Lecture Notes in Electrical Engineering 1145

Jerry Chun-Wei Lin
Chin-Shiuh Shieh
Mong-Fong Horng
Shu-Chuan Chu *Editors*

Genetic and Evolutionary Computing

Proceedings of the Fifteenth International Conference on Genetic and Evolutionary Computing (Volume I), October 6–8, 2023, Kaohsiung, Taiwan

Springer

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ISSN 1876-1100 ISSN 1876-1119 (electronic)
Lecture Notes in Electrical Engineering
ISBN 978-981-97-0067-7 ISBN 978-981-97-0068-4 (eBook)
https://doi.org/10.1007/978-981-97-0068-4

This Springer imprint is published by the registered company Springer Nature Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

Preface

This volume composes the proceedings of the 15th International Conference on Genetic and Evolutionary Computing (ICGEC 2023), which was held in Kaohsiung City, Taiwan, on October 6–8, 2023. The aim of ICGEC 2023 is to provide an internationally respected forum for scientific research in the areas of artificial intelligence, genetic and evolutionary computing, intelligent data analysis, machine learning, and all the associated applications.

The ICGEC 2023 was co-sponsored by Western Norway University of Applied Sciences (Norway), National Kaohsiung University of Science and Technology (Taiwan), Shu-Te University (Taiwan), Nanchang Institute of Technology (China), Taiwan Association for Web Intelligence Consortium, Ubiquitous International Co., Ltd, and Changzhou College of Information Technology (China). We would like to express our sincere thanks to the authors, reviewers, and organizing committee members for their contributions of making this conference a success. We would also like to thank the publisher, Springer, for their work and support in publishing the proceedings.

October 2023

Jerry Chun-Wei Lin
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Contents

Analysis on the Influence of Regional Agricultural Planting Factors on Grain Yield Based on Genetic Feedback Process Neural Network

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Abstract. With the accumulation of Agricultural Big Data, the management and decision-making of agricultural planting production based on single factor expose the problem of lack of comprehensive analysis. In this paper, considering the high dimensions and time-varying characteristics of agricultural big data, a new time series analysis model based on Genetic Feedback Process Neural Network (GFPNN) is proposed to analyze the influence of regional agricultural planting factors on grain yield. Take China as an example, the data of 11 agricultural planting factors in China from 1980 to 2020 constitute a time series. Analyze the time series by GFPNN to establish the influence model of agricultural planting factors on grain yield. Results show that this model can estimate grain yield with an accuracy of 97.83%, which is more accurate and efficient than traditional neural network. It can evaluate the influence of changes in agricultural planting factors on grain yield. It can be a reference for taking measures to deal with the change of grain yield and making grain policy; in the long run, developing and introducing appropriate agricultural machinery, popularizing efficient water-saving irrigation technology, further investing in rural education, and reducing planting costs can improve the grain yield to a certain extent.

Keywords: Regional Agricultural Planting Factors · Grain Yield · Genetic Feedback Process Neural Network · Time Series Analysis

1 Introduction

Changes in the world situation are having an all-round impact on grain. As an important new strategic resource, Agricultural Big Data plays an important role in the coupling of production factors and coordination of agricultural systems. It is becoming an important force driving the efficient development of agricultural science. Based on big data analysis, Agricultural Big Data uses the concept, technology and method of big data to deal with a large amount of data generated in the whole chain of agricultural production and

J. C.-W. Lin et al. (Eds.): ICGEC 2023, LNEE 1145, pp. 1–13, 2024.
https://doi.org/10.1007/978-981-97-0068-4_1

sales to obtain useful information and guides the process of agricultural production and management, circulation and consumption of agricultural products [1].

In China, agriculture is the first industry. Food problem is the top priority of the national economy and people's livelihood. With the strong support of the state, Chinese Agricultural Big Data has developed rapidly and accumulated more abundant. From the perspective of management and policy, the development of Chinese Agricultural Big Data has a good top-level design, especially in statistical data, a standardized system of collection, processing and release has been established; however, the research and practice on data transaction and data sharing are not enough [2].

