Application of an Improved Grey Neural Network in Grain Yield Prediction

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***Abstract*—Grain yield presents a complex nonlinear relationship with variables, and takes on randomness and mutability. It is hard to describe the prediction model with traditional linear model. Grey model can be used to process samples with great stochastic volatility. In this paper, we propose to use the grey neural network to predict the grain yield. Experiments are carried out on the beans yield, rice yield and corn yield respectively to evaluate the prediction performance. The promising experimental results validate the effectiveness of our prediction model.**

Keywords-grey neural network; grey model; grain yield prediction

I. INTRODUCTION

Traditional prediction model [1,2] assumes that the distribution of grain yield following linear variation rules, however, in fact that the grain yield presents a complex nonlinear relationship with variables such as policy factors, climate, pests diseases, food prices, etc. [3,4], and takes on randomness and mutability. It is hard to describe the prediction model with traditional linear model. The formation process of grain yield can be seen as a dynamic grey system which contains both known information and unknown information. The grey prediction method is suitable for data prediction with exponential growth only, and when the simply Grey Model (GM) used for the data with great stochastic volatility, it could get poor fit performance and lower prediction accuracy [5-7]. Neural networks [8, 9] can approximate the non-linear relationship between the input data and output data infinitely, and is adaptive to the prediction problem with the data of non-linear and great stochastic volatility. It widely used in the field of industrial and agricultural production forecasting. So grey prediction model and neural networks can be combined to complement each other, constitute a grey neural network, increase the grain yield prediction accuracy.

In this paper, we apply the grey neural network to predict the grain yield, and evaluate the effectiveness of the prediction model by experiments. This paper is organized in this way: Section 2 gives a detailed description about the grey neural network and its application on grain yield; Section 3 presents experimental data and results. Finally, concluding remarks are given in Section 4.

II. GREY NEURAL NETWORK MODEL

Grey system theory studies uncertainty system which has small data, poor information [11]. The valuable information is extracted from the generation and development of partial known information, the behavior and evolution rule of the uncertainty system could be described properly and controlled effectively. The grey theory was proposed by Deng Julong [12,13], and it considered that any random process could be seen as a varied grey process within a certain time and space, while a erratic sequence of the system could be transformed into a regular sequence by generation transform.

A. *Grey Model with Time Sequence*

Grey system built GM, which is a differential equation based on original data. The most typical GM is based on time sequence, it transforms the time sequence data to a differential equation and uses the system information to quantize the abstract model, finally predicts the system output in the lack of the system features.

The original data array is accumulated to generate a certain regular pattern at first, then the typical curve could be used to fit the required curve. Assume that the time data array $x^{(0)}$ can be described by the following formula:

$$x^{(0)} = (x_t^{(0)} \mid t = 1, 2, ..., n) = (x_1^{(0)}, x_2^{(0)}, ..., x_n^{(0)}) \quad (1)$$

Accumulate $x^{(0)}$ to generate the new time data array $x^{(1)}$, the new array $x^{(1)}$'s t item is the sum up of the first t items of the original array $x^{(0)}$ as follows:

$$x^{(1)} = (x_t^{(1)} \mid t = 1, 2, ..., n) = (\sum_{t=1}^{1} x_t^{(0)}, \sum_{t=1}^{2} x_t^{(0)}, ..., \sum_{t=1}^{n} x_t^{(0)}) \quad (2)$$

According to the new array $x^{(1)}$, the whitening equation could be build as $\frac{dx^{(1)}}{dt} + ax^{(1)} = u$, and the solution of the equation is $x_t^{*(1)} = (x_1^{(0)} - u/a)e^{-a(t-1)} + u/a$. Where $x_t^{*(1)}$ is the

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estimated value of $x_t^{(1)}$, the regression of the $x_t^{*(1)}$ is the estimated value of $x_t^{*(0)}$, that is $x_t^{*(0)} = x_t^{*(1)} - x_{t-1}^{*(1)} \quad t = 2,3,...$

B. Grey Neural Network

The differential equation of grey neural network with n parameters can be described as follows:

$$\frac{dy_1}{dt} + ay_1 = b_1 y_2 + b_2 y_3 + ... + b_{n-1} y_n \tag{3}$$

Where $y_2, y_3, ..., y_n$ are system input parameters and y_1 is the system output parameter, $a, b_1, b_2, ..., b_{n-1}$ are coefficients of parameters in the differential equation.

