollutants and the proportion of coal consumption decrease significantly. Two promotions represent that water quality and greening continue to improve steadily. Besides, the renewable energy sources of the HB grid continued to maintain a rapid development trend in 2016, with the year-on-year growth of 80.2%. This year there were 31 new inputs of photovoltaic power stations and the power generating capacity increased by 1.253 million kW. Wind farms increased by two, with 270,000 kW capacity. The total installed wind power and photovoltaic capacity was up to 3.255 million kW, among which the installed wind power capacity was 1.0618 million kW with the year-on-year growth of 34.4% and the installed photovoltaic capacity was 1.111 million kW with a year-on-year growth of 112.8%. From the information above, we can conclude that clean energy has accounted for 13.1% of the total installed capacity of the HB grid with a year-on-year increase of 3.7%. Therefore, it is important to evaluate and forecast the security early warning of ECCE in HB as this is of much practical significance.

In summary, this paper will analyze the assessment and forecasting of the security early warning of ECCE in HB. First, based on the P-S-R model framework, an evaluation index system is established to assess the security early warning of ECCE in HB. Then, during 2000–2014, from two dimensions of time series and spatial patterns, the synthetic index and subsystem index of the security early warning of ECCE are analyzed and evaluated in HB. Finally, the model of BPNN optimized by the KA is utilized to predict and analyze the security early warning of ECCE in HB. The rest of the paper is structured as follows: Section 2 introduces the algorithms used in this paper, including the calculation method of the ECCE security index, BPNN and KA. The construction process of the evaluation index system of the security early warning of ECCE is introduced in Section 3. In Section 4, two dimensions of the time series and spatial pattern are used to analyze the security early warning of ECCE in HB from 2000 to 2014. Section 5 provides predictive analysis concerning the security early warning of ECCE in HB during the period 2015–2020. Section 6 summarizes the research results.

2. Methodology

2.1. The Security Early Warning Index of ECCE

(1) Data standardization

Set x_{ij} as the original value of the jth evaluation indicator for the i years, and make standardized processing of the original data by using the range method. The equations are as follows:

For the profit type indicator:

$$x'_{ij} = \frac{x_{ij} - x_{\min j}}{x_{\max j} - x_{\min j}} \tag{1}$$

For the cost type indicator:

$$x'_{ij} = \frac{x_{\max j} - x_{ij}}{x_{\max j} - x_{\min j}} \tag{2}$$

where x'_{ij} represents the standardized values for the jth indicator in the i years, $x_{\max j}$ and $x_{\min j}$ are the maximum and minimum values of the jth indicator.

(2) Indicator weighting

The variance method is utilized to weight the indicator for eliminating the error caused by human factors. Steps are as follows:

The mathematical description of calculating the mean value E_j of each indicator is as follows:

$$E_j = \frac{1}{n}\sum_{i=1}^{n} x'_{ij} \tag{3}$$

The mathematical description of calculating the mean square deviation σ_j of each indicator is as follows:

$$\sigma_j = \sqrt{\sum_{i=1}^{n}\left(x'_{ij} - E_j\right)^2} \tag{4}$$

The mathematical description of calculating the weight ω_j of the jth indicator is shown below:

$$\omega_j = \frac{\sigma_j}{\sum\limits_{j=1}^{n} \sigma_j} \tag{5}$$

(3) Security early warning index calculation

The method of multiplying the standardized data of each indicator by the weight of each indicator, can be utilized to obtain the index of the security earning warning of ECCE. The formula is as follows:

$$F_i = \omega_1 x'_1 + \omega_2 x'_2 + \cdots + \omega_n x'_n \tag{6}$$

where F_i represents the index value of the security early warning of ECCE in the ith year.

2.2. Back Propagation Neural Network

BPNN, which was proposed by a team of scientists headed by Rumelhart and McClelland [22] in 1986, is a multilayer feed forward networks trained by an error back propagation algorithm. As shown in Figure 1, the input signal X_i acts on the output node through the hidden layer node and generates the output signal Y_k by the non-linear transformation. Each sample of a network training includes an input vector X and an expected output t. The deviation between the network output value Y and an expected output t by adjusting the connection weight w_{ij} between an input node and a hidden layer node, the connection weight between a hidden layer node and an output node w_{jk}, and a threshold to decrease the error along the gradient direction. After repeated learning and training, the weights and thresholds corresponding to the minimum errors are determined. At this stage, training is stopped. Meanwhile, the trained neural network toward input information of similar samples can output the information of non-linear conversion of the smallest error by itself. BPNN specific operational process can be found out in the references [31].

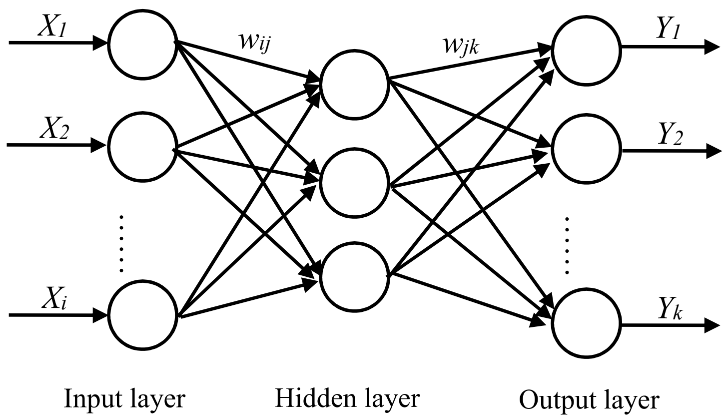


Figure 1. BPNN structure.

The connection weights and thresholds of BPNN mainly affect the network performance. They are obtained by giving a set of initial weights and thresholds, and adjusting gradually in training. Finally, we can get better weights and thresholds. However, due to the blind initial point selection and difficulty in selecting global initial points, the possibility of the BPNN falling into the local extremum increases. Thus, this paper utilizes the KA to optimize connection weights and thresholds of the BPNN.

2.3. Kidney-Inspired Algorithm

KA is a new and effective meta-heuristic algorithm, which is based on population theory and imitates operation procedures of the biological kidney process by Jaddi and others in 2016 [25]. The components involved in the KA are simply introduced as follows [25]:

(1) Movement of virtual solutes

Each solution in the population of the KA represents a solute in the biological kidney. A new solution is generated by moving the solution from the previous iteration toward the best solution found by the algorithm so far. This movement is formulated as follows:

$$S_{i+1} = S_i + rand(S_{best} - S_i) \tag{7}$$

where S represents a solution in the population. S_i is the solution in the ith iteration. The value of *rand* is a random number between zero and a given number and S_{best} is the best solution found by the algorithm in past iterations.

(2) Filtration

The solutions in the population are filtered by using a filtration rate that is calculated by a filtration function at each iteration. The *fr* (filtration rate) is calculated as follows:

$$fr = \alpha \times \sum_{i=1}^{p} f(x_i)/p \tag{8}$$

where a is a constant value in a range of (0, 1), p is the population size, and $f(x_i)$ is the objective function of solution x at iteration i.

(3) Reabsorption

The reabsorption operator is a process that gives a solution that has been assigned to W (waste) a chance to become part of FB (filtered blood). A solution assigned to W can be moved to FB if, after applying the movement operator (Equation (7)) again, it satisfies the filtration rate and can be assigned to FB.

(4) Secretion

Secretion is an operator for the solutions that have been assigned to FB. If a solution that has been assigned to FB is not better than the worst solution in FB, it is secreted and is moved to W; otherwise this solution remains in FB and the worst solution in FB is secreted and is transferred to W.

(5) Excretion

The solutions in W are excreted if, after giving them a chance of reabsorption, they cannot satisfy the filtration rate to become part of FB. These solutions are excreted if they do not have the ability to be FB after two times moving. In this case, such a solution in W is replaced with a random solution. The insertion of random solutions imitates the continuous insertion of solutes and water into the glomerular capillaries of the kidney. The schematic process of the KA is shown in Figure 2. The solute in the initial group (Figure 2a) is divided into FB and W by measuring the solute and filtration rate in the filtration stage (Figure 2b). Then, each solute (depending on FB or W) and its value of the objective function reabsorb, secret or excrete the operator (Figure 2c). In this process, some solutes that are strong enough to be distributed to the FB during the filtration phase remain as FB components. Some of these solutes are distributed to W, and solutes that achieve reabsorption are discharged if they still cannot be distributed to the FB, but some solutes can be successfully reabsorbed. After placing each solute (Figure 2d), the FB and W are merged as a new group to study and to continue this iteration process until the termination condition is satisfied (Figure 2e).

