Study on Prediction of Grain Yield Based on Grey Theory and Fuzzy Neutral Network Model

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Abstract: *In order to improve the prediction precision of grain yield, the grey system theory and the fuzzy neutral network are combined to construct the combined prediction model, which is applied in predicting the grain yield. Firstly, the basic theory of the grey system theory is analyzed. Secondly, the mathematical model of fuzzy neutral network is studied, and the corresponding algorithm procedure is designed. Finally, the grain yields in China are used as the researching object, and the corresponding prediction analysis is carried out, and the prediction results of grain yield are agreed with real values, results show that the combined prediction model can be applied in predicting the grain yield effectively.*

Key words: *Prediction precision, Grey system theory, Fuzzy neutral network, Grain yield.*

Introduction

The grain is the basic consumer goods of human survival, which is the basis of agriculture. The grain problem is a matter of prime importance for national economy and the people's livelihood, and grain yield relates to survival and development of our country. The grain yield is also an important problem relating with national economic development. The grain yield can stabilize the political situation of China stability and unity. In recent years, the grain supply should be ensured, the balance between supply and demand of grain for the urban and rural residents should be achieved. The grain yield is affect by many factors, such as policy, climate, grain price, plant diseases and insect pests. The grain yield has big dynamic change characteristics, it is necessary to predict the grain yield effectively, and then the national grain safety can be ensured, which can offer basis for scientific decision-making of the government, the prediction of grain yield has been concerned in recent years, it is significant to predict the grain yield correctly for ensuring the grain safety of China and establishing the grain producing policies by government [6].

In recent years, there are many predicting model of grain yield, such as artificial neutral network, linear regression model, however current prediction models exist some disadvantages, the artificial neutral network lack perfect theoretical system, linear regression model has higher requirement for variables, in order to improve the predict effect of grain yield, the grey system theory and the fuzzy neutral network are combined to establish the prediction model of grain yield, then the corresponding prediction precision of grain yield can be improved [7].

Basic theory of the grey system theory

The grey system theory was established in 1982, which can cope with less information system and small sample problem, its can be applied in analyzing the uncertainty system with less information when a subset of the information is known, while a subset of the information is unknown, the valued information is chosen through generating a subset of the known information, correct description and effective monitor of the evolution is obtained. And the important feature of the grey system theory need not especial demand of the sample, and the data is not fit for any distribution. The grey system theory overcomes the restriction of the traditional precision mathematics, it is easy to be applied, and therefore it has wide application value in the field of perdition of grain yield [9].

The grey prediction model is expressed as follows:

$$V = E \times W\ , \tag{1}$$

where V is the prediction vector of the m subjects predicted, $V = [v_1, v_2, \dots, v_m]^{\mathrm{T}}$, and the series of grain yield is carried out based on value of V; W is the weight vector of n prediction indexes, $W = [w_1, w_2, \dots, w_m]^{\mathrm{T}}$, and the following equation can be obtained: $\sum_{i=1}^{n} w_i = 1$; E is the prediction matrix of every index, the corresponding expression is defined by [2]:

$$E = \begin{bmatrix} e_1(1) & e_1(2) & \dots & e_1(n) \\ e_2(1) & e_2(2) & \dots & e_2(n) \\ \vdots & \vdots & & \vdots \\ e_m(1) & e_m(2) & \dots & e_m(n) \end{bmatrix}, \tag{2}$$

where $e_i(k)$ is the relational factor between k^{th} index and k^{th} optimal index for i^{th} subject predicted, which is defined by:

$$e_i(k) = \frac{\min\limits_i \min\limits_k \left|C_k^* - C_k^i\right| + \lambda \max\limits_i \max\limits_k \left|C_k^* - C_k^i\right|}{\left|C_k^* - C_k^i\right| + \lambda \max\limits_i \max\limits_k \left|C_k^* - C_k^i\right|}, \tag{3}$$

where λ is the amending coefficient, $\lambda = 0.5$, C_k^* is the optimal value of k^{th} index of i^{th} prediction object.

Mathematical model of fuzzy neutral network

Fuzzy neutral network has many advantages, which has good knowledge expression level and fault tolerance level. It has good language processing level, and it can express and store the knowledge effectively. The fuzzy neutral network can be applied in prediction of grain yield effectively, and the correctness of prediction for grain yield can be improved [4].

The structural diagram of fuzzy neutral network is shown in Fig. 1. The function of input layer is to input language, which is the first layer. The membership degree function is the second layer, which can obtain fuzzy sub collection membership degree of different input variable, during the procession of prediction for grain yield, the membership degree can express prediction variable, and then the grain yield can be predicted correctly. Therefore, a kind of classic fuzzy membership function can be used, fuzzy function can predict the deviation of prediction value, then the less, optimal and bigger membership degree of prediction value can be obtained, and the parameter in inputting layer can be input into the fuzzy neutral network [5].