The time response of the above equation is

$$z(t) = (y_1(0) - \frac{b_1}{a} y_2(t) - \frac{b_2}{a} y_3(t) - ... - \frac{b_{n-1}}{a} y_n(t))e^{-at}$$
$$+ \frac{b_1}{a} y_2(t) + \frac{b_2}{a} y_3(t) + ... + \frac{b_{n-1}}{a} y_n(t) \tag{4}$$

Assume that $d = \frac{b_1}{a} y_2(t) + \frac{b_2}{a} y_3(t) + ... + \frac{b_{n-1}}{a} y_n(t)$, the above equation is transformed to be

$$z(t) = ((y_1(0) - d) \cdot \frac{e^{-at}}{1+e^{-at}} + d \cdot \frac{1}{1+e^{-at}}) \cdot (1+e^{-at})$$
$$= ((y_1(0) - d)(1 - \frac{1}{1+e^{-at}}) + d \cdot \frac{1}{1+e^{-at}}) \cdot (1+e^{-at})$$
$$= ((y_1(0) - d) - y_1(0) \cdot \frac{1}{1+e^{-at}} + 2d \cdot \frac{1}{1+e^{-at}}) \cdot (1+e^{-at}) \tag{5}$$

According to equation 5, the mapped neural network could be built as shown in Fig. 1.

In Fig. 1, t is the time order of input, $y_2(t), ..., y_n(t)$ are input parameters of network input. $w_{21}, w_{22}, ..., w_{2n}, w_{31}, w_{32}, ..., w_{3n}$ are weights of network, y_1 is the estimated value of network. LA, LB, LC, LD represent the four layers of the grey neural network respectively.

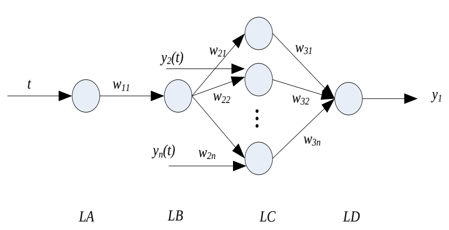

FIGURE I. GREY NEURAL NETWORK.

Assume that $\frac{2b_1}{a} = u_1, \frac{2b_2}{a} = u_2, ..., \frac{2b_{n-1}}{a} = u_{n-1}$, the initial weights of network can be presented as

$$w_{11} = a, w_{21} = -y_1(0), w_{22} = u_1, w_{23} = u_2, ..., w_{2n} = u_{n-1}$$
$$w_{31} = w_{32} = ... = w_{3n} = 1 + e^{-at}.$$

The threshold of the LD output layer is $\theta = (1+e^{-at})(d - y_1(0))$.

The study process of the grey neural network is:

Step1: According to the training data to initialize the structure of network, parameters such as a,b, and use a, b to calculate u.

Step2: According to the definition of network weights to compute $w_{21}, w_{22}, ..., w_{2n}, w_{31}, w_{32}, ..., w_{3n}$.

Step3: For each input data array $(t, y(t)), t = 1, 2, 3, ..., N$, calculate the output of each layer.

LA layer: $a = w_{11} t$

LB layer: $b = f(w_{11} t) = \frac{1}{1+e^{-w_{11} t}}$

LC layer: $c_1 = bw_{21}, c_2 = y_2(t) bw_{22}, c_3 = y_3(t) bw_{23}, ..., c_n = y_n(t) bw_{2n}$

LD layer: $d = w_{31} c_1 + w_{32} c_2 + ... + w_{3n} c_n - \theta_{y1}$

Step4: Calculate the deviation between network prediction output and expectation output, and adjust the weights and threshold according to the deviation.

Deviation in LD layer: $\delta = d - y_1(t)$

Deviation in LC layer: $\delta_1 = \delta(1+e^{-w_{11} t}), \delta_2 = \delta(1+e^{-w_{11} t}), ..., \delta_n = \delta(1+e^{-w_{11} t})$

Deviation in LB layer:

$$\delta_{n+1} = \frac{1}{1+e^{-w_{11} t}} (1 - \frac{1}{1+e^{-w_{11} t}})(w_{21}\delta_1 + w_{22}\delta_2 + ... + w_{2n}\delta_n)$$

Adjust the weights according to prediction deviation.

Adjust the connection weights between LB layer and LC layer.

$$w_{21} = -y_1(0), w_{22} = w_{22} - \mu_1 \delta_2 b, ..., w_{2n} = w_{2n} - \mu_{n-1} \delta_n b$$

Adjust the connection weights between LA layer and LB layer.

$$w_{11} = w_{11} + at\delta_{n+1}$$

Adjust the threshold

$$\theta = (1+e^{-w_{11} t})(\frac{w_{22}}{2} y_2(t) + \frac{w_{23}}{2} y_3(t) + ... + \frac{w_{2n}}{2} y_n(t) - y_1(0)).$$

Step5: Judge if the training is finish, if not, go to step 3.