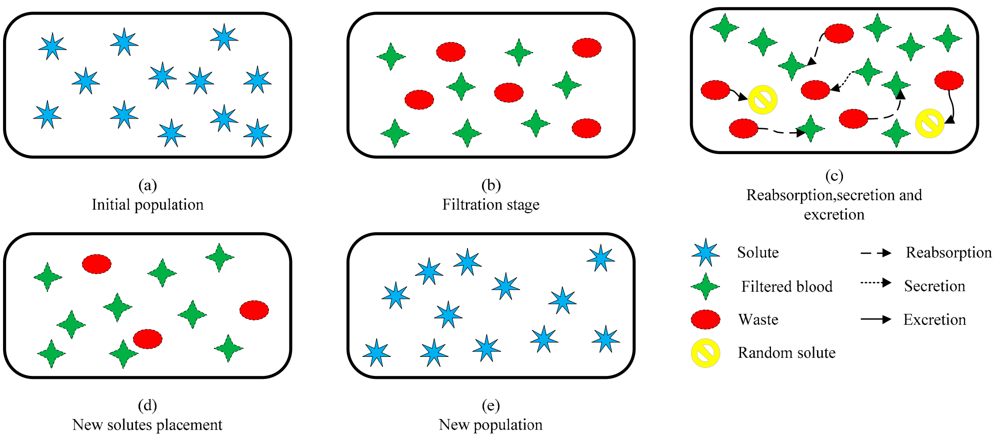


Figure 2. The operating mechanism of the KA. (**a**) Initial population; (**b**) Filtration stage; (**c**) Reabsorption, secretion and excretion; (**d**) New solutes placement; and (**e**) New population.

The connection weight and threshold in the BPNN are taken as the population of the KA, and the training error of the BPNN is taken as the fitness function of the KA. Through the optimization of the KA, the optimal connection weights and thresholds of BPNN can be obtained. The hybrid model is abbreviated as KA-BPNN.

2.4. Assessment and Forecasting Framework of the Security Early Warning of ECCE

This thesis consists of two parts: one is based on the P-S-R model to evaluate the security early warning of carbon emissions, and the other is based on the KA-BPNN model to predict the security early warning of carbon emissions. The corresponding flow chart is shown in Figure 3.

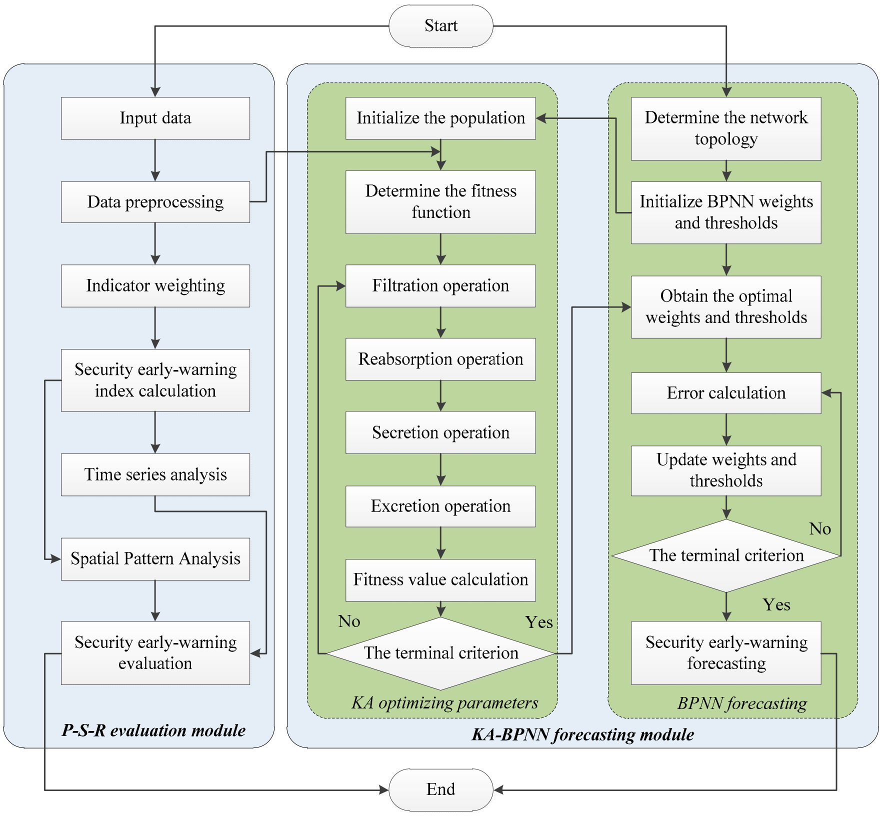


Figure 3. The flow chart of assessment and forecasting of the security early warning of ECCE.

3. The Security Early Warning Evaluation Index System of ECCE

In order to select the early warning indicators of ECCE, the security characteristics of ECCE are fully considered, including the current situation of regional ECCE, the impact of human activities, and the population, economy, resources and social indicators related to ECCE. In this section, the early warning evaluation index system of ECCE security in HB is constructed based on the framework of P-S-R model and regional practice in HB, which is listed in Table 1.

Table 1. The security early warning evaluation index system of ECCE.

Target Layer	Criterion Layer	Indicator Layer	Indicator Type
The security early warning evaluation index system of ECCE	Pressure system (A)	Natural population growth rate (A_1)	–
		Population density (A_2)	–
		Urbanization level (A_3)	–
		Proportion of the second industry (A_4)	–
		Proportion of coal consumption (A_5)	–
		Average annual growth rate of carbon emissions (A_6)	–
	State system (B)	Forest coverage (B_1)	+
		Urban per capita disposable income (B_2)	+
		Rural per capita pure income (B_3)	+
		Energy consumption per unit of GDP (B_4)	–
		Carbon emissions per unit of GDP (B_5)	–
	Response system (C)	Real GDP per capital (C_1)	+
		Proportion of environmental governance investment accounted for GDP (C_2)	+
		Proportion of non-fossil fuels (C_3)	+
		Proportion of R&D investment accounted for GDP (C_4)	+
		Carbon emissions per capita (C_5)	–

Note: In the indicator type, "+" indicates the profit indicator, which is proportional to the security index; "–" indicates the cost indicator, which is inversely proportional to the security index.

Among them, the pressure indicator refers to the reason why social and economic activities bring pressure on ECCE and the "negative effect" that can affect the security of ECCE; state indicator, which can reflect the current status or trend of ECCE, is the result of "pressure" and the purpose of "response". In addition, response indicator reflects how people eliminate or mitigate the negative effects of ECCE and prevent the deterioration of ECCE security, so as to achieve the goal of sustainable development. Specific indicators are interpreted as follows:

(1) The natural population growth rate is the difference between the birth rate and the mortality rate of the population and it represents the pressure of population growth.
(2) The population density, representing the population carrying pressure, is equal to the population divided by area.
(3) The urbanization level is equal to the total number of the urban population divided by the total number of region population then multiplied by 100% which refers to urbanization pressure.
(4) The proportion of the second industry, referring to the pressure of industrial structure, is equal to the second industry GDP divided by total GDP then multiplied by 100%.
(5) The proportion of coal consumption is equal to the coal consumption divided by the total amount of energy consumption then multiplied by 100%, which refers to the pressure of energy structure.
(6) The average annual growth rate of carbon emissions, referring to the pressure of carbon emissions growth, is equal to the difference between this year's carbon emissions and last year's carbon emissions divided by last year's carbon emissions then multiplied by 100%.
(7) The forest coverage is equal to forest area divided by total land area then multiplied by 100%, which refers to the regional carbon sink status.
(8) The urban per capita disposable income is equal to the total income of urban households minus the income tax and social security fee, which reflects the living conditions of urban residents.
(9) The rural per capita pure income is equal to the total income of the rural households minus the cost of production and nonproduction operating expenses, taxes and the amount paid to the collective task, which reflects the living conditions of rural residents.
(10) The energy consumption per unit of GDP reflects the status of energy consumption intensity and is equal to total primary energy supply divided by GDP.
(11) The carbon emissions per unit of GDP is equal to the total carbon emissions divided by GDP and reflects the status of carbon emissions.
(12) The real GDP per capital is equal to GDP divided by the total population which reflects the developmental level of the regional economy.
(13) The proportion of environmental governance investment accounted for GDP, reflecting the society's emphasis on the carbon emissions control work, is equal to the total investment in environmental governance divided by GDP then multiplied by 100%.
(14) The proportion of non-fossil fuels is equal to the total amount of non-fossil energy consumption divided by the total amount of energy consumption then multiplied by 100%, which reflects the society's emphasis on the improvement of energy structure.
(15) The proportion of R&D investment accounted for GDP reflects the society's emphasis on the carbon emission reduction technology, is equal to R&D input divided by GDP then multiplied by 100%.
(16) The carbon emissions per capita is equal to the total amount of carbon emissions divided by the total population, which reflects the level of per capita carbon emissions.

In this paper, on the basis of reference to the results of ecological security police degree division [32,33] and combined with the security warning index of the ECCE, the security alarm of ECCE in HB is divided into five levels, listed in Table 2.

Table 2. The division of the security early warning level of ECCE.