Nowadays, research on Agricultural Big Data is still in the basic stage. Researchers have realized the research value and invested in the analysis and processing of Agricultural Big Data. Agricultural Big Data can assist precision agricultural operation [3] and intelligent agricultural management [4]. In the process of agricultural planting and production, there are many factors affecting decision-making and complex correlations with decision-making objectives. Establishing intelligent modeling is an effective technical way to deal with Agricultural Big Data.

Teng Qingfang et al. use BP neural network to approximate the mapping relationship between wheat yield and fertilizer consumption, establish a prediction model of soil fertilization amount and achieve good application results [5]. Lan Weijuan et al. use RBF neural network to make fertilization decision, establish the relationship model between soil nutrients, fertilization amount and yield, and achieve good estimation results [6]. Yu Helong et al. combine K-means clustering with BP neural network to establish a new fertilization model based on the experimental data of farmland fertilizer effect, which can effectively guide precision fertilization [7]. Chen Guifen et al. propose a weighted fuzzy hierarchical clustering algorithm, which combines the analytic hierarchy process (AHP) with spatial fuzzy dynamic clustering and uses F distribution to determine the best classification, can effectively distinguish the imbalance among soil attributes [8]. Gou Guohua uses BP neural network modify the residual error of grey model to establish the grey BP neural network prediction model, which can provide a reference for the prediction of the total power of agricultural machinery, taking the total power of agricultural machinery in Zhengzhou as an example [9]. Zhang Zimin et al. use LM-BP neural network to predict the gross agricultural product with the relevant indicators such as crop planting area, grain yield and various economic crops yield, and achieve good results [10].

At present, most of the research on agricultural production based on intelligent modeling is mainly based on traditional neural network, clustering, association analysis algorithms. The research on agricultural planting production management decision-making is mainly to analyze the change and influence of a single factor or a few factors. Most of them ignore the high dimension of agricultural data and the correlation between different dimensions, and do not combine the time-varying characteristics of agricultural data. There are few studies on establishing overall analysis and prediction model based on multi-dimensional agricultural data.

Therefore, in this paper, a new time series analysis model based on Genetic Feedback Process Neural Network (GFPNN) is proposed to analyze the influence of regional agricultural planting factors on grain yield. 11 regional agricultural planting factors are selected from the three aspects of nature, scientific and technological development, social economy, which have significant influence on grain yield. Take China as an example, collect the relevant data every year to form a time series. Train the time series by GFPNN to establish the influence model of planting factors on grain yield in China and analyze the effects of changes in planting factors on grain yield.

2 Time Series Analysis Model Based on Genetic Feedback Process Neural Network

2.1 Feedback Process Neural Network

Process neuron consists of weighting, aggregation and excitation operation. The difference between it and traditional neuron is that the input, output and corresponding weight of process neuron are time-varying, and its aggregation operation includes both multi-input aggregation of space and cumulative aggregation of time [11].

Feedback process neural network (FPNN) is composed of several process neurons according to a certain topology with feedback mechanism [12]. Its model has three layers: input layer, hidden layer of process neurons and output layer. The input layer completes the input of time-varying process signal and receives feedback from hidden neurons to the system. The hidden layer of process neurons completes the excitation operation and the spatial weighted aggregation of system input signals, outputs neurons' output signal and feeds it back to the input layer. The output layer completes the time-varying aggregation operation of the output signal from the hidden layer and the system output.

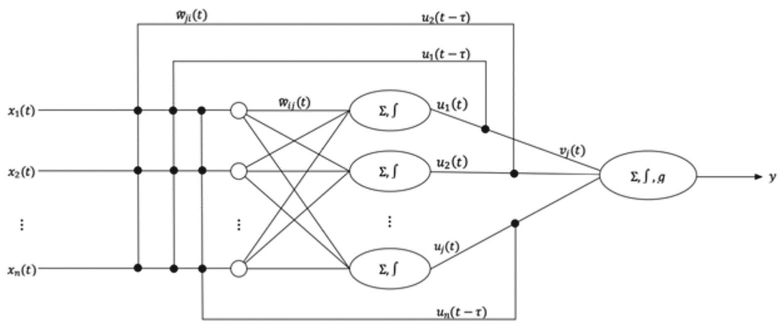

Fig. 1. Topological structure of FPNN.

Figure 1 shows a three-layer FPNN with multiple inputs and single output. Input layer contains n nodes, hidden layer contains m process neuron nodes, and output layer is composed of process neurons.

