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Grey Holt-Winters Model and Grey Wolf Optimization for the Egg Price Forecasting in China

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Abstract: To deal with the egg price forecasting in China, the grey Holt-Winters model is optimized by the Grey Wolf Algorithm. The optimized grey Holt-Winters model outperform support vector regression for forecasting the price of eggs in the four provinces of China. The seasonality of egg price is also discussed in the current study. The forecast accuracy is gauged through the Mean Absolute Percent Error and the Root Mean Square Error. The proposed model's forecasts will provide the egg producers and consumers with better long-term information.

Keywords: Grey Holt-Winters Model; China; Grey Wolf Optimizer; Support Vector Regression; Egg Price; Forecasting

1. Introduction

Eggs and their products, widely used all over the world, are the main kind of the traditional food. Frequent and abnormal fluctuation of egg price had a serious impact on residents' daily life and poultry farmers' income (Wang & He, 2015), so it has become the focus of public concerns (Chen, 2024). For example, a potential barrier to increasing the consumption of egg among low-income individuals is related to the volatility of egg price, which is more severe than all other major food groups (Conrad *et al.*, 2017). For the egg market in the Norwegian, the merger had no effect on consumer prices, but led to higher average price paid by the downstream firms to the merged firm (Nilsen *et al.*, 2016). Egg production in China is reviewed (Yang *et al.*, 2018). On the Korean egg market, the retail and farm egg prices are connected by the wholesale price, and the wholesale-retail and the farm-wholesale margins increase during the avian influenza period (Seok *et al.*, 2018). In order to stabilize egg prices, governments should pay more attention to the prices of corn and layer feed (Xu *et al.*, 2011). A partial equilibrium approach to quantifying the effect of the highly pathogenic avian influenza outbreak that occurred in the United States in late 2014 and early 2015 is provided (Dobrowolska & Brown, 2016). Although egg is the most reasonably priced among all agriculture commodities (Oguri *et al.*, 1992), the number of egg-laying hens in operation, egg production, feed cost, climate and seasonality may affect the future egg price. Forecasting egg price is a complex phenomenon. Therefore, it is important to predict the trend of egg price accurately, find the change rule of egg price and develop appropriate policies and measures, which is helpful for stabilizing the whole industry of egg.

Egg price has been predicted by two main classes of methods. The first class is the artificial intelligence models, such as, the weekly retail price of egg is predicted by chaotic neural network in China (Li *et al.*, 2013). Dynamics of egg prices in major markets of India and the econometric analysis is given (Hebbar *et al.*, 2016). Empirical prediction and risk assessment of chicken egg price in China are discussed by using support vector machine algorithm (Zhang & Liu, 2015). The second class is the traditional statistical model, such as, the German egg price is analyzed by using the coefficient moving average model (Chen *et al.*, 2016). However, the explanation of the above models is lower. Therefore, considered the seasonality of egg price, the grey Holt-Winters model with good understandability is optimized to predicted the monthly egg price in China in this paper.

The rest of the paper proceeds as follows. Data and method are presented in Section 2. The empirical analysis and result discussions is proposed in Section 3. Some conclusions are given in the last Section.

2. Data and method

In 2010, the total output eggs in China reached 23.83 million tons, far ahead of other countries in the world. The per capita possession of eggs reaches 17.8 kg. It is almost twice times higher than the global average (9.3 kg), which is second only to Mexico's 21.9 kg and Japan's 19.7 kg, and ranked third in the world. The egg output of Hebei, Henan and Shandong ranks the top three in China. The egg consumption of Shandong, Guangdong and Henan ranks the top three in the country. Therefore, the monthly egg price of Hebei, Henan, Shandong, Guangdong (four provinces) are predicted in this paper. The simple map of the four provinces is shown in *Figure 1*. The data is from https://www.caaa.cn/html/fw/market/. The variation trends of monthly egg price in these provinces from January 2000 to February 2018 are shown in *Figure 2*, respectively.