Early Warning Index Interval	(0, 0.2)	(0.2, 0.4)	(0.4, 0.6)	(0.6, 0.8)	(0.8, 1.0)
Alarm level Security evaluation	Very severe warning Morbidity	Severe warning Insecurity	Moderate warning Critical state	Slight warning Semi-secure	No warning Security

4. Time Series and Spatial Pattern Assessment Analysis of the Security Early Warning of ECCE

4.1. Data Selection

In this section, the security early warning of ECCE is analyzed in HB from 2000 to 2014. The original data comes from the Hebei Economic Yearbook (2001–2015) and the China Urban Statistical Yearbook (2015). After data reprocessing, the trend of the indicators is presented in Figure 4.

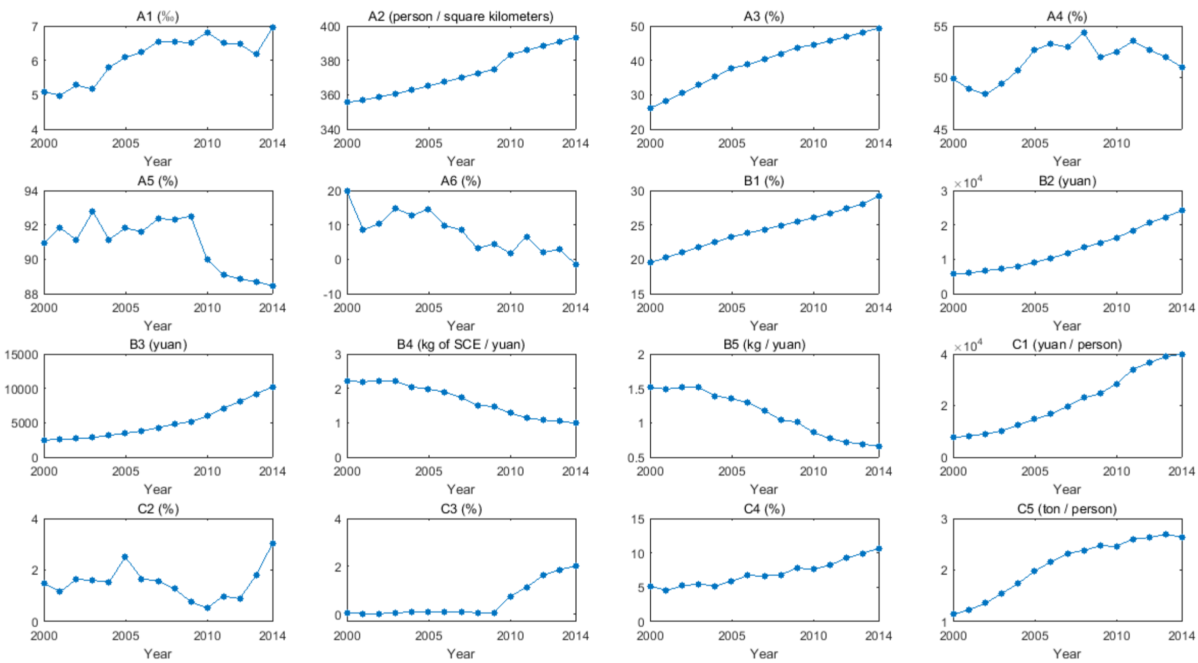


Figure 4. The historical data of evaluation indicator. A1–A6: The pressure system indicators; B1–B5: The state system indicators; C1–C5: The response system indicators.

4.2. Time Series Assessment Analysis

The original data are standardized according to Equations (1) and (2), and the Equation (3) is used to give the weight of each index, as is shown in Table 3. Meanwhile, the Equation (4) is utilized to calculate the security early warning index of ECCE during 2000–2014 in HB. And the results are shown in Table 4.

Table 3. The weight of each indicator.

Indicator	Weight	Indicator	Weight	Indicator	Weight
A_1	0.0627	B_1	0.0565	C_1	0.0676
A_2	0.0646	B_2	0.0629	C_2	0.0486
A_3	0.0600	B_3	0.0616	C_3	0.0700
A_4	0.0574	B_4	0.0725	C_4	0.0576
A_5	0.0656	B_5	0.0729	C_5	0.0669
A_6	0.0526	-	-	-	-

Table 4. Assessment results of security early warning of ECCE.

Year	Comprehensive Index	Subsystem Index			Assessment Level	Alarm Level
		Pressure System	State System	Response System		
2000	0.3478	0.2549	0.0006	0.0924	Insecurity	Severe warning
2001	0.3614	0.2743	0.0099	0.0771	Insecurity	Severe warning
2002	0.3690	0.2669	0.0139	0.0883	Insecurity	Severe warning
2003	0.3247	0.2160	0.0227	0.0860	Insecurity	Severe warning
2004	0.3337	0.2028	0.0517	0.0793	Insecurity	Severe warning
2005	0.3191	0.1496	0.0695	0.1001	Insecurity	Severe warning
2006	0.3242	0.1475	0.0897	0.0869	Insecurity	Severe warning
2007	0.3285	0.1243	0.1205	0.0838	Insecurity	Severe warning
2008	0.3584	0.1165	0.1586	0.0833	Insecurity	Severe warning
2009	0.3810	0.1253	0.1739	0.0818	Insecurity	Severe warning
2010	0.4603	0.1394	0.2129	0.1080	Critical state	Moderate warning
2011	0.5237	0.1336	0.2490	0.1411	Critical state	Moderate warning
2012	0.5965	0.1502	0.2760	0.1702	Critical state	Moderate warning
2013	0.6637	0.1593	0.2994	0.2051	Semi-secure	Slight warning
2014	0.7229	0.1504	0.3264	0.2462	Semi-secure	Slight warning

Then, this part will make a timing analysis about the comprehensive index of the early warning of carbon emissions and the index of each subsystem.

(1) Comprehensive index analysis

It can be seen from Figure 5 that the security index of ECCE shows a fluctuating upward trend in general in HB from 2000 to 2014. Its trend is "Insecurity" (2000–2009)–"Critical state" (2010–2012)–"Semi-secure" (2013–2014), while the trend of the alarm level is "Severe warning" (2000–2009)–"Moderate warning" (2010–2012)–"Slight warning" (2013–2014).

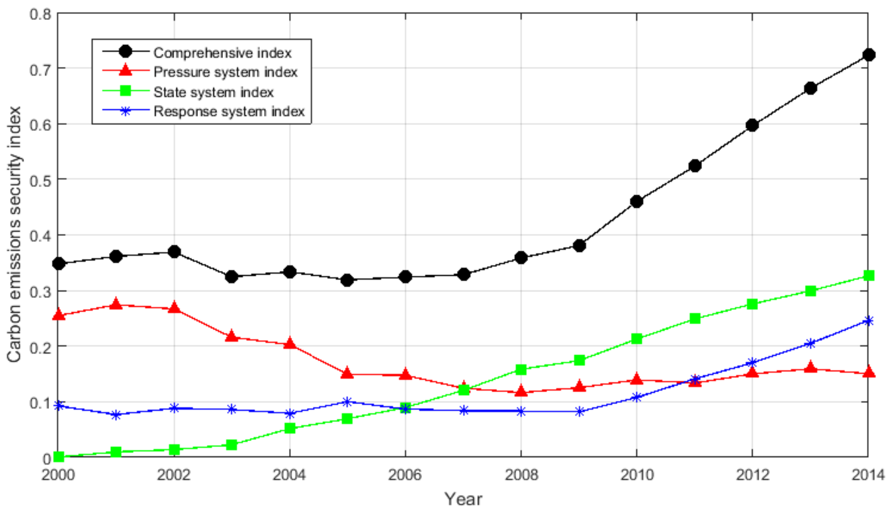


Figure 5. Assessment results of safety early warning of the carbon emissions.

The comprehensive index of ECCE tended to rise in HB from 2000 to 2002, which rose from 0.3478 in 2000 and 0.3614 in 2001 to 0.3690 in 2002. During the period 2003–2007, the security situation of ECCE tended to fluctuate in a deteriorating state and the security index fell from 0.3690 in 2002 to 0.3247 in 2003. During 2008–2009, the comprehensive index, which was on an upward trend, rose from 0.3285 in 2007 to 0.3584 in 2008 and 0.3810 in 2009, demonstrating that the security situation of ECCE has improved. In 2009, HB government implemented the energy-saving and emission-reduction demonstration project named "Double Thirty", established the green credit system, and carried out the evaluation of green credit policy, highlighting the one-vote veto of environmental protection in the credit approval system. On the construction of legal system, "Regulations of HB on Reducing Pollutant Discharge and Supervision" and "Management Measures of HB on Preventing and Controlling Environmental Pollution" were issued, providing a strong legal guarantee to strengthen environmental law enforcement and deepen pollution reduction. Thus, since then, the security status of ECCE has changed significantly, during which the security index increased at an average annual rate of 13.73%, from 0.3810 in 2009 to 0.7229 in 2014. Considering the change trend, it is indicated that the work of energy-saving and emission-reduction has achieved some success in recent years in HB. Moreover, it can be demonstrated that HB has made great efforts to the efficiency of energy consumption since 2008, especially with the Beijing Olympic Games as well as the 2014 APEC (Asia-Pacific Economic Cooperation) conference held in Beijing.

