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Research Article

Study on Prediction and Controlling of Grain Price Based on Combined Predicting Algorithm

[1]Wang Shu Zhen and [2]Han Wen Hui
[1]Department of Management, Hefei University,
[2]Huishang Futures Limited Corporation, Anhui, Heifei, 230601, China

Abstract: In order to improve the predicting correctness of the grain price effectively and offer the theoretical basis for establishing measurement of controlling grain price, the combined prediction algorithm combining the grey prediction model and least squares support vector machine prediction model is applied in predicting the grain price. Firstly, grey prediction model is constructed. Secondly, the least squares support vector machine prediction model is constructed. Thirdly, the combined prediction model is established. Finally, the prediction analysis of grain price is carried out based on combined prediction model and results show that the combined prediction algorithm can improve the prediction precision of grain price effectively.

Keywords: Grain price, grey prediction model, least squares support vector machine prediction model, prediction and controlling

INTRODUCTION

The grain is a special commodity with strategic significance, which is an important basic material relating with national economy and the people's livelihood, the grain price is the money form of reflecting the grain value, which is an important factor of predicting the grain product and safety. The grain price generates a big fluctuation for a long time, because some factors affected the grain price, such as cost, supply and demand, financial and monetary policy, speculation, psychological expectations and so on (Brian and Carlo, 2011). In recent years, the grain price has been accelerating. The grain price is important for China, because China is a big population and agricultural country, the grain price is an important means for regulating grain product and ensuring the grain safety, therefore it is necessary to grasp the trends of grain price and regulate every index of predicting it. The grain price is the critical factor of overall situation of the national economy, it is necessary to establish the predicting model of grain price (Mercy *et al*., 2014). The current predicting models conclude time-series method, regression analysis, grey model, neural network and system dynamics method, these methods are mainly dominated by single model, only part of useful information is considered and the entire reorganization for system is lack, every prediction method has its own particular using conditions. Because the grain price has many predicting factors, therefore it is difficult to predict the grain price based on single prediction model and therefore the combined predicting algorithm can overcome the disadvantage of single prediction model, the combined predicting algorithm can be applied in predicting the grain price effectively. This research is to apply the combined predicting algorithm in predicting grain price.

GREY PREDICTION MODEL

The grey system theory is put forward by Deng ju hong in the 1980s and it can establish a model of extending from pass to future based on current information in past and at present. This model has some advantages, such as wide applicable range, single operation. The grey prediction model is put forward based on grey model, which can find out rules from irregular data and then the corresponding model is established through processing these data. The grey evaluation model of is constructed depended on the actual state, which is shown in the following steps (Zhang *et al*., 2012):

- Set up the reference sequences, the number of ith kind of grain price is defined by i, $i = 1, 2, \ldots, m$; the number of kth kind of grain price is defined by k, $k = 1, 2, \ldots, n$; the kth evaluation index of ith object is defined by v_{ik}.

The reference sequeces is expressed as follows:

$$V_0 = (v_{01}, v_{02}, \cdots, v_{0n}) \tag{1}$$

Corresponding Author: Wang Shu Zhen, Department of Management, Hefei University, Anhui, Heifei, 230601, China

where, v_{0k} = *Optimum*(