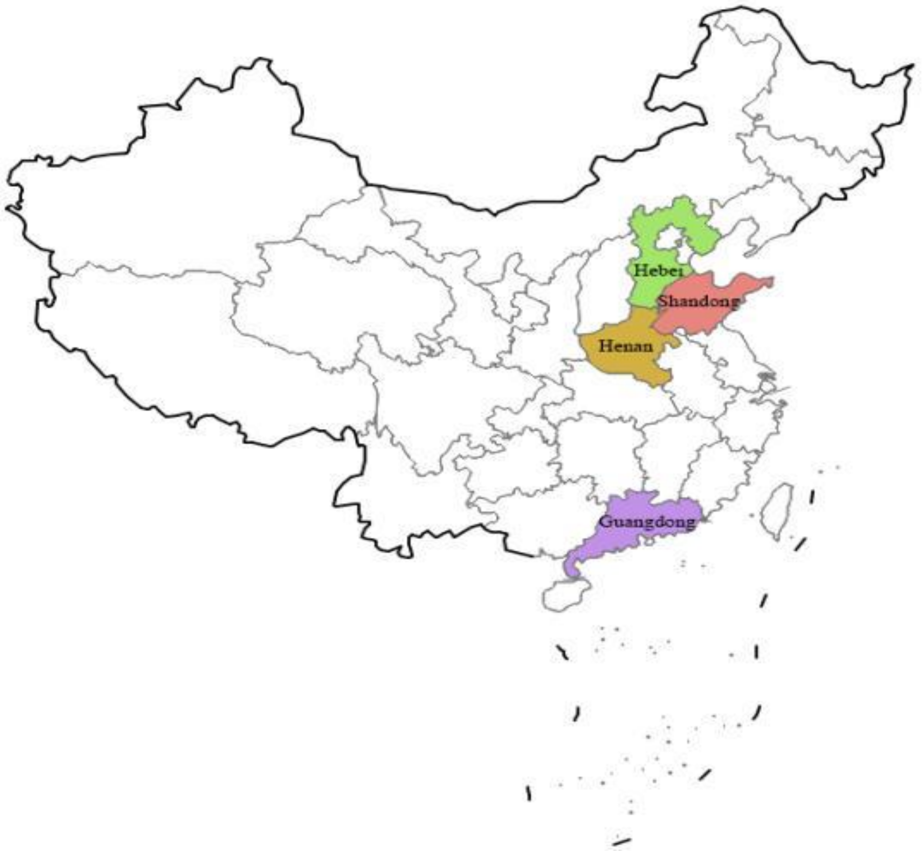

Fig 1. The location of the four provinces in China

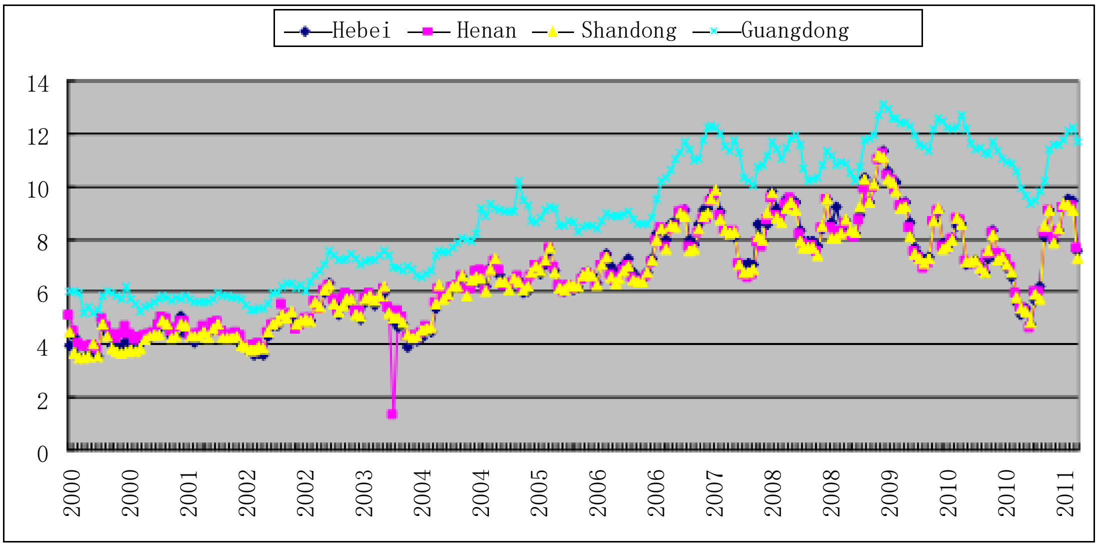

Fig 2. The trend of monthly price of egg (January 2000—March 2018)

