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Dynamically Monitoring Agricultural Economy based on Decision Support Technology

Mingqi Sun*, Dezhi Pang

Harbin University of Science and Technology Rongcheng Campus, Shandong Rongcheng, 264300, China 124505282@qq.com

In this paper, we focus on the problem of dynamically monitoring agricultural economy, which is a key problem in economic development of the national economy. Firstly, we describe the structure of the dynamically monitoring agricultural economy system, which is made up of four steps: 1) collecting the agricultural economy data, 2) estimating parameters of the proposed monitoring model, 3) obtaining the agricultural economy prediction results, and 4) calculating the error rate. As the time series data of agricultural economy includes both complex linear and nonlinear patterns, it is not easy to promote the prediction accuracy rates using only linear or neural network models. Therefore, the decision support process for agricultural economy dynamically monitoring is implemented via combining the linear regression model and the neural network model. Thirdly, experiments are designed to make performance evaluation, and experimental results show that our algorithm can effectively lower the error rate of agricultural economy monitoring both with time and region changing.

1. Introduction

Agriculture is regarded as the basis for the economic development of the national economy, and it is very important to enhance the social and economic development (Nguyen et al., 2015). Currently, economic development in our country faces great challenges, some measures should be taken to promote the development level of agriculture (Musvoto et al., 2015). Agriculture can provide the source of food and clothing for humans, and it is basic position of the existence development of industrial and other material production department. It is the necessary conditions for its directly decided to our national economic development (Klomp, 2014). As is well known that China is a large agricultural country with more than 1.3 billion people, among which more than a half is belonged to the rural people. Moreover, the agricultural economic development has been one of the main influencing factors on economic development (Chang et al., 2014; Guariso et al., 2014). After a long period of rapid development; China's agricultural economy has come into a very crucial period. First of all, the agricultural economy of China has developed from traditional agriculture to modern one (Berhanu et al., 2014; Mukherji et al., 2014). Moreover, the agricultural economic system of China has changed from a planned system to a marketing system. On the other hand, the agricultural growth is the connotation development instead of the extensive pattern.

In recent years, agricultural economic structure has developed from a single grain crop diversification to the overall restructuring mode. In order to enhance the quality of agricultural products and to promote the income of peasants are considered as the objectives in modern agricultural economic development (Jerven 2014; Xue et al., 2013). Therefore, in this paper, we propose a novel method to dynamically monitor the agricultural economy development level in China.

2. Related works

As a powerful computing tool, Decision Support Technology has been widely used in many fields, and in this section, we introduce the related works about applications of Decision Support.

Singh et al. presented a decision support system for computing the total operating cost and break-even units of farm machinery. The decision support system leading to computer software developed in Visual Basic programming can give the intuitive user interfaces through linking databases (Singh et al., 2015).

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Liu et al. developed a group decision support system to promote the speed of network reconfiguration under some certain security constraints. In this paper, group decision-making is able to provide an aggregated cardinal ranking of candidate restoration schemes (Liu et al., 2015).

Bukharov et al. studied a novel decision support system structure which can be exploited in a wide range of difficult to formalize tasks and get a high speed of calculation and decision-making. In this paper, the authors examine different methods to obtain the dependence of a target variable on input data and review the most common statistical forecasting approaches (Bukharov et al., 2015).

Gulbin et al. applied an analytic network process to construct a decision model for choosing the most feasible construction approach. Data collected through interviews with highway construction experts are utilized to compute the dependency between decision parameters. (Ozcan-Deniz et al., 2015).

Aviza et al. provided a case study to analyze the correlation of the thickness of the thermo-insulation layer. Then, a multiple criteria decision support system for analyzing the correlation between the thickness of the thermo-insulation layer and its payback period is given, and this system is made up 1) a database, 2) a database management system, 3) a model-base, 4) a model-base management system and 5) a user interface (Aviza et al., 2015).

Abdelkhalek et al. paper presented a new multi-objective node placement problem which has the ability to optimize concurrently four objectives, that is, 1) maximizing communication coverage, 2) minimizing the active structures' costs, 3) maximizing of the total capacity bandwidth and 4) minimizing the noise level in the network (Abdelkhalek et al., 2015).

3. Architecture of the dynamically monitoring agricultural economy system

As is shown in Figure 1, there are four steps in the dynamically monitoring agricultural economy system. In the first step, we collect different types of agricultural economy data. In addition, it is not easy to find any pattern when very little historical agricultural economy data is available. On the other hand, the data quality may be promoted by trying to reduce the variation and discovery the leading indicators. In the second step, we estimate parameters of the proposed monitoring model. In the third step, we can obtain the agricultural economy prediction results. In the fourth step, we calculate the error forecasting rate to demonstrate the effectiveness of our proposed algorithm.