System inputs are $x_1(t), x_2(t), \ldots, x_n(t), t \in [0, T]$, $[0, T]$ is the system input process interval. The output of hidden layer process neuron node is

$$u_j(t) = f\left(\sum\nolimits_{i=1}^{n}\left(w_{ij}(t)\left(x_i(t) + \sum\nolimits_{j=1}^{m}\tilde{w}_{ji}(t)u_j(t-\tau)\right)\right)\right), j = 1, 2, \ldots, m \quad (1)$$

where $u_j(t)$ is the output of the j^{th} node in hidden layer at time t;f is the excitation function of hidden layer process neuron; $w_{ij}(t)$ is the connection weight function between the i^{th} node of input layer and the j^{th} node of hidden layer; $\tilde{w}_{ji}(t)$ is the feedback connection weight function between the j^{th} node of hidden layer and the i^{th} node of input layer; τ is the time delay.

The system output of FPNN is

$$y = g\left(\int_0^T \left(\sum\nolimits_{j=1}^{m} v_j(t)u_j(t)\right)dt - \theta\right) \tag{2}$$

where y is the system output; g is the excitation function of output node; $v_j(t)$ is the connection weight function between the j^{th} node of hidden layer and output node; θ is the excitation threshold of process neurons in output layer.

The network error function is defined as

$$E = \sum\nolimits_{p=1}^{P} \left(y_p - d_p\right)^2 \tag{3}$$

where P is the number of samples; y_p is the actual output of the p^{th} sample; d_p is the expected output of the p^{th} sample.

The calculation of FPNN mostly introduces a set of appropriate standard orthogonal basis functions into the input space. The input data is expressed as the expansion of the orthogonal basis function under a certain precision. The weight functions of hidden layer are expressed as the expansion of the same set of orthogonal basis functions as the input space. The orthogonality of basis function can reduce the complexity of time-varying operation and the calculation quantity of FPNN. This method can improve the stability and convergence rate of network learning, which makes the learning process of process neural network have the same computational complexity as the traditional neural network [13].

The network weight functions $v_j(t)$, $w_{ij}(t)$ and $\tilde{w}_{ji}(t)$ are expressed as the finite term expansion of the standard orthogonal basis functions $b_1(t), b_2(t), \ldots, b_l(t), \ldots, b_L(t)$:

$$v_j(t) = \sum\nolimits_{l=1}^{L} v_j^{(l)} b_l(t) \tag{4}$$

$$w_{ij}(t) = \sum\nolimits_{l=1}^{L} w_{ij}^{(l)} b_l(t) \tag{5}$$

$$\tilde{w}_{ji}(t) = \sum\nolimits_{l=1}^{L} \tilde{w}_{ji}^{(l)} b_l(t) \tag{6}$$

where $v_j^{(l)}$, $w_{ij}^{(l)}$, $\tilde{w}_{ji}^{(l)}$ are the expansion coefficient of $v_j(t)$, $w_{ij}(t)$, $\tilde{w}_{ji}(t)$ about $b_l(t)$.

According to the gradient descent algorithm, the network weight correction rule is:

$$v_j^{(l)} = v_j^l + \alpha\Delta v_j^{(l)}, j = 1, 2, \ldots, m \tag{7}$$

$$w_{ij}^{(l)} = w_{ij}^{(l)} + \beta\Delta w_{ij}^{(l)}, i = 1, 2, \ldots, n; j = 1, 2, \ldots, m \tag{8}$$

$$\tilde{w}_{ji}^{(l)} = \tilde{w}_{ji}^{(l)} + \gamma \Delta \tilde{w}_{ji}^{(l)}, i = 1, 2, \ldots, n; j = 1, 2, \ldots, m \tag{9}$$

$$\theta = \theta + \lambda \Delta \theta \tag{10}$$

The information transmission of FPNN has both forward flow like feedforward neural network and continuous information feedback from hidden layer nodes to input layer. Therefore, FPNN can be used not only as a function approximator, but also as an associative memory machine.