Descriptive statistics of monthly egg price from January 2000 to February 2018 in these provinces are shown in *Table 1*, respectively. It can be seen that the monthly price of egg has the characteristics of periodicity, seasonality and long-term volatility. In terms of the whole year, the change rule of the price can be concluded that the lower price was distributed from February to April. Time from May to September was the rise period of the egg price. Before the National Day (1st October), the price reached their highest point, and then it began to decline slowly. The price also had a short callback around the Spring Festival. The change characteristics are influenced by the supply and demand of egg. On the supply side, supply is mainly affected by seasonal climate. Because the gradually warming climate is the most suitable for laying hens, spring is the peak season for laying eggs. The supply of eggs has increased, so the price also has dropped. The hot summer weather affects the feed intake of laying hens, which led to the laying rate of hens dropped. This is the slack season for laying eggs. The egg production will decline. The supply will decrease and the price of egg will rise. On the demand side, it is mainly influenced by the consumer habits. The people tend to have a light diet in summer, the demand for egg is increased and the egg price is increased. Conversely, the consumption in winter is relatively reduced, and the egg price are decreased. The annual traditional festivals (such as the Spring Festival, Mid-Autumn Festival) generally makes the egg market demand entered a peak period. The price of eggs will rise. In short, this characteristic of periodic demand adds seasonality in the egg price in the year. In addition, due to the increased complexity of agricultural prices in recent years, the fluctuations of egg price had been greatly increased from both frequency and amplitude.

The Holt-Winters method can capture seasonality in data series (Dantas *et al.*, 2017; Petropoulos *et al.*, 2019). Thus, the grey Holt-Winters method is optimized to predict the price of egg. The modelling process is given in this Section and the flow chart is given in *Figure 3*.

STEP 1: The original time series is $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\}$, $x^{(0)}(k) \geq 0$, $k = 1,2,\cdots,n$. Let

$$x^{(1)}(1) = x^{(0)}(1)$$

Table 1. Descriptive statistics

	Maximum	*Minimum*	*Mean*	*Std. Deviation*
Hebei	11.32	3.46	6.53	1.87
Henan	11.21	1.32	6.52	1.76
Shandong	11.19	3.47	6.49	1.81
Guangdong	13.11	5.2	8.85	2.38