Figure 1: Structure of the dynamically monitoring agricultural economy system

4. Description of the agricultural economy dynamically monitoring approach

In our approach, we construct time series data from the original agricultural economy data, and then linear regression model is utilized to promote the monitoring accuracy. In this paper the decision support process is implemented by integrating linear regression model and the neural network model.

The linear regression model is implemented through describing the following computing process.

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$$\mathbf{y}_t = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \mathbf{x}_t + \boldsymbol{\varepsilon}_t \tag{1}$$

where symbol y_t means the value of the response or dependent variable from the t^{th} pair, parameters β_{0} , β_{1} denote two weights respectively. On the other hand, X_t refers to the value of the independent variable based on the t^{th} pair. Then, the prediction result of the proposed linear regression model is computed as follows.

$$\overline{y_t} = b_0 + b_1 x_t \tag{2}$$

Where b_0 , b_1 denote the intercept and slope parameter respectively. Next, we develop a hybrid neural network model to monitor agricultural economy by the following steps: Step 1: Constructing a training sample dataset which is represented as the following equation.

$$D = \{x_i, y_i\}_{i=1}^N, y_i \in Y$$
(3)

Step 2: Training the support vector classifier which is corresponding to D.

Step 3: If |Y| is equal to two

Step 4: We train a binary support vector based on dataset D

Step 5: else if |Y| is larger to two

Step 6: we train a multi-class support vector classifier

Step 7: we develop several decision function $f_i \in R$.

Step 8: updating the dataset D as \widehat{D} as follows.

$$D = \{x_i, \{f_1(x_i), \dots, f_c(x_i)\}\}_{i=1}^N$$

Step 9: building up a multiple output artificial neural network with \hat{D} Step 10: predicting results are calculated by the given regression functions using this artificial neural network.



Figure2: Structure of the hybrid neural network

As agricultural economy data are belonged to time series data, this data type is made up of both linear autocorrelation structure and non-linear structure as follows.

$$y_t = L_t + N_t \tag{5}$$

Where the symbol L_t , N_t mean the linear and non-linear part respectively.

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(4)

Next, we utilize the linear regression model to forecast the linear module L_t by computing the residual series e_t as follows.

$$e_t = y_t - L_t \tag{6}$$

Afterwards, we provide e_t to the above hybrid neural network to obtain the forecasting results N_t , and then it is integrated with L_t to forecast the final agricultural economy dynamically monitoring results as follows.

$$y_t = N_t + L_t \tag{7}$$

where y_t refers to the agricultural economy dynamically monitoring result at the time slot t



Figure 3: Index system for agricultural economy dynamically monitoring

5. Experiment

In this section, we design an experiment to show the effectiveness of our method in dynamically monitoring the agricultural economy. Moreover, index system for agricultural economy dynamically monitoring is shown in Figure 3.

Afterwards, we make indexes being dimensionless by the following equation.

$$B(e) = \frac{e - \min}{\max - \min}$$
(8)

Where *e* refers to the real value, max and min denote the largest value and the minimal value respectively. It is means that we using the linear transformation to map the original data into the range B(e)=[0,1]. Then, using the Analytic Hierarchy Process, weight of each index is obtained (shown in Table. 1)

Table 1: Index weight description

Index ID	1	12	13	14
weight	0.127	0.167	0.096	0.109
Index ID	15	16	17	18
weight	0.134	0.103	0.102	0.16

Next, we will show the experimental data of five regions in the year 2010 (shown in Table. 2)

Table 2: Experimental data of five regions in the year 2010

Region ID	11	12	13	14	15	16	17	18
R1	0.509	0.260	0.364	0.254	0.514	0.514	0.241	0.101
R2	0.401	0.331	0.222	0.235	0.631	0.524	0.295	0.161
R3	0.284	0.342	0.293	0.227	0.534	0.368	0.278	0.131
R4	0.463	0.266	0.181	0.253	0.633	0.385	0.290	0.182
R5	0.252	0.296	0.232	0.274	0.497	0.529	0.274	0.161