(2) Pressure system index analysis

Figure 6 shows that, the pressure system index presented a trend of fluctuant reduction during 2000–2004 in HB. Among these, the maximum value, 0.2743, appeared in 2001, and it remained above 0.2000 with an average of 0.2430 from 2000 to 2004. In 2005, the pressure system index decreased significantly and remained at an average of 0.1396 since then.

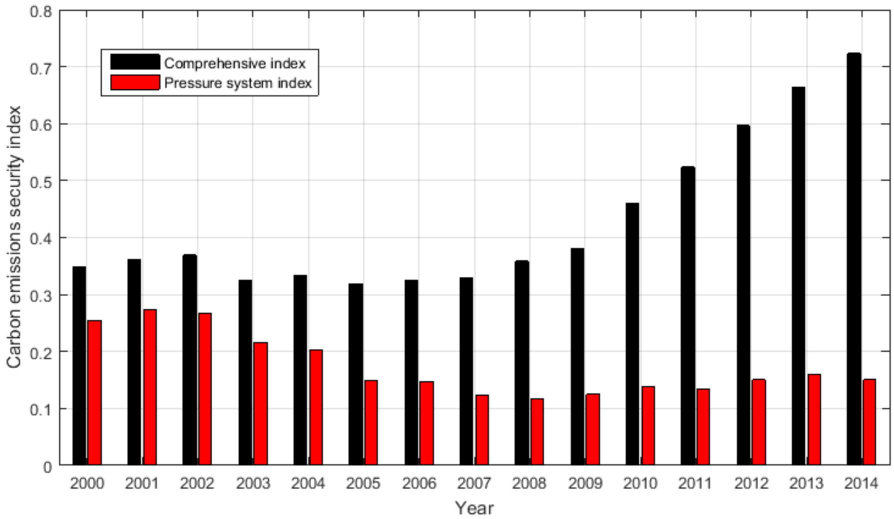


Figure 6. The pressure system index of the security early warning of ECCE.

In this period, not only the natural population growth rate increased from 5.09 per thousand in 2000 to 6.95 per thousand in 2014, but also the population density increased from 355.58 people per square kilometer in 2000 to 393.41 people per square kilometer in 2014, which illustrated that the pressure of population was increasing in HB. Meanwhile, due to the accelerated urbanization (the urbanization rate increased from 26.09% in 2000 to 49.33% in 2014), the propulsion of heavy-industrialization (the second industry share remained at more than 48% throughout), and the proportion of traditional fossil energy consumption remaining high, the security early warning of ECCE bored a greater pressure, which leaded to a downward trend in the overall pressure system index.

(3) State system index analysis

As presented in Figure 7, the state system index basically implied a straight upward trend from 2000 to 2014 in HB. It grew from 0.0006 in 2000 to 0.3264 in 2014. However, the annual growth rate of the state system index has dropped and maintained at an average of 12.84% since 2009.

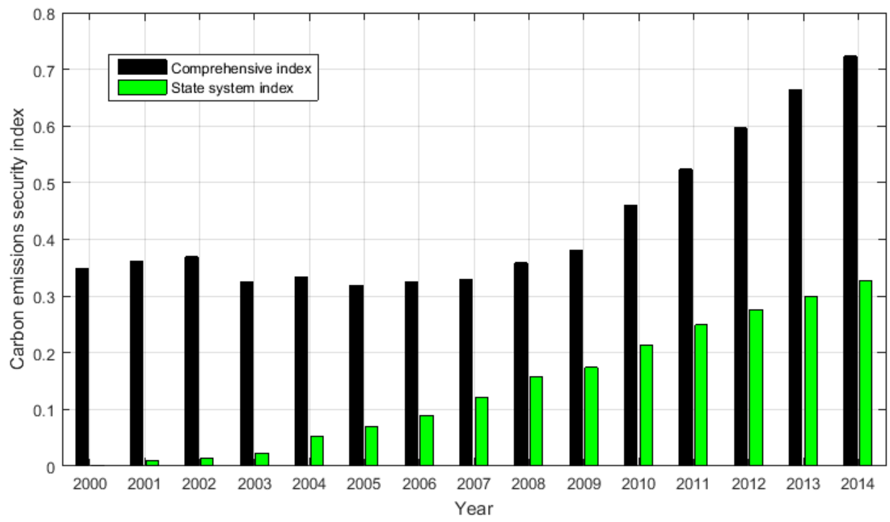


Figure 7. The state system index of the security early warning of ECCE.

In this period, the forest coverage has been greatly improved, from 19.5% in 2000 to 29.2% in 2014. The urban per capita disposable income and the rural per capita pure income also grew rapidly. Energy efficiency has been greatly improved and the energy consumption per unit of GDP dropped from 2.21 kg of standard coal/yuan in 2000 to 0.99 kg of standard coal/yuan, leading to a continuous improvement for the state system index of the same period. Nevertheless, more energy consumption will be produced when the income level of urban and rural residents increases. And the energy consumption per unit of GDP will also be more difficult to continue to decline after it falls to a certain extent. Especially with the acceleration of urbanization, the forest land, agricultural land and other carbon sink resources will likely reduce, which will undoubtedly increase the pressure that the state system index of the security early warning of ECCE will rise in HB.

(4) Response system index analysis

From Figure 8, it can be found that the response system index generally showed a fluctuating growth trend as same as the growth trend of the comprehensive index. The response system index was at a low level with an average of 0.0859 from 2000 to 2009. After 2009, the growth rate increased significantly with an annual growth rate of 22.95%.

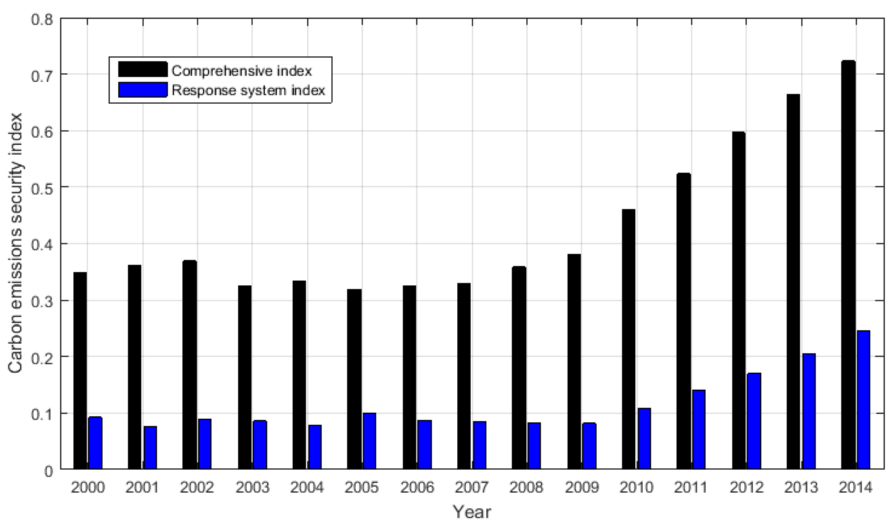


Figure 8. The response system index of the security early warning of ECCE.

In order to strengthen the environmental pollution control in Beijing-Tianjin-Hebei region, HB increased investment in environmental protection every year, during which the proportion of environmental governance investment accounted for GDP increased from 1.48% in 2000 to 3.02% in 2014. HB has accelerated the development of new energy projects so as to optimize the energy structure and improve the energy structure dominated by coal consumption. Especially in Zhangjiakou, Chengde and other cities, a lot of photovoltaic power generation pilot bases have been built. The proportion of R&D investment accounted for GDP increased from 5.19% in 2000 to 10.65% in 2014, which promoted the improvement of response system index of security early warning of ECCE to a large extent.

4.3. Spatial Pattern Assessment Analysis

According to the relevant data of HB in 2014, the comprehensive index and each subsystem index in 2014 are calculated, applying the aforementioned calculation method.

(1) Comprehensive index analysis

It can be seen from Figure 9 that the security alarm of ECCE was relatively high in north HB, while it was relatively low in the other areas.