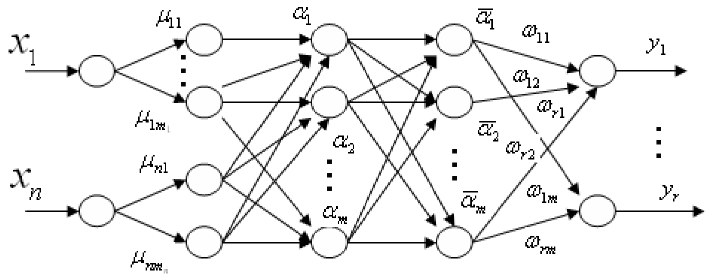

Fig. 1 Structural diagram of fuzzy neutral network

The mathematical model of fuzzy membership degree function is expressed as follows:

(a) If the sign parameter is small, the mathematical model of membership degree is expressed as follows:

$$\mu_L = \begin{cases} 1 & \text{when} \quad \Delta x < \Delta x_{\min} \\ \dfrac{\Delta x_0 - \Delta x}{\Delta x_0 - \Delta x_{\min}} & \text{when} \quad \Delta x_{\min} < \Delta x < \Delta x_0 \end{cases} \tag{4}$$

(b) If the sign parameter is good, the mathematical model of membership degree is expressed as follows [8]:

$$\mu_L = \begin{cases} \dfrac{\Delta x - \Delta x_{\min}}{\Delta x_0 - \Delta x_{\min}} & \text{when} \quad \Delta x_{\min} < \Delta x < \Delta x_0 \\ \dfrac{\Delta x - \Delta x_{\max}}{\Delta x_0 - \Delta x_{\max}} & \text{when} \quad \Delta x_0 < \Delta x < \Delta x_{\max} \\ 0 & \text{other} \end{cases} \tag{5}$$

(c) If the sign parameter is relative high, the corresponding mathematical model of membership degree is expressed as follows [3]:

$$\mu_L = \begin{cases} \dfrac{\Delta x - \Delta x_0}{\Delta x_{\max} - \Delta x_0} & \text{when} \quad \Delta x_0 < \Delta x < \Delta x_{\max} \\ 1 & \text{when} \quad \Delta x > \Delta x_{\max} \\ 0 & \text{other} \end{cases} \tag{6}$$

where, $\Delta x_{\max}$ is the maximum value of positive offset of prediction value of grain yield,

$\Delta x_{\min}$ is the minimum value of negative offset of prediction value of grain yield, Δx_0 is the offset of optimal prediction parameter, $\Delta x_0 = 0$.

The second layer of fuzzy neutral network is reasoning level, which has one to one correspondence with fuzzy controlling rules, and the fitness degree of every rule can be obtained.

The fourth and third layers has same number of nodes, which is benefit for normalization, the fifth layer of fuzzy neutral network is output layer, and the computing precision of output layer is higher. The arrow between neutral elements is signal transmission direction between elements in fuzzy neutral network. The relationship between input and output of fuzzy neutral network can be expressed as follows [10]:

$$y = \frac{\sum_{i=1}^{m}\left(\prod_{i=1}^{m}\mu_j^i(x_j)\right)y^i}{\sum_{i=1}^{m}\left(\prod_{i=1}^{m}\mu_j^i(x_j)\right)}. \tag{7}$$

Training algorithm of fuzzy neutral network

In order to prevent algorithm falling into local optimal, the traditional particle algorithm is amended. The chaos has the ergodic property, which is introduced into the traditional algorithm, the chaos variable can be obtained through Logistic mapping, and the corresponding expression is listed as follows:

$$y_{i+1} = u \cdot y_i \cdot (1 - y_i), \tag{8}$$

where, y_{i+1} and y_i are the i^{th} and $(i + 1)^{\text{th}}$ time iteration results of variable y, u is controlling variable. Therefore the chaos optimization can make the particle swarm have characteristics of diversity, the any particle formed in the searching space can be used to replace the undesirable particle, and the corresponding algorithm procedure is listed as follows [1]:

Step 1: The initialization of particle swarm is carried out, the basic parameters of chaos particle algorithm is confirmed.

Step 2: The velocity and location of updated particle can be calculated based on velocity and location of particle, and object function value of different particle can be obtained at same time, 20% of optimal particles in particle swarm can be saved.

Step 3: The chaos optimal method is applied to map the current particle swarm on interval [0, 1], and the corresponding expression is listed as follows:

$$y_1^{(k)} = \frac{p_g^{(k)} - q_{\min}^{(k)}}{p_g^{(k)} - q_{\max}^{(k)}}, \tag{9}$$

where $q_{\min}^{(k)}$ and $q_{\max}^{(k)}$ are the upper and bottom limits of k^{th} time iteration particle searching.