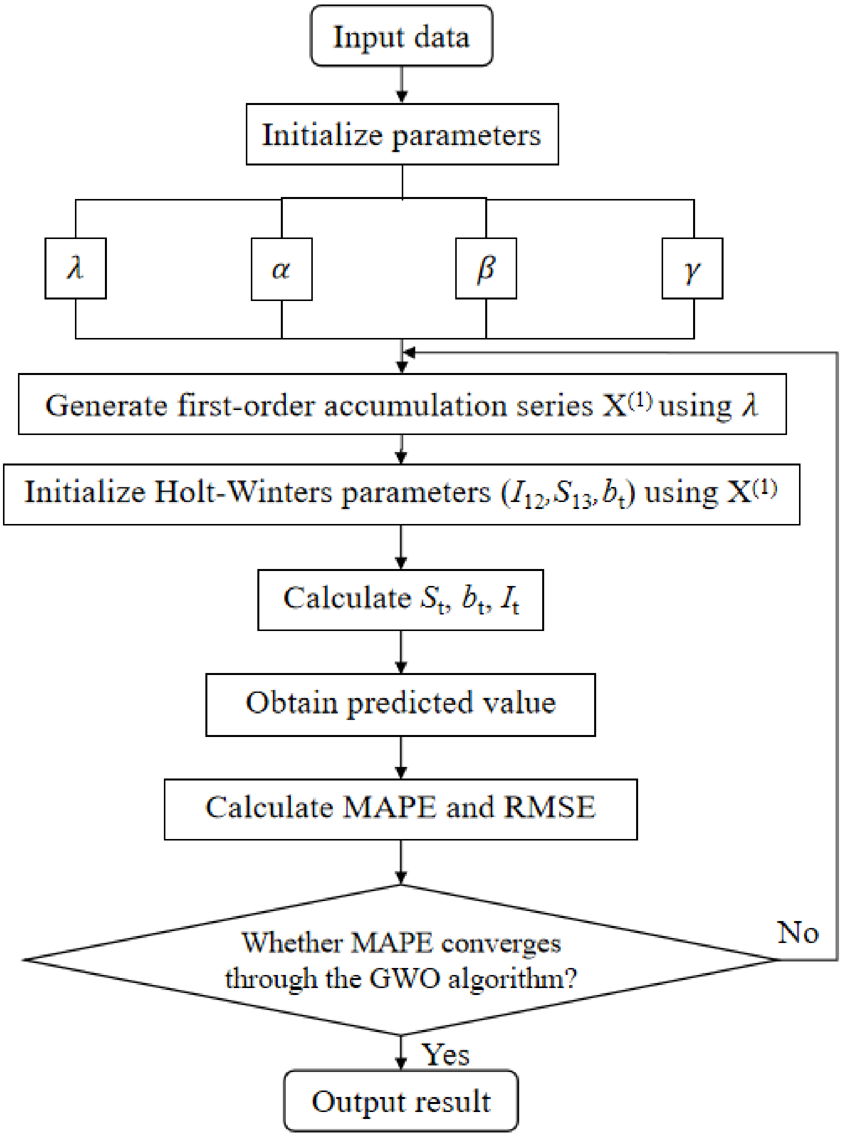

Fig 3. Flow chart of grey Holt-Winters model

$$x^{(1)}(2) = \lambda x^{(0)}(1) + x^{(0)}(2)$$
$$x^{(1)}(3) = \lambda x^{(0)}(2) + x^{(0)}(3)$$
$$\vdots$$
$$x^{(1)}(n) = \lambda x^{(0)}(n+1) + x^{(0)}(n)$$

Where $\lambda \in (-1,1)$. λ is called grey adjacent accumulation generation parameter, which is used to adjust the weight of new and old data in the process of sequence generation. $X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\}$ is the grey first-order adjacent accumulation generation series of $X^{(0)}$ (Zhao & Wu, 2020). The first-order accumulation generation operator is a unique technique of grey system theory. Grey adjacent accumulation generation is an extended form of accumulation generation operator. Grey adjacent accumulation generation is introduced into the traditional Holt-Winters model. We can call this model as grey Holt-Winters method. By doing so, it can develop and extend the traditional grey forecasting model.

STEP 2: The grey Holt-Winters method follows the equations

$$S_t = \alpha \frac{x^{(1)}(t)}{I_{t-12}} + (1-\alpha)(S_{t-1} + b_{t-1})$$

$$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1}$$

$$I_t = \beta\frac{x^{(1)}(t)}{S_t} + (1-\beta)I_{t-12}$$

Where 12 is the length of seasonality. I_t is the correction coefficient of seasonality, b_t is the trend of egg price, and S_t is the seasonal component at time point t. The smoothing parameter α, γ, and β require to in the interval $[0,1]$. Then, the initial values are given by

$$I_{12} = \frac{\bar{x}^{(1)}(12)}{\bar{x}^{(1)}(t)}$$

$$S_{13} = \bar{x}^{(1)}(13)$$

$$b_t = \frac{x^{(1)}(13) - x^{(1)}(1) + x^{(1)}(14) - x^{(1)}(2) + x^{(1)}(16) - x^{(1)}(3)}{3L}$$

where $\bar{x}^{(1)}(L)$ is the average value of the same quarter in different years and $\bar{x}^{(1)}(t)$ is the average of actual values.