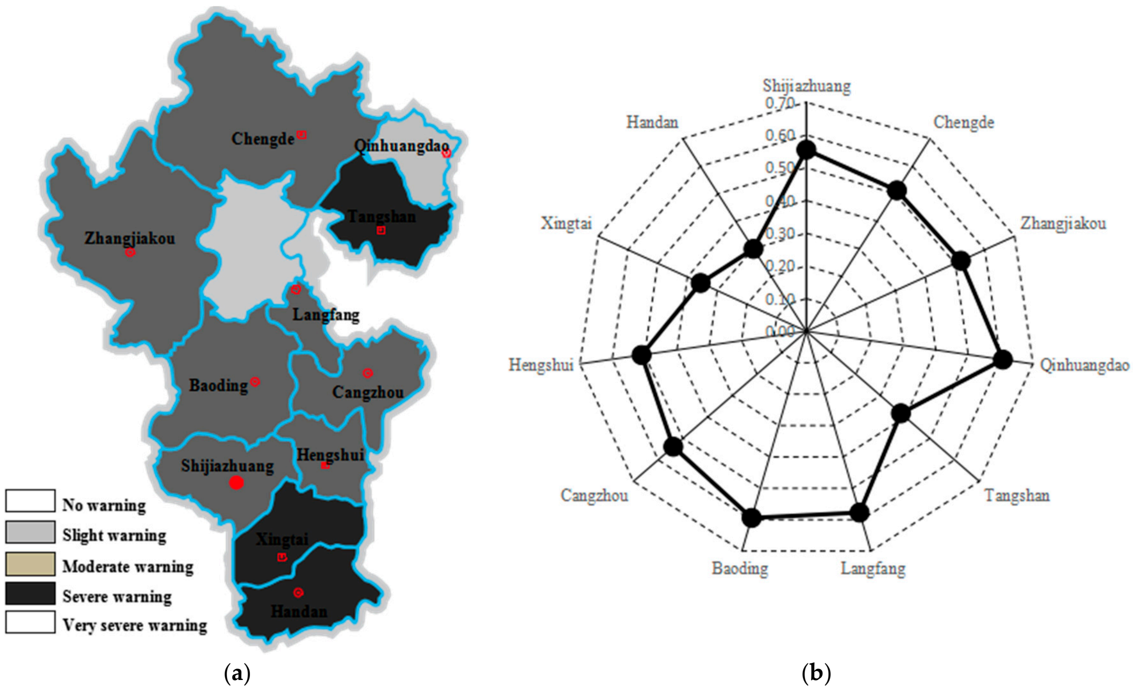


Figure 9. Spatial pattern of comprehensive index note: (**a**) represents the spatial distribution of the comprehensive index; (**b**) is a radar chart representing the comprehensive index.

Qinhuangdao (0.6072) belonged to "light warning". As an excellent tourist city and low-carbon pilot city, whose tourism and port trade revenue accounted for a relatively large proportion of GDP, and it was in a "semi-secure" state in terms of security of ECCE. Shijiazhuang (0.555), Chengde (0.5120), Zhangjiakou (0.5194), Langfang (0.5773), Baoding (0.5943), Cangzhou (0.5386) and Hengshui (0.5093) all belonged to "moderate warning". Among them, the economic development level of Shijiazhuang, Baoding and Cangzhou, whose pillar industries were textile, automobile manufacturing and petrochemical, was relatively good, while the other cities presented relatively low levels of economic development. This reveals that the security of ECCE is not entirely related to the level of regional economic development, but the comprehensive effect of manifold causes. Tangshan (0.3825), Xingtai (0.3557) and Handan (0.2995) all belonged to "severe warning". These three cities are all heavy industrial cities and especially in Tangshan and Handan, the heavy industrialization degree is higher. To some extent, it is necessary to enhance regional industrial structure adjustment to promote the security of regional ECCE.

(2) Pressure system index analysis

As shown in Figure 10, in the pressure system, the security index of the ECCE was relatively high in north HB, while it was relatively low in the central and southern regions.

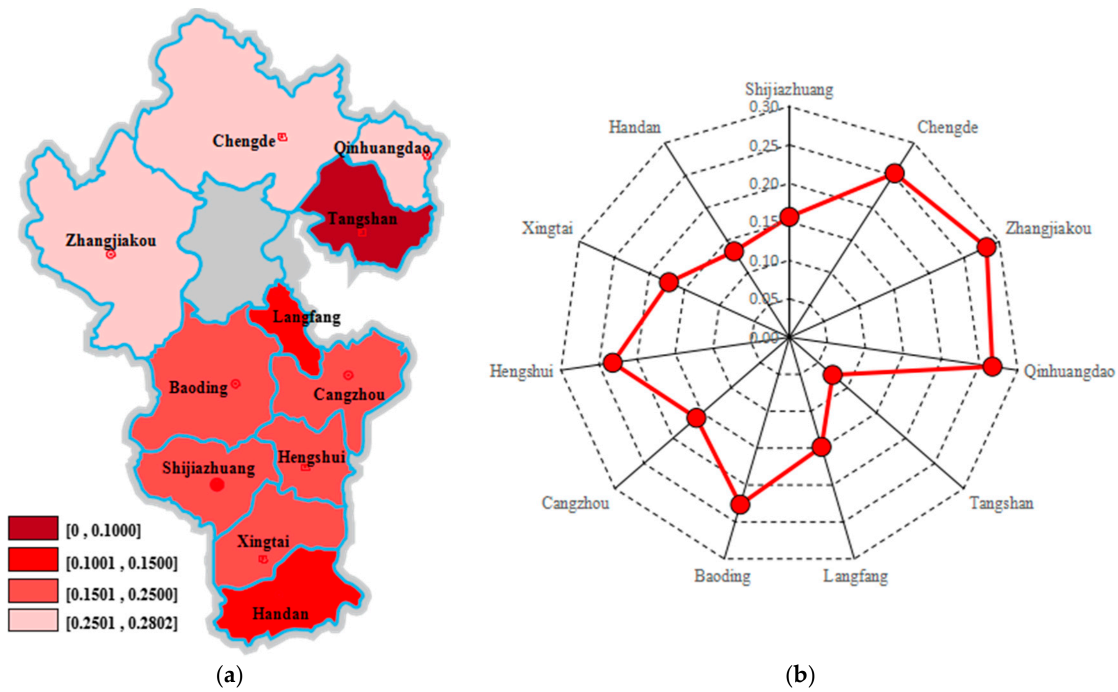
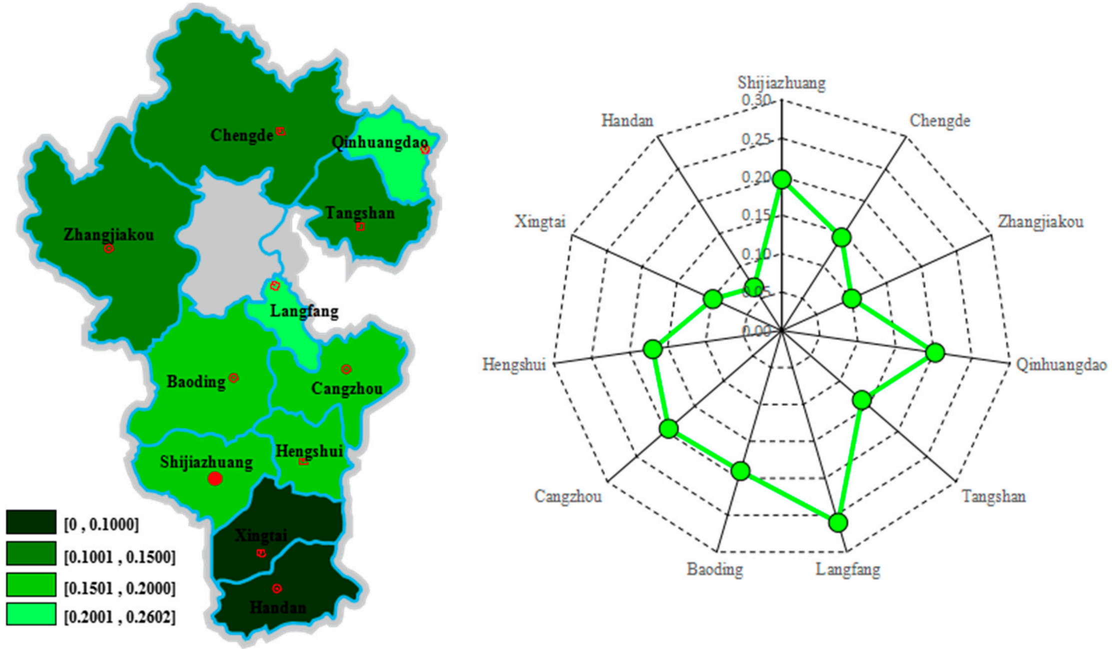


Figure 10. Spatial pattern of pressure system index. Note: (a) represents the spatial distribution of the pressure system index; (**b**) is a radar chart representing the pressure system index.