Step 4: The chaos series $y(k) = (y_1^{(k)}, y_1^{(k)}, \ldots, y_M^{(k)})$ are obtained based on M iteration, $y(k)$ is inversely mapped on original interval, and the $p_g^{(*k)} = (p_{g1}^{(*k)}, p_{g2}^{(*k)}, \ldots, p_{gM}^{(*k)})$ can be formed, the corresponding calculating model is expressed as follows:

$$p_{gn}^{(*k)} = Z_{\min}^{(k)} + (Z_{\max}^{(k)} - Z_{\min}^{(k)}) y_n^{(k)}, \quad n = 1, 2, \ldots, M. \tag{10}$$

Step 5: The new solution is evaluated based on the series $p_{gn}^{(*k)}$, when the new solution is better than original solution, the new solution can be considered as the optimal value of chaos optimization, otherwise, $k = k + 1$, return to *Step 4*.

Step 6: $p_i^{(k)}$ and $p_g^{(k)}$ are updated, when the predefined precision is satisfied, the searching operation can be over, the final value is output, otherwise, return to next step.

Step 7: The searching space is reduced, and other 80% of particles can generate in group, return *Step 2*, and the corresponding calculation expression can be obtained:

$$\begin{cases} Z_{\min}^{(k)} = \max\{Z_{\min}^{(k)}, p_i^k - r \cdot (Z_{\max}^{(k)} - Z_{\min}^{(k)})\} \\ Z_{\max}^{(k)} = \min\{Z_{\max}^{(k)}, p_i^k - r \cdot (Z_{\max}^{(k)} - Z_{\min}^{(k)})\} \end{cases}, \quad 0 < r < 1. \tag{11}$$

Combined prediction algorithm combing grey system theory and fuzzy neutral network

Step 1: The prediction precision a_{it} at t moment of i^{th} method is calculated, and the corresponding expression is listed as follows:

$$a_{it} = \begin{cases} 1 - |(x_t - \hat{x}_{it}) / x_t|, & \text{when} \quad |(x_t - \hat{x}_{it}) / x_t| < 1 \\ 0, & \text{when} \quad |(x_t - \hat{x}_{it}) / x_t| \geq 1 \end{cases}. \tag{12}$$

Step 2: The induced ordered weighted arithmetic mean value at t moment of m kinds of prediction method is calculated, and the corresponding expression is listed as follows:

$$f_{it} = (< a_{1t}, x_{1t} >, < a_{1t}, x_{1t} >, \ldots, < a_{1t}, x_{1t} >) = \sum_{i=1}^{m} l_i x_{a-index(it)}. \tag{13}$$

Step 3: The error of combined prediction model is calculated, which is calculated by the following expression:

$$e_t = x_t - f_{it} = x_t - \sum_{i=1}^{m} l_i x_{a-index(it)}. \tag{14}$$

Step 4: The optimal model is constructed using minimum quadratic sum of error of combined prediction model as objective function:

$$\min S(L) = \sum_{t=1}^{N} e_t^2 \tag{15}$$

$$s.t. \sum_{t=1}^{m} l_i = 1,\ l_i \geq 0\,. \tag{16}$$

Step 5: Calculate $L = [l_1, l_2, \ldots, l_m]^{\mathrm{T}}$, then the weighted coefficients of every prediction method can be obtained.

Step 6: The combined prediction model is applied in predict the grain yield.

Grain yield prediction simulation

The prediction sample of grain yield chooses from real data in from 2005 to 2014. Firstly, the logarithmic transformation preprocessing is carried out for these original grain yield data, then the smooth property of original data series can be improved then the combined prediction model is applied in predict the grain yield. The prediction programmer is compiled by MATLAB software, and the prediction results are shown in Table 1.

Table 1. China prediction results of grain yield in from 2005 to 2014

Year	Grain yield, [million tons]	Combined prediction results, [million tons]	Error, [%]
2004	46947	46976	0.06
2005	48401	48421	0.04
2006	49746	49736	0.02
2007	50150	50141	0.02
2008	52850	52838	0.02
2009	53082	53065	0.03
2010	54641	54672	0.06
2011	57121	57168	0.08
2012	58957	58987	0.05
2013	60194	60178	0.03
2014	60709	60715	0.01

As seen from Table 1, the combined prediction model has higher prediction precision, the prediction value of grain yield is consistent with the real value. The prediction analysis shows that the combined prediction mode combing the grey prediction theory and fuzzy neutral network can be applied in prediction of grain yield effectively.

The combined prediction is applied to predict the grain yield in from 2015 to 2020, and the corresponding prediction results are shown in Table 2.

Table 2. China prediction results of grain yield in from 2015 to 2020

Year	Combined prediction results of grain yield, [million tons]
2015	62483
2016	63713
2017	64724
2018	65486
2019	66732
2020	67512

As seen form Table 2, the China grains yield in from 2015 to 2020 are predicted, the prediction results can offer effective basis for establishing grain product policy.

Conclusions

The grey system theory and fuzzy neutral network are combined to construct the combined prediction model, which is applied in predicting the grain yield. The corresponding theory model is constructed, and the algorithm procedure is designed. The China grain yield in from 2005 to 2014 is predicted based on the combined prediction model, and the prediction results show that the combined prediction model has higher precision, which can be applied in predicting the grain yield effectively.

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