STEP 3: The predicted value at time t of the value n periods ahead is given by

$$x^{(1)}(t+n) = (S_{t-1} + nT_{t-1})I_{t-12+n}$$

STEP 4: The cumulative reduction formula of Eq. (1) is

$$\hat{x}^{(0)}(t+n+1) = \hat{x}^{(1)}(t+n+1) - \lambda\hat{x}^{(0)}(t+n)$$

STEP 5: To judge the accuracy of the forecasting approaches, mean absolute percent error (MAPE) and root mean square error (RMSE) are determined and compared with the other models. The smoothing parameters λ, α, γ, and β are taken in such a way that the values of MAPE will be small. The objective function is MAPE, and λ, α, γ, and β are unknown parameters. This single objective problem can be solved by grey wolf optimizer algorithm (GWO). The GWO is developed by Mirjalili *et al.* (2014). It is inspired by grey wolves in nature that searching for the optimal way for hunting preys and is simple, easy to use, flexible, scalable (Mirjalili *et al.*, 2014; Faris *et al.*, 2018). Therefore, it has been widely used to solve optimization problems. In this work, the optimal values of λ, α, γ, and β are determined by the GWO through a coded program in MATLAB.

$$\text{MAPE} = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)}\right| \times 100\%$$

$$\text{RMSE} = \sqrt{\frac{\sum_{k=1}^{n}\left(x^{(0)}(k) - \hat{x}^{(0)}(k)\right)^2}{n}}$$

3. Results and discussions

These data were processed and graphed using MATLAB and Excel software. These data is divided into training data set, which contain data for 216 months from January 2000 to December 2017, and testing data set, which contain data from January to February 2018. Taking the monthly egg price in Hebei province as the example, the optimal values are α =0.8552, β = 0.01, and γ = 0.6937. The corresponding MAPE is 4.77.

To compare the proposed model with support vector regression, x_t (egg price) denotes the output value and the price of layer feed denotes the input value. The result of two models is listed in *Table 2* and *Table 3*. The performances of two models are shown in *Figure 4*. By comparing the MAPE in Table 2-3, the example of egg price forecasting in Hebei province demonstrated the applicability and validity of the Grey Holt-Winters method. Therefore, the egg price in the other

Table 2. The fitting results of two models

	Grey Holt-Winters method	*Support vector regression*
MAPE (%)	4.65	8.85
RMSE	0.41	0.72

Table 3. The forecasting results of two models

Month	*Actual value*	*Grey Holt-Winters method*	*Support vector regression*
201801	9.53	9.05	7.37
201802	9.48	8.45	7.47
201803	7.56	7.95	7.53
MAPE (%)		7.06	14.8
RMSE		0.7	1.7