2.2 Genetic Algorithm

Genetic algorithm (GA) is a global adaptive optimization search algorithm proposed by Professor Holland of the University of Michigan in the United States, which simulates the biological genetics and evolutionary patterns in natural environment [14]. For chromosome crossover and mutation in the process of biological evolution, the exploration of the optimal solution by genetic algorithm is completed by the corresponding genetic operators. The basic genetic operators include:

Selection: Based on certain rules and individual fitness, several excellent individuals are selected from the current generation $P(T)$ and inherited into the next generation $P(T+1)$.

Crossover: Each individual in generation $P(T)$ is randomly paired, exchange the corresponding part of chromosomes between each pair of individuals with crossover rate.

Mutation: The gene values at several loci of generation $P(T)$ are changed into other alleles by a mutation rate.

Compared with the traditional search optimization algorithm, genetic algorithm has the characteristics of self-organization, self-learning and self-adaptability. In genetic algorithm, the only factor that determines whether an individual is inherited to the next generation is its individual fitness. The search process generally does not need other external information. The choice of fitness function has a great influence on the convergence speed and the quality of the solution. Fitness function represents the fitness of a species to its living environment. Individuals with high fitness are more likely to be inherited to the next generation than individuals with low fitness. If the objective function is the minimum problem, the fitness function can be set as:

$$Fit(f(x)) = \frac{1}{1 + c + f(x)}, c \geq 0, c + f(x) \geq 0 \tag{11}$$

where $f(x)$ is the objective function; c is an adjustable parameter.

2.3 Time Series Analysis by Hybrid Genetic Feedback Process Neural Network

Genetic algorithm is a random search algorithm widely used in optimization problems, which has advantages in the analysis of complex multi-parameter optimization problems and global optimization problems. Genetic algorithm is introduced into FPNN to form the hybrid Genetic Feedback Process Neural Network (GFPNN). It can help FPNN model have the ability of self-evolution and self-adaptation, avoid the problem of local minimum, and improve the network training accuracy. GFPNN realizes the complementary advantages of FPNN and genetic algorithm.

The learning process of GFPNN is described as follows:

Step 1: Set learning accuracy ε, training times $s = 0$, maximum training times N. Choose a set of standard orthogonal basis functions $b_l(t), l = 1, 2, \ldots, L$ for input space.

Step 2: Initialize network weight functions $v_j^{(l)}, w_{ij}^{(l)}, \tilde{w}_{ji}^{(l)}$ and threshold θ. Express the input functions and weight functions as the finite term expansion of the chosen standard orthogonal basis functions.

Step 3: Initialize the genetic algorithm parameters like population size, objective function, iteration times, crossover rate, mutation rate, etc.

Step 4: Train model parameters. Calculate the error function E from Formula (3). If $E < \varepsilon$ or E has no change accumulated 20 iterations or $s > N$, go to step 6; else, go to step 5.

Step 5: Modify the weight functions and threshold according to Formulas (7)–(10) combined with genetic algorithm, $s = s + 1$, go to step 4.

Step 6: Output the training results.

The biggest feature of time series is the order of data, and its essence is the time varying characteristic of time series. Time series has its own evolutionary law and time series analysis is an evolutionary analysis process. Time series have many characteristics, such as the structure of the series, the causal relationship between it and other time series, etc. The sum of these characteristics determines the change trend of time series.

Therefore, in the process of time series analysis, the change of the former will have a certain influence on the latter, which is a kind of feedback information. The hybrid GFPNN model can realize the functions of time-varying feature accumulation operation and feature extraction of time series, deal with the influence of feedback information in time series, and have a good iterative process. GFPNN is able to meet the requirements of time series analysis and has unique advantages in dealing with the problems of time series analysis.

3 Influence Model of Regional Agricultural Planting Factors on Grain Yield Based on Genetic Feedback Process Neural Network

3.1 Data Description

Grain yield is the basis of grain supply, and the factors affecting grain yield are complex. In this paper, 11 agricultural planting factors affecting grain yield are selected as analysis indicators from three aspects: nature, development of science and technology, society and economy. As shown in Fig. 2. The nature factors include the sown area of grain crops and the area affected by natural disasters, which can be divided into drought, flood and other disasters. The development of science and technology factors include the total power of agricultural machinery, the effective irrigation area and the amount of agricultural chemical fertilizer. The society and economy factors include the average education time of rural labor force, the per capita disposable income of rural residents, the total value of agricultural output and the price index of agricultural means of production.