C. *Application in Grain yield Prediction*

We apply the grey neural network model into the prediction of grain yield, using the grain yields as time sequence, and other relevant factors as parameters. In the fitting processing of neural network, the initial values of parameters are important to fitting result. In grey theory, grey correlation analysis of the grey system is used to implement modeling analysis of sequence relations by acquiring the boundary, analyzing the importance of factors and recognizing the pattern. The grey correlations between relevant variants and the grain yield are calculated as the initial coefficients value of parameters about the grey neural network.

The grey correlation degree can be calculated as follows:

Step1: Normalize the initial value of each item:

$$X_i' = X_i / x_i(1) = (x_i'(1), x_i'(2), \cdots, x_i'(n)),\ \ (i = 0, 1, 2, \cdots, m)$$

Step2: Calculate the difference:

$$\Delta_i(k) = \left| x_0'(k) - x_i'(k) \right|$$

$$\Delta_i = (\Delta_i(1), \Delta_i(2), \cdots, \Delta_i(n)), \quad (i = 1, 2, , m)$$

Step3: Calculate the maximum and minimum:

$$M = \max_i \max_k \Delta_i(k)$$

$$m = \min_i \min_k \Delta_i(k)$$

Step4: Calculate the correlation coefficients:

$$\gamma_{0i}(k) = \frac{m + \xi M}{\Delta_i(k) + \xi M}$$

$$\xi \in (0,1),\ k = 1, 2, \cdots, n; \quad i = 1, 2, \cdots, m$$

Step5: Calculate the correlation degree of each item:

$$\gamma_{0i} = \frac{1}{n}\sum_{k=1}^{n} \gamma_{0i}(k), \quad i = 1, 2, \cdots, m$$

III. EXPERIMENTAL RESULTS

The experiment data was sorted from the China Statistical Abstract 2013, including total power of agricultural machinery, total power of agricultural machinery, electricity for rural use, consumption of chemical fertilizers, total area of planted and the yield from 1990 to 2012 [10]. Experiments are carried out on three kinds of grain including corn, rice and beans. The accuracy of the prediction model is evaluated by the average error rate:

$$errorRate = \frac{|AY - PY|}{AY} \times 100\% \qquad (6)$$

Where AY is the actual yield and PY is the predicted yield which is acquired by the grey neural network prediction model.

We compare our methods Gray Neural Network (GNN) with three different methods to show the effective performance. The three different methods are Logistic Regression Model (LRM) [1], Gray Model (GM) [4], and Gray Model with Logistic Regression Model (LRM-GM) [14].

Experiment 1: Corn yield prediction. The data from 1991 to 2007 is used as train data, and the data from 2008 to 2013 is used as test data. The compare between the predicted yield and the actual yield is shown in Figure 2 and Table 1.

From the result, It is clearly that GNN achieves the best prediction performance with error rate 4.21%, and GM get the worst prediction performance with error rate 11.82%.

TABLE I. CORN YIELD COMPARE.

Year	2008	2009	2010	2011	2012	2013	Average Error Rate
Actual Yield (Thousands Tons)	165914	163974	177245	192781	205614	218489	
LRM Predicted Yield(Thousands Tons)	157500	169920	176850	183900	196880	192230	0.0497
GM Predicted Yield(Thousands Tons)	148370	157240	163600	172130	183030	195120	0.1182
LRM-GM Predicted Yield(Thousands Tons)	149600	158970	165400	173980	185070	196680	0.0822
GNN Predicted Yield(Thousands Tons)	168070	174700	181680	188520	196130	200750	0.0421

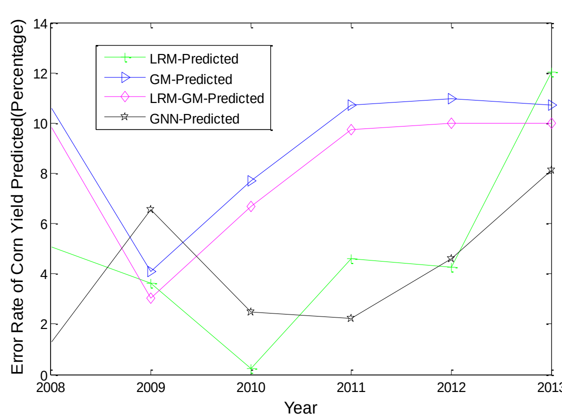

FIGURE II. ERROR RATE OF CORN YIELD PREDICTION.