The pressure system index of Tangshan was 0.0745, which was the lowest in the 11 cities. Tangshan is a typical traditional heavy industry city in HB, whose natural population growth rate was 7.13 per thousand, ranking third in the province; the second industry accounted for 58.7%, ranking first in the province. As a result, its security pressure of the ECCE was relatively large. The pressure system index in Handan and Langfang were 0.1328 and 0.1484 respectively, which were slightly higher than Tangshan. Among them, Handan is also a heavy industrial city with steel smelting as the pillar industry and its natural population growth rate was 7.73 per thousand, ranking first in the province and resulting in its relatively low pressure index system. Langfang, adjacent to Beijing, is the main residence of migrant workers in Beijing, whose population density reached 695.04 people per square kilometer ranking first in the province, leading to a relatively low pressure system index in Langfang. The pressure index in Baoding (0.2265), Cangzhou (0.1598), Shijiazhuang (0.1565), Hengshui (0.2320) and Xingtai (0.1722) was between 0.1501~0.2500, belonging to a relatively high level. Among them, Shijiazhuang is the capital city of HB. Its level of urbanization ranked first in the province, while its population density and the proportion of secondary industry were in the middle level, and the average annual growth rate of carbon emissions was negative, indicating that its energy saving and emission reduction measures have achieved remarkable results. The pressure system index in Zhangjiakou (0.2820), Chengde (0.2534) and Qinhuangdao (0.2668) was the highest. In these three northern cities of HB, the land area is broad, the population is relatively scarce and the urbanization level is also low, taking some pressure off for the security of ECCE.

(3) State system index analysis

Figure 11 illustrates that in the state system, the security index of ECCE was relatively high in the central region, was at a moderate level in the northern region and was relatively low in the southern region.



(**a**) (**b**)

Figure 11. Spatial pattern of state system index. Note: (**a**) represents the spatial distribution of the state system index; (**b**) is a radar chart representing the state system index.

The state system index in Langfang and Qinhuangdao were 0.2602 and 0.2017 respectively, which was rang 0.2001 to 0.2602 and ranked the top two in the province. This was mainly because Langfang and Qinhuangdao's economic level was relatively high, whose urban per capita disposable income and rural per capita pure income were at the forefront of the province, but the energy consumption per unit of GDP and carbon emissions per unit of GDP were in the low level. The state system index in Baoding (0.1903), Cangzhou (0.1947), Shijiazhuang (0.1966), Hengshui (0.1696) was between 0.1501 and 0.2000. Although they were below 0.2000, they were in the upper reaches of HB. The state system index in Zhangjiakou (0.1001), Chengde (0.1440), and Tangshan (0.1378) was between 0.1001 and 0.1500. The forest coverage in Zhangjiakou and Chengde was relatively high, but the relatively low urban per capita disposable income, especially the lower rural per capita pure income affected the improvement of their state system index. On the contrary, Tangshan's economic development level was high, but the forest coverage, energy consumption per unit of GDP and carbon emissions were not ideal, resulting in a lower score of the state system index. The state system index in Xingtai (0.0986) and Handan (0.0669) were at the lowest level and the two cities are characterized by low forest coverage, income, energy consumption per unit of GDP and carbon emissions with unsatisfactory scores.

(4) Response system index analysis

As shown in Figure 12, the response system index was relatively high in the central region, was at a moderate level in the northern region and was relatively low in the southern region.

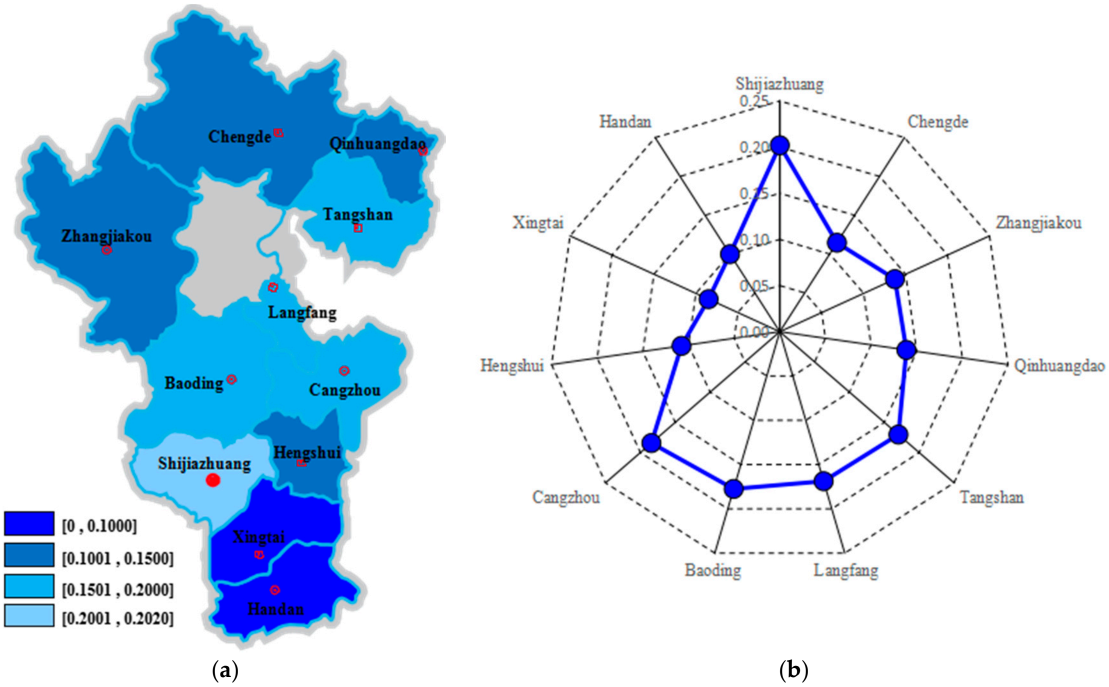


Figure 12. Spatial pattern of response system index. Note: (**a**) represents the spatial distribution of the response system index; (**b**) is a radar chart representing the response system index.

The state system index in Shijiazhuang was 0.2020, which was the highest in the province. This was mainly due to the high level of economic development in Shijiazhuang, the correspondingly high per capita GDP, and more investment in environmental governance. The response system index in Tangshan (0.1702), Langfang (0.1688), Baoding (0.1775), Cangzhou (0.1842) was between 0.1501 and 0.2000. The per capita GDP in Tangshan, Langfang and Hengshui was relatively high, but the per capita carbon emissions and proportion of R&D investment accounted for GDP were not ideal. On the contrary, the per capita GDP level in Baoding was low, yet the proportion of environmental governance investment accounted for GDP and the per capita carbon emissions were ideal, thus making up for its economic disadvantage. The state system index in Zhangjiakou (0.1372), Chengde (0.1146), Qinhuangdao (0.1387) and Hengshui (0.1077) was between 0.1001~0.1500. The state system index in Xingtai (0.0849) and Handan (0.0999) was lowest, which was mainly because the proportion of environmental governance investment accounted for GDP and the proportion of R&D investment accounted for GDP was at a low level with the relatively high per capita carbon emissions.

5. The Security Early Warning Forecasting of ECCE

In this section, KA-BPNN model is utilized to forecast the security early warning of ECCE from 2015 to 2020 in HB. The subsystem indexes of the security of ECCE from 2000 to 2014 in HB are considered as the basic data. Since the amount of the sample data is small, the neural network can not be adequately trained. Thus, the annual data is disassembled into monthly data to expand the amount of sample data. The specific procedures are shown as follows:

(1) Suppose the energy consumption value of each month in annual year as $s_{i,j}$, $i = 2000, 2001, \cdots, 2014$, $j = 1, 2, \cdots 12$, where i represents year and j means month. The proportion of energy consumption in each month can be obtained, and the unified treatment format is shown in Formula (9).

$$s_{i,1} : s_{i,2} : \cdots : s_{i,12} = a_{i,1}k_i : a_{i,2}k_i : \cdots : a_{i,12}k_i, \quad i = 2000, 2001, \cdots, 2014 \tag{9}$$

In which, k_i is the proportion coefficient of energy consumption in year i, and $a_{i,j}$ represents the multiple of proportion coefficient in month j, year i.

(2) Set the security value of month j in year i as $F_{i,j}$, and it can be obtained from Formula (10).

$$\frac{\sum_{j=1}^{12} F_{i,j}}{12} = \frac{\sum_{j=1}^{12} a_{i,j}k_i}{12} = F_i, \quad i = 2000, 2001, \cdots, 2014 \tag{10}$$

where F_i is the security value of ECCE in year i.

At this point, the annual data has been disassembled into monthly data. Similarly, the monthly data of subsystem can also be calculated based on the above process.

Therefore, we can get 180 monthly samples of 15 years. Then, the data of the first five months and the month label l_j are taken as input samples. The month label is used to strengthen the classification ability of neural network, and its value range is $\{1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12\}$. At present, there are 175 sets of samples in total, of which the first 125 groups are as training samples and the latter 50 groups are as testing samples. In this paper, a classical three-layer mode of BPNN is selected. It is composed of one input layer with 6 inputs, one hidden layer with 3 hidden neurons, and one output layer with one output. Then the max iteration is set to 100, error precision to 0.001 and learning rate to 0.05. In KA, the number of the iteration is 100 and the population size of this paper is 20. In order to fully account for the advantages of the proposed model, the standard BPNN algorithm is compared with the traditional GM (1, 1) algorithm, and the parameter settings are the same.