Table 3: Real value and monitoring comparison of the five regions

Region ID	type	2010	2011	2012	2013	2014
	Real value	57.80	58.98	61.55	64.39	69.36
RI	Monitoring value	56.44	62.65	56.07	64.63	61.46
D 2	Real value	43.70	45.63	49.06	49.82	52.96
R2	Monitoring value	44.70	42.77	50.12	48.11	48.37
D3	Real value	69.10	75.31	81.77	86.90	91.40
NJ	Monitoring value	68.25	78.24	79.62	89.80	89.49
D4	Real value	85.30	88.79	87.85	92.58	93.47
N 4	Monitoring value	81.04	83.64	82.20	88.92	86.33
D5	Real value	42.60	43.16	44.72	46.86	47.94
КJ	Monitoring value	41.07	43.84	46.28	48.21	49.90

Afterwards, we illustrate the error rate of agricultural economy monitoring with time and region changing in Figure 4 and Figure 5 respectively.

Integrating all the experimental results, we can see that our proposed method can obtain high accurate agricultural economy monitoring results with the error rate lower than 8%.



Figure 4: Error rate of agricultural economy monitoring with time changing



Figure 5: Error rate of agricultural economy monitoring with region changing

6. Conclusion

This paper aims to solve the problem of dynamically monitoring agricultural economy. The structure of the dynamically monitoring agricultural economy system is given in advance. Then, the decision support process for agricultural economy dynamically monitoring is developed through integrating linear regression model and the neural network together. Finally, experimental results show that our algorithm is suitable to be used in agricultural economy dynamically monitoring.

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References

- Abdelkhalek O., Krichen S., Guitouni A., A genetic algorithm based decision support system for the multiobjective node placement problem in next wireless generation network, Applied Soft Computing, 2015, 33: 278-291. doi:10.1016/j.asoc.2015.03.034.
- Aviza D., Turskis Z., Kaklauskas A., A Multiple criteria decision support system for analyzing the correlation between the thickness of a thermo-insulation layer and its payback period of the external wall, Journal of Civil Engineering and Management, 2015, 21(6): 827-835.
- Berhanu K., Poulton C., The political economy of agricultural extension policy in Ethiopia: Economic Growth and Political Control, 2014, 32(2): S199-S216.
- Bukharov O.E., Bogolyubov D.P., Development of a decision support system based on neural networks and a genetic algorithm, Expert Systems With Applications, 2015, 42(15-16): 6177-6183. doi:10.1016/j.eswa.2015.03.018.
- Chang H.H., Zilberman D., 2014, On the political economy of allocation of agricultural disaster relief payments: application to Taiwan, European Review of Agricultural Economics, 41(4): 657-680.
- Guariso A., Squicciarini M.P., Swinnen Johan, 2014, Food price shocks and the political economy of global agricultural and development policy, Applied Economic Perspectives and Policy, 36(3): 387-415.
- Jerven M., 2014, The political economy of agricultural statistics and input subsidies: evidence from India, Nigeria and Malawi, Journal of Agrarian Change, 14(1): 129-145.
- Klomp J., 2014, The political economy of agricultural liberalization in Central and Eastern Europe: An empirical analysis, FOOD POLICY, 49: 332-346, doi:10.1016/j.foodpol.2014.08.003.
- Liu Y.T., Sun P.B., Wang C.Y., 2015, Group decision support system for backbone-network reconfiguration, International Journal of Electrical Power & Energy Systems, 71: 391-402.
- Mukherji A., Das A., 2014, The political economy of metering agricultural tube wells in West Bengal, India, Water International, 39(5): 671-685.
- Musvoto C., Nortje K., de Wet B., Mahumani B.K., Nahman A., 2015, Imperatives for an agricultural green economy in South Africa, South African Journal of Science, 111(1-2), Article No. 2014-0026.
- Nguyen T.T., Saito H., Isoda H., Ito S., 2015, Balancing Skilled with Unskilled Migration in an Urbanizing Agricultural Economy, World Development, 66: 457-467, doi:10.1016/j.worlddev.2014.09.015.
- Ozcan-Deniz G., Zhu Y.M., 2015, A multi-objective decision-support model for selecting environmentally conscious highway construction methods, Journal of Civil Engineering And Management, 21(6): 733-747.
- Singh K., Mehta C.R., 2015, Decision support system for estimating operating costs and break-even units of farm machinery, Ama-agricultural Mechanization In Asia Africa And Latin America, 46(1): 35-42.
- Xue L., Zhu Y.P., Xue Y., 2013, RAEDSS: An integrated decision support system for regional agricultural economy in China, Mathematical and Computer Modelling, 58(3-4): 480-488.

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