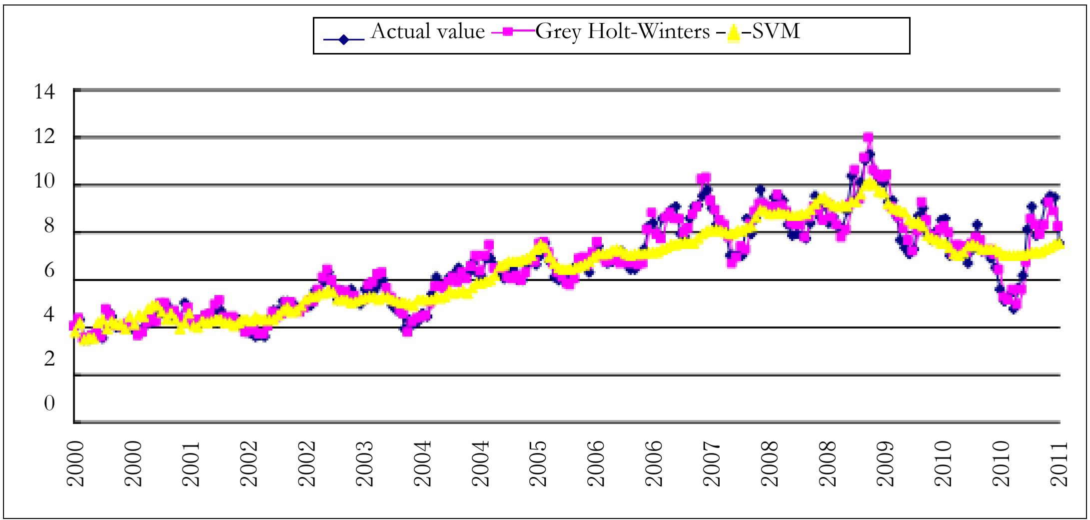

Fig 4. The performance of two models for the egg price in Hebei province

provinces can be forecasted by the Grey Holt-Winters method. The result of egg price in the other provinces is listed in *Table 4*.

In *Table 4*, the smaller MAPE and RMSE means that the optimized grey Holt-Winters model is suitable for egg price forecasting. The forecasting results are presented in *Table 5*.

The change trend of egg price in these provinces is shown in *Table 5*. The seasonality is obvious. The trend is consistent with the actual situation. The egg price in the four provinces is predicted in this paper. Actually, the egg price has the same trend throughout China. The producer and consumer must know this trend. The egg producer must grasp this rule and gain more benefit. The egg consumer must follow this law and plan dietary consumption rationally.

By and large, the egg price in Guangdong province is highest among the four provinces. Because the egg consumption is larger and the egg production is smaller in Guangdong province. The logistics cost is higher. Overall, egg prices have the same seasonal trend, but there are some differences between different regions. The geographical areas between Hebei, Henan and Shandong are near and the development pace is close. The egg prices have similar situation. On the contrary, Guangdong is far apart and has different development pace. Although it has the same fluctuant trend as the other three provinces, the egg price is significantly higher than the other three regions. Therefore, when people consider the egg price, they need to take into account the area in which they are located.

Table 4. The fitting results of grey Holt-Winters model

	Henan	*Shandong*	*Guangdong*
α	0.95	0.96	0.98
γ	0.01	0.05	0.85
β	0.01	0.15	0.05
MAPE (%)	6.15	4.18	2.12
RMSE	0.55	0.4	0.28

Table 5. The forecasting results of grey Holt-Winters model

	Hebei	*Henan*	*Shandong*	*Guangdong*
201801	9.05	8.84	9.24	11.27
201802	8.45	8.35	8.65	11.16
201803	7.95	7.79	8.15	10.7
201804	8	7.84	8.3	10.44
201805	8.42	8.13	8.64	10.51
201806	8.72	8.5	8.98	10.65
201807	8.68	8.48	8.95	10.74
201808	9.64	9.51	10.1	11.25
201809	10.3	10	10.5	11.72
201810	9.43	9.26	9.46	11.55
201811	9.27	9.07	9.45	11.34
201812	9.38	9.21	9.49	11.42
201901	9.31	9.31	9.54	11.6
201902	9.12	9.11	9.34	11.62
201903	8.43	8.28	8.48	11.26
201904	8.32	8.14	8.48	10.9
201905	8.52	8.28	8.7	10.84
201906	8.66	8.56	8.93	11.12
201907	8.67	8.31	8.79	11.19
201908	9.74	9.48	10.1	11.61
201909	10.3	10.1	10.7	12.02
201910	9.47	9.24	9.48	11.9
201911	9.34	8.42	9.41	11.7
201912	9.32	9.18	9.58	11.74

5. Conclusion

The monthly egg price of Hebei, Henan, Shandong, Guangdong are predicted in this paper. The situation in the four provinces can represent the situation throughout China. Thus, the seasonality is obvious in China. The lower price was distributed from February to April. Time from May to September was the rise period of the egg price. Before 1st October, the price reached the highest point, and then it began to decline slowly. The price also had a short callback around the Spring Festival.

The optimized grey Holt-Winters model can obtain better results. It indicates that GWO has strong searching ability and ideal convergence. The optimized Grey Holt-Winters model can be used to the price of the other agricultural products in China. Because the price of the agricultural products is influenced by climate and seasonality and have the obvious seasonality.

In future, in order to validate the proposed model, it may be used to predict other time series with seasonality. The performance of the method can be compared with other models as well.

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