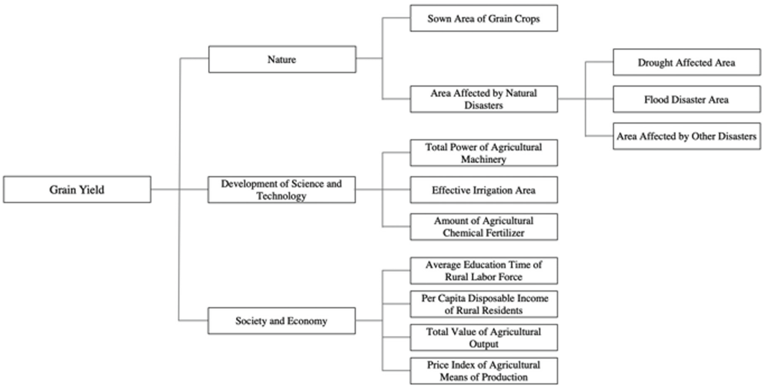

Fig. 2. 11 agricultural planting factors influencing grain yield.

In this paper, take China as an example, establish the influence model of agricultural planting factors on grain yield in China. Relevant data sources are China Statistical Yearbook [15] and China Rural Statistical Yearbook [16]. For each factor, we select the relevant data from 1980 to 2020 after the reform and opening up.

3.2 Data Preprocessing

Normalize the original data of each agricultural planting factor, select Min-Max Scaling for normalization. Linearize the original data to the range of [0,1], normalization formula is as follows:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{12}$$

where X_{norm} is the normalized data; X is the original data; X_{max}, X_{min} are the maximum and minimum values of the original data.

3.3 Experiment Details

The simulation software for experiment is MATLAB R2019b, the specific running environment is MacBook Pro (16-inch, 2019), 2.3 GHz, 8 core CPU, Intel Core i9,16GB of memory and 1T hard drive.

The preprocessed data of 11 agricultural planting factors in China from 1980 to 2020 are used as experimental data. The data of 41 years compose a time series with interval of 1 year and length of 41. The training set consists of the preprocessed data from 1980 to 2008, accounting for 70% of all data sets. The test set consists of the preprocessed data from 2009 to 2020, accounting for 30% of all data sets.

The sample structure is as follows:

$$\{x_1(t), x_2(t), \ldots, x_i(t), \ldots, x_{11}(t), d\}$$

where $x_i(t)(i = 1, 2, \ldots, 11)$ is the data of 11 planting factors every year; d is the grain yield of the same year.

The structure of GFPNN is set to 11 input nodes, 15 hidden layer nodes of process neurons, 1 output node. Time delay τ of hidden layer is 2. The excitation function is Tan-Sigmoid function. The maximum number of iterations is 1000. Learning accuracy ε is 0.0001. The network training termination strategy is that the training time reaches the maximum number of iterations, or the network error has no change accumulated 50 iterations. For genetic algorithm, the maximum number of iterations is 100, crossover rate is 0.55, mutation rate is 0.2. The objective function is the network error function, as shown in Formula (3). According to Formula (11), set the fitness function as

$$Fit(f(x)) = \frac{1}{1 + f(x)} \tag{13}$$

The normalized input data and the hidden layer weight function of GFPNN are expressed as the expansions of the same set of standard orthogonal basis functions. Select the trigonometric function as the orthogonal basis function. After fitting experiment, the trigonometric orthogonal basis function is set to 12 parameters. The error of the expansions is shown in Table 1, the average error is 1.52E-31.

Table 1. Error of input data of trigonometric orthogonal basis function expansions.