The first 125 groups of samples are put into the proposed model for training. Then the iterative process of the KA-BPNN model and the standard BPNN model is shown in Figure 13, from which it can be seen that the initial training error of the BPNN model after KA optimization is much lower than that of the standard BPNN model, and the proposed model converges after 46 iterations. Finally, the last 50 groups of samples are put into the trained model to test and the testing results are displayed in Figure 14.

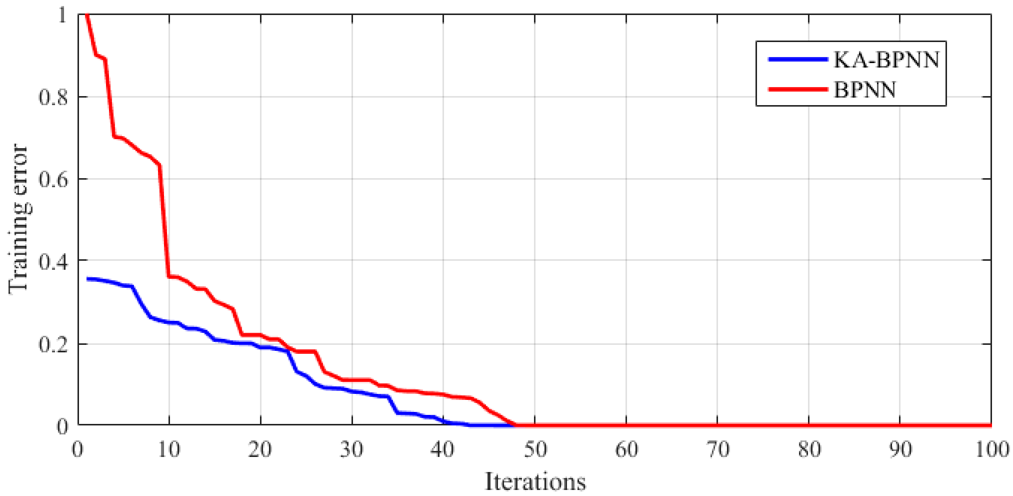


Figure 13. The training process of KA-BPNN and BPNN model.

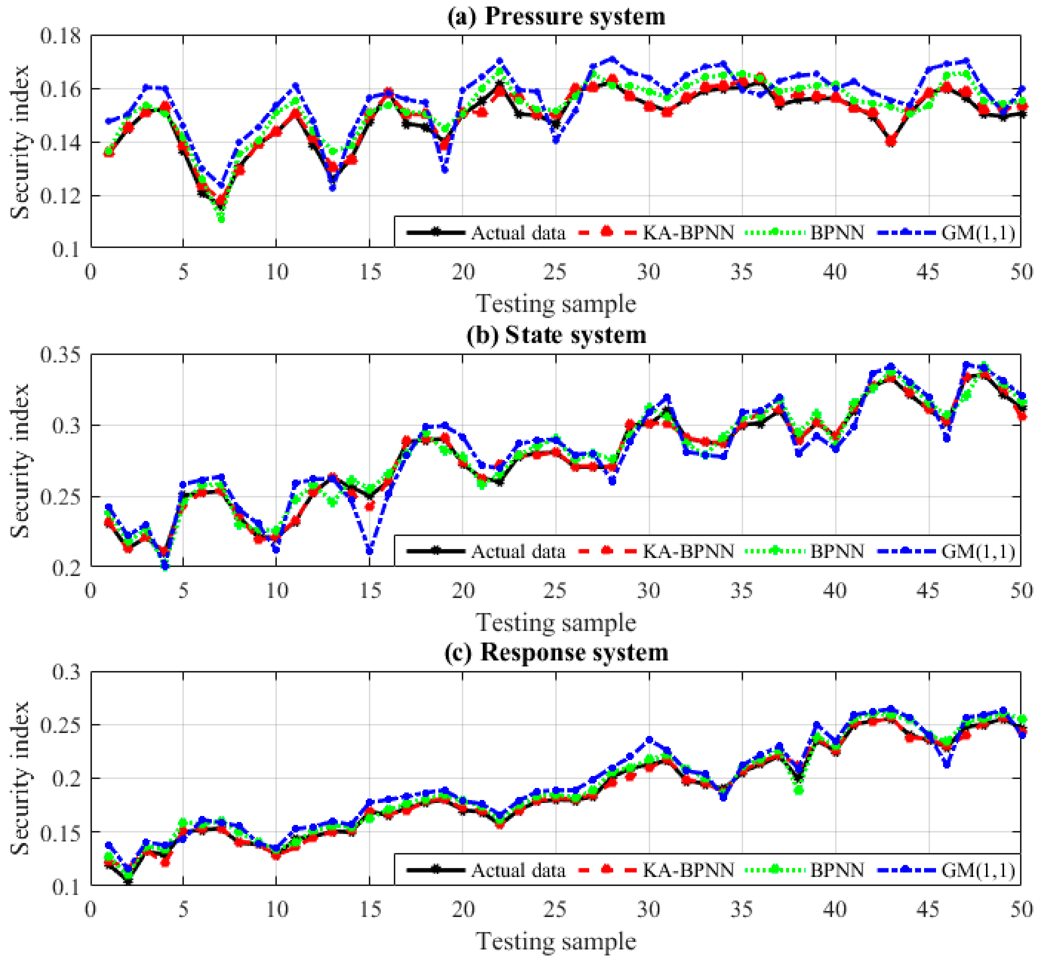


Figure 14. Testing results. (**a**) The pressure system testing results; (**b**) The state system testing results; and (**c**) The response system testing results.

MSE (mean square error) and MAPE (mean absolute percentage error) are selected to evaluate and compare the forecasting performance of those models in this paper. The calculation equation of these two kind of errors are shown as follows:

$$\text{MSE} = \frac{1}{N}\sum\nolimits_{t=1}^{N}\sqrt{(x_t - \hat{x}_t)^2} \tag{11}$$

$$\text{MAPE} = \frac{1}{N}\sum\nolimits_{t=1}^{N}|(x_t - \hat{x}_t)/x_t| \tag{12}$$

where x_t denotes the actual value and $\hat{x}_t$ represents the forecasting value.

The errors results are shown in Figure 15. As can be seen, KA-BPNN has the highest forecasting accuracy for the three subsystem index, followed by the standard BPNN model and the GM (1, 1) model has the worst forecasting effect, which indicates that the model proposed in this paper can accurately and steadily predict the security early warning of ECCE.

According to the above-mentioned trained models, the subsystem index from September 2014 to December, 2014 and the month label are used as input to predict the value of each subsystem index in January 2015, which will be used as the input sample for predicting the value of each subsystem index in February 2015, and so on until the values of the subsystem index in December 2020 are predicted. Then, the annual subsystem indexes are respectively obtained by summing up the whole twelve months' values.

The forecasting values of each subsystem index are added as the predictive values of the comprehensive index, and the forecasting results are revealed in Table 5 and Figure 16.

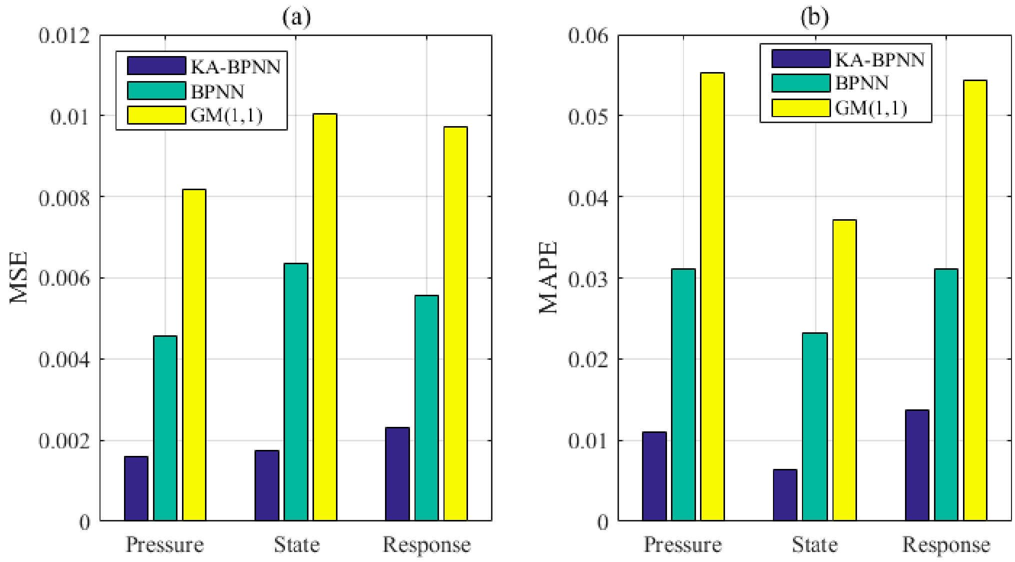


Figure 15. Testing error analysis. (**a**) The MSE of testing results; (**b**) The MAPE of testing results.