Experiment 2: Rice yield prediction. The data from 1991 to 2007 is used as train data, and the data from 2008 to 2013 is used as test data. The compare between the predicted yield and the actual yield is shown in Figure 3 and Table 2.

From Table 2, we can see that LRM achieves the best prediction performance and our method GNN get the second best prediction performance, the LRM-GM get the worst prediction performance.

TABLE II. RICE YIELD COMPARE.

Year	2008	2009	2010	2011	2012	2013	Average Error Rate
Actual Yield(Thousands Tons)	191896	195103	195761	201001	204236	203612	
LRM Predicted Yield(Thousands Tons)	184690	192730	195750	196010	198060	200130	0.0203
GM Predicted Yield(Thousands Tons)	179250	181590	184230	186570	189600	192780	0.0651
LRM - GM Predicted Yield(Thousands Tons)	177360	180350	182980	184920	188030	191320	0.0727
GNN Predicted Yield(Thousands Tons)	187790	189340	190420	191680	193660	194750	0.0366

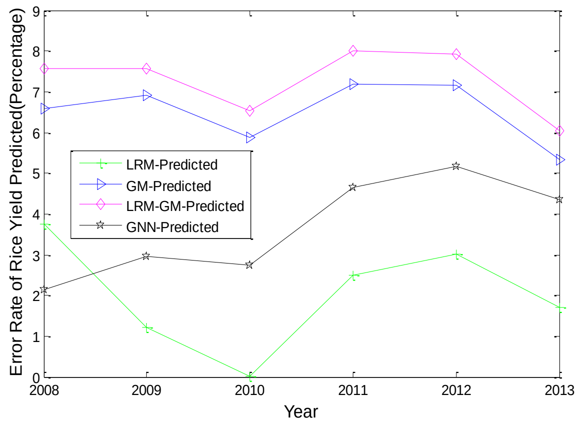

FIGURE III. ERROR RATE OF RICE YIELD PREDICTION.

Experiment 3: Beans yield prediction. The data from 1991 to 2007 is used as train data, and the data from 2008 to 2013 is used as test data. The compare between the predicted yield and the actual yield is shown in Figure 4 and Table 3.

TABLE III. BEANS YIELD COMPARE.

Year	2008	2009	2010	2011	2012	2013	Average Error Rate
Actual Yield(Thousands Tons)	20433	19303	18965	19084	17305	17988	
LRM Predicted Yield(Thousands Tons)	18841	19065	17646	16700	15933	18050	0.0613
GM Predicted Yield(Thousands Tons)	21570	21547	21258	20947	20715	20182	0.1182
LRM - GM Predicted Yield(Thousands Tons)	20836	20882	20515	20187	19998	19370	0.0789
GNN Predicted Yield(Thousands Tons)	20057	20012	19393	18858	18157	19088	0.0333

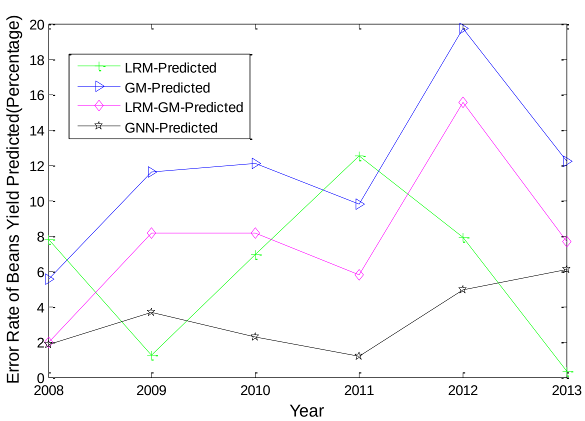

FIGURE IV. ERROR RATE OF BEANS YIELD PREDICTION.

Table 3 and Figure 4 show that our GNN method acquires the best prediction performance with error rate 3.33%, and the GM prediction method gets the worst performance with error rate 11.82%.

IV. CONCLUSIONS

We apply the grey neural network on the grain yield prediction, use the differential equation of gray model to describe the time series and map the equation on neural network to fit the equation with parameters. From the above three experiments, we can see that our proposed GNN method achieves two best prediction performance in three of them, we can conclude that our proposed GNN method improved the yield prediction performance.

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