Year	Error	Year	Error
1980	1.17E-31	2001	1.03E-31
1981	1.11E-31	2002	1.50E-31
1982	3.37E-32	2003	1.06E-31
1983	1.00E-31	2004	6.80E-32
1984	5.18E-32	2005	1.30E-31
1985	4.93E-32	2006	7.09E-32
1986	6.02E-32	2007	9.01E-32
1987	6.64E-32	2008	1.04E-31
1988	9.25E-32	2009	2.94E-31
1989	8.94E-32	2010	1.93E-32
1990	2.60E-32	2011	2.41E-31
1991	2.09E-32	2012	2.84E-31
1992	1.34E-31	2013	1.51E-31
1993	5.34E-32	2014	1.93E-31

(*continued*)

Table 1. (*continued*)

Year	Error	Year	Error
1994	5.59E-32	2015	5.06E-31
1995	7.49E-32	2016	3.90E-31
1996	3.41E-32	2017	3.23E-31
1997	4.18E-32	2018	8.12E-31
1998	7.78E-32	2019	3.21E-31
1999	1.41E-31	2020	3.26E-31
2000	9.94E-32		

Initialize the weight functions of GFPNN hidden layer randomly and expand them with trigonometric orthogonal basis function. It can reduce the error of function fitting and the complexity of operation. Train the influence model of agricultural planting factors on grain yield in China by the training set.

After 87 iterations, the network reaches convergence. The comparison between the predicted grain yield and the actual grain yield of the training set is shown in Fig. 3. The prediction accuracy of the training set is 97.90%. The prediction of the test set is shown in Table 2, and the prediction accuracy is 97.67%. The prediction accuracy for the whole data set is 97.83%.

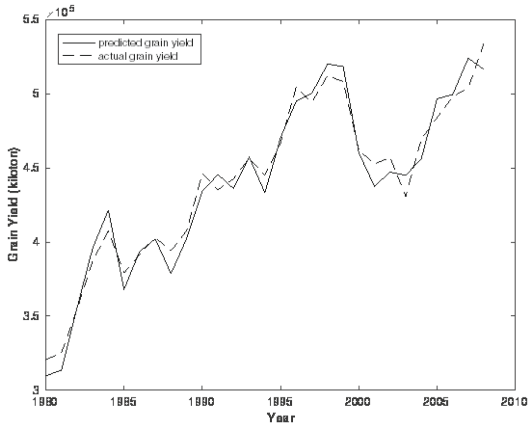

Fig. 3. Comparison between predicted grain yield (kiloton) and actual grain yield (kiloton) of the training set.

Table 2. Comparison between predicted grain yield (kiloton) and actual grain yield (kiloton) of the test set.

Year	Predicted grain yield	Actual grain yield
2009	536935.4	539409.0
2010	541519.0	559113.0
2011	610238.9	588493.0
2012	587963.9	612226.0
2013	644348.1	630482.0
2014	655885.0	639648.0
2015	680087.9	660603.0
2016	638478.8	660435.0
2017	656302.6	661607.0
2018	645253.7	657892.0
2019	679778.9	663843.0
2020	665818.6	669492.0

In order to further verify the advantages of this model, different influence model of agricultural planting factors on grain yield is established based on Feedback Process Neural Network (FPNN) and BP neural network by the same data set. Compared with the influence model of agricultural planting factors on grain yield based on GFPNN proposed in this paper, the comparison of iteration times and prediction accuracy of different models is shown in Table 3.

Table 3. Comparison of iteration times and prediction accuracy of different models.

Different Models	Prediction Accuracy	Iteration times
GFPNN	97.83%	87
FPNN	96.98%	94
BP Neural Network	96.47%	115

It can be seen from Table 3 that the grain yield influence model based on GFPNN proposed in this paper has higher prediction accuracy than models based on FPNN and BP neural network, and requires fewer iteration times. The results show that the genetic algorithm is used to optimize the parameters of FPNN, which improves the training efficiency and accuracy of the network. GFPNN fully extracts the time-varying characteristics of agricultural planting factors data, and the result is better than traditional BP neural network model. In terms of the overall performance, the GFPNN proposed in this paper has more advantages in the analysis on the influence of agricultural planting factor on grain yield.

3.4 Result Analysis

Through the trained influence model of agricultural planting factors on grain yield in China, changing the planting factor data can obtain the corresponding grain yield. Among the 11 agricultural planting factors, take the data in 2020 as an example to analyze the influence of agricultural planting factors on grain yield, as shown in Table 4.

Table 4. Influence of the change in planting factors on Grain Yield in 2020

Planting Factors	Change in Planting Factors	Predicted Grain Yield	Change in Grain Yield
Total power of agricultural machinery	↑5%	679668.3 kiloton	↑1.52%
	↑10%	686631.0 kiloton	↑2.56%
Effective irrigation area	↑5%	678329.3 kiloton	↑1.32%
	↑10%	679333.5 kiloton	↑1.47%
Average education time of rural labor force	increase to 9 years	684488.6 kiloton	↑2.24%
Price index of agricultural means of production	↓1%	674044.5 kiloton	↑0.68%
Area affected by drought disaster	29259 thousand hectares	655164.9 kiloton	↓2.14%
Area affected by flood disaster	17525 thousand hectares	657642.0 kiloton	↓1.77%

In the planting factors data of 2020, use control variable method, when other data remain unchanged, if the total power of agricultural machinery is increased by 5%, the grain yield could reach 679668.3 kiloton and increase by 1.52%; if the total power of agricultural machinery is increased by 10%, the grain yield could reach 686631.0 kiloton and increase by 2.56%; if the effective irrigation area is increased by 5%, the grain yield could reach 678329.3 kiloton and increase by 1.32%; if the effective irrigation area is increased by 10%, the grain yield could reach 679333.5 kiloton and increase by 1.47%;if the average education time of rural labor force is increased to 9 years, the grain yield could reach 684488.6 kiloton and increase by 2.24%; if the price index of agricultural means of production is decreased by 1%, the grain yield could reach 674044.5 kiloton and increase by 0.68%; referring to the nationwide drought in 2009, if the area affected by drought disaster in 2020 also becomes 29259 thousand hectares, the grain yield will become 655164.9 kiloton and decrease by 2.14%; referring to the flood disaster area caused by torrential rain in 2010, if the area affected by flood disaster in 2020 also becomes 17525 thousand hectares, the grain yield will become 657642.0 kiloton and decrease by 1.77%.

Therefore, the following 5 advices are drawn:

Advice 1: Actively developing and introducing appropriate agricultural machinery and popularizing efficient and water-saving irrigation in farmland can effectively improve grain yield in China.

Advice 2: China has been continuously investing in rural education, clarifying the important position of rural education. The education level of rural labor force continues to improve. Popularizing nine-year compulsory education and encouraging higher education will greatly improve the agricultural production in the long run.

Advice 3: Chinese government has implemented preferential policy of vat exemption on means of agricultural production. It can reduce the cost of agricultural planting, increase the enthusiasm of farmers, promote agricultural production development, and increase the grain yield.

Advice 4: When natural disasters occur, the current year's grain yield can be estimated based on the affected areas and planting data, which could be used as a reference for taking preventive measures to maintain the national food supply and price stability.

Advice 5: Planning ahead for agricultural planting factor data can accurately predict the grain yield. It can provide reference for making food policy in advance, such as the policy of lowest price of grain purchase, the plan of food import, etc.

4 Conclusion

In this paper, genetic algorithm is introduced into Feedback Process Neural Network (FPNN), and a time series analysis method based on Genetic Feedback Process Neural Network (GFPNN) is proposed. On the one hand, GFPNN can make full use of the advantages of FPNN in dealing with time-varying data, the time variability of multi-dimensional agricultural planting factors time series data is fully incorporated into the grain yield analysis. On the other hand, the global optimization advantage and robustness of genetic algorithm can improve the efficiency and the accuracy of model. Thus, the time series analysis model based on GFPNN have complementary advantages of FPNN and genetic algorithm, which provides an effective way to solve the problem of regional grain yield analysis and prediction.

In this paper, 11 agricultural planting factors affecting grain yield are selected as analysis indicators from three aspects: nature, development of science and technology, society and economy. Taking China as an example, the relevant data from 1980 to 2020 are sorted out year by year. Firstly, normalize the agricultural planting factors and grain yield data of China, the preprocessed data compose a time series. Then, GFPNN is used to analyze the time series and establish the influence model of agricultural planting factors on grain yield in China. Finally, the trained model is used to analyze and evaluate the influence of the changes in agricultural planting factors on grain yield.

The informatization degree of agricultural data is not enough. Many kinds of planting factor data cannot be added to model training due to the difficulty of collection. More dimensional data will greatly improve the integrity and accuracy of the grain yield influence model. There is still a lot of research space for the development and application of agricultural big data.

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Analysis of the Coordination of Highway Network in Urban Agglomerations Based on Fractal Theory

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Abstract. The complexity of highway network planning is closely related to the scale of integrated development of urban agglomerations. In view of the current situation of the development of inter-city highway network, urban economic and population factors, this paper establishes an analysis model of urban cluster highway coordination based on fractal theory, and further evaluates the internal structure of urban agglomerations through the matching relationship between inter-city highway and urban economic and population. For the purpose of quantitatively characterizing the coordination of the development of urban agglomerations' highway network, the method is validated using data from the Yangtze River Delta, Beijing-Tianjin-Hebei and Guangdong-Hong Kong-Macao Greater Bay Area as the data samples. The results of the study can provide data and theoretical references for the planning of highway traffic in other urban agglomerations.

Keywords: Highway network coordination · Urban agglomerations · Fractal theory · Quantitative characterization

1 Introduction

Highway network planning is an important task in the comprehensive development of cities. Quantifying the highway network is the infrastructure to maintain the economic growth, which influences the direction and scale of urban development. Transportation integration is the basis and prerequisite for the coordinated development of urban agglomerations, which makes the analysis of highway network traffic patterns become an important direction in the study of urban traffic and urban planning. The highway is a bridge to the city and is characterized by a complex and irregular spatial distribution in terms of morphology. This spatial morphological distribution is in line with the theoretical description of fractal theory for the inherent self-organization and self-similarity characteristics of complex spatial entities. The American mathematician Mandelbrot [1] first proposed the theory of self-similarity and elaborated on the phenomenon of

J. C.-W. Lin et al. (Eds.): ICGEC 2023, LNEE 1145, pp. 14–25, 2024.
https://doi.org/10.1007/978-981-97-0068-4_2

similarity of systems or substances in the space-time dimension as a way to reflect the comprehensive characteristics of things changing from macroscopic to microscopic scales. Chen et al. [2] used multiple fractal measures to model and analyze urban morphology, confirming that Beijing's urban landscape has multi-scale fractal properties. The correlation between the geometry of complex spatial structures and their functional characteristics has been well documented and the corresponding research results which laying the theoretical basis for the introduction of fractal theory have provided. Based on fractal theory, the researchers have studied ground transport and road networks in French, Portuguese and Indian cities respectively, analyzing the geometric space hierarchy and evaluating applications [3–5]. Yang et al. [6] used fractal theory methods to conduct statistical analysis and robustness tests on the level of economic development in coastal tourism cities to improve the efficiency of economic growth in coastal tourism cities. Doménech [7] used fractal theory to establish the connection between the topology of transport network and population size and analyzed the non-linear relationship between them. The above studies show that the fractal dimension can describe the spatial correlation between traffic patterns and geometric spatial elements of urban agglomerations. It also summarized the stage trends of traffic development. However, all these studies are based on a single fractal feature analysis, lacking the consideration of the matching degree between population size and economic volume. In order to further promote the sustainable development of urban economy and population, this paper proposes a method for evaluating the coordination index of urban agglomerations' highway network based on fractal theory. On the basis of this method, three typical urban agglomerations, which named Yangtze River Delta, Beijing-Tianjin-Hebei and Guangdong-Hong Kong-Macao Greater Bay Area, are used as data samples to demonstrate and analyze the evaluation method, in order to achieve a comprehensive evaluation of the planning coordination of urban agglomerations highway network.

2 Fractal Model

Fractals are morphological features that fill space in non-integer form as things change from whole to local, with self-similarity and scale-invariance. The fractal model, which uses fractal dimensions to measure fractal morphological features and delineate the properties of fractal sets, is now widely used in various fields such as mechanics [8], transport and the arts.

The radius of gyration model is an important fractal model for quantitatively characterizing the distribution of geometric structures such as points, lines and areas in space. The model assumes that the geometric structures in the measurement area are cohesively distributed around the center and vary uniformly in all directions, so that the measurements at different observation scales can be represented in the form of a cumulative distribution. With the average center of the urban agglomerations as the center O and r as the radius of gyration to form a concentric ring of n, as shown in Fig. 1 [9]. The measurement relationship of the geometric structure in the space defined by the radius of gyration model can be expressed as:

$$N(r)=\sum_{t=1}^{r} N(t), t \leq r, r=1,2,\cdots,n \tag{1}$$