Table 5. Forecasting results of security early warning of ECCE in HB from 2015 to 2020.

Year	Pressure System	State System	Response System	Comprehensive Index	Forecasting Level	Forecasting Alarm
2015	0.1476	0.3278	0.2524	0.7278	Semi-secure	Slight warning
2016	0.1341	0.3365	0.2579	0.7285	Semi-secure	Slight warning
2017	0.1310	0.3541	0.2624	0.7475	Semi-secure	Slight warning
2018	0.1267	0.3719	0.2729	0.7715	Semi-secure	Slight warning
2019	0.1273	0.3826	0.2798	0.7897	Semi-secure	Slight warning
2020	0.1112	0.4052	0.2834	0.7998	Semi-secure	Slight warning

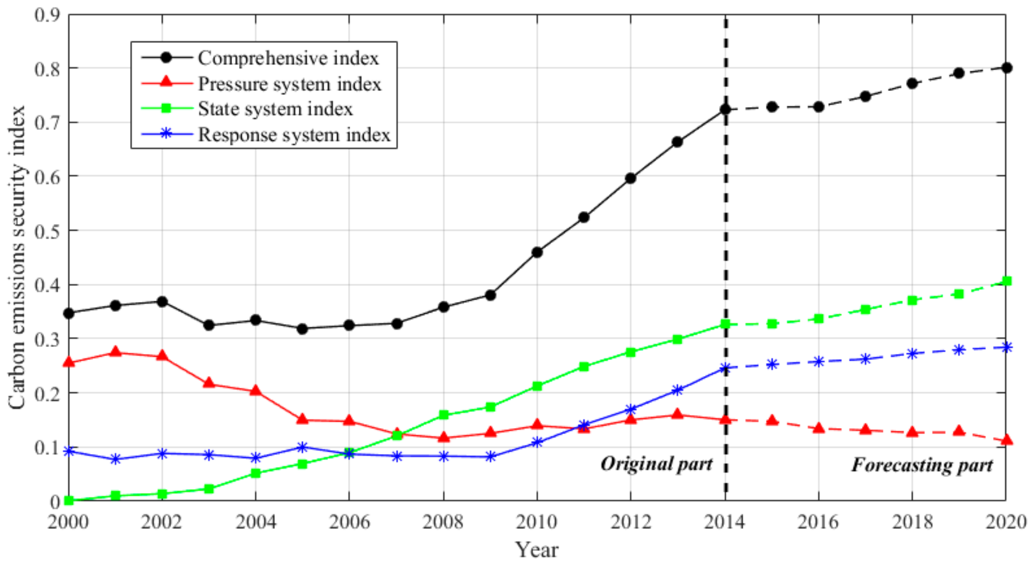


Figure 16. Forecasting results.

From Table 5 and Figure 16, it can be found that the security of ECCE will indicate the state of continued improvement in HB in the next period of time. Its comprehensive index will gradually increase, meanwhile the security level will remain in the state of "Semi-secure" for a long time and the corresponding alarm is still in the state of "Slight warning", which shows that the security situation of ECCE is still not optimistic. Then detailed analysis are as follows:

(1) Forecasting analysis of pressure system index

The pressure system index of the security of the ECCE decreases from 0.1476 in 2015 to 0.1112 in 2020, which will bring greater pressure on the security of ECCE in HB. From a practical point of view, the natural population growth rate and the city population density will be further increased with the implementation of the "second-child" policy, leading to a new round of population growth pressures and population density pressures in HB. The acceleration of urbanization will also lead to excessive urbanization pressure; industrial structure is difficult to evolve to the late stages of industrialization in the short term and the middle stage of industrialization that takes heavy industrialization as the leading growth feature will bring pressure on industrial structure that the proportion of high energy consuming industries is too high. It is also difficult for coal consumption to have a large degree of improvement in the short term, which will also bring greater pressures for energy consumption; and due to the whole advancement of population growth, urbanization, industrial structure and energy structure pressure, HB will also face greater growth pressures of ECCE. The above factors are also the main reasons for the further decline of the security pressure system index of ECCE in HB from 2015 to 2020.

(2) Forecasting analysis of state system index

The state system index showed an upward trend, which played a certain role in promoting the comprehensive index of security early warning of energy consumption carbon emissions in HB from 2015 to 2020. The forest coverage will be further improved and the economic development will grow at a steady pace, which can promote the steady improvement of living standards of urban and rural residents in HB in the next few years. Meanwhile, energy consumption per unit of GDP and carbon emissions per unit of GDP will also show a downward trend due to the technological progress, making the state system index steadily improve.

(3) Forecasting analysis of response system index

The response system index shows a slow upward trend from 2015 to 2020. Specifically, with the intensification of haze problem, the government will pay more attention to environmental protection, so there will be more funds to invest in the research and development of environmental governance and energy saving technology in HB. Meanwhile, with the upgrading of industrial structure, the use of wind energy, solar energy and other new energy will expand, thereby enhancing the proportion of renewable energy. However, with the increase of ECCE, the per capita carbon emissions will be further improved in HB, thus hindering the improvement of the response system index.

Based on the forecasting results of security early warning of ECCE in HB, the following three policy suggestions can be implemented in the future: (1) The government should speed up the transformation and upgrading of the industrial structure, actively adjust the energy structure, strengthen regional ecological management, increase the carbon sink capacity, build a low-carbon planning system, and strengthen policy support; (2) Enterprises should accelerate low-carbon technological innovation, improve energy efficiency, and promote the development of low-carbon finance; (3) Residents should build a low carbon consumption model to reduce energy consumption.

6. Conclusions

This paper constructs the assessment index system of security early warning of ECCE based on the P-S-R model. In addition, the variance method and linearity weighted method are applied to calculate the index of the security early warning of ECCE in HB. Then from two dimensions of time series and spatial pattern, further analysis of the condition of the security early warning of ECCE is given. Finally, the KA-BPNN is utilized to predict the security early warning of carbon emissions during the period 2015–2020. The main results are as follows:

(1) The security index of ECCE demonstrates a fluctuating upward trend in HB from 2000 to 2014, which is "Insecurity" (2000–2009)–"Critical state" (2010–2012)–"Semi-secure" (2013–2014), while the trend of the alarm level is "Severe warning" (2000–2009)–"Moderate warning" (2010–2012)–"Slight warning" (2013–2014). Meanwhile, the pressure system index implies a downward trend in overall volatility; the state system index shows a straight upward trend; and the response system index generally presents a volatility growth trend.
(2) There is a great spatial difference in the security of ECCE in HB. The security alarm of ECCE is relatively high in the North, while it is relatively low in the other areas. In the pressure system, it is relatively high in the North while relatively low in the central and southern regions. In the state system, it is relatively high in the central region, is at a moderate level in the northern region and is relatively low in the southern region. Moreover, in terms of the response system, the security index of ECCE is relatively high in the central region, is at a moderate level in the northern region and is relatively low in the southern region.
(3) During 2015–2020, the security index of ECCE shows the state of continued improvement owing to its rises from 0.7278 to 0.7998 in HB. However, the security level remains the state of "Semi-secure" for a long time and the corresponding alarm is still in the state of "Slight warning". In terms of the pressure system, on account of the whole advancement of population growth, urbanization, industrial structure and energy structure pressure, HB confronts with greater growth pressures of ECCE. The state system index steadily grows, with the further increase of forest coverage, steady economic growth, and the progress of energy saving and emission reduction technology. Besides, the increase of environmental protection investment and the upgrading of industrial structure play positive roles, while the rising per capita carbon emissions plays a negative role, making the response system index rise slowly. Generally, the future of security situation of ECCE is still not optimistic.

Acknowledgments: This work is supported by the Natural Science Foundation of China (Project No. 71471059).

Author Contributions: Yi Liang designed this research and wrote this paper; Dongxiao Niu provided professional guidance; Haichao Wang and Hanyu Chen collected all the data and revised this paper.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The abbreviations in this study are as follows:

ECCE	energy consumption carbon emissions
P-S-R	Pressure-State-Response model
KA-BPNN	back propagation neural network based on kidney-inspired algorithm
BPNN	back propagation neural network
KA	kidney-inspired algorithm
HB	Hebei Province, China
fr	the filtration rate in kidney-inspired algorithm
W	the waste in kidney-inspired algorithm
FB	the filtered blood in kidney-inspired algorithm
GDP	gross domestic product
R&D	research and development
MSE	mean square error
MAPE	mean absolute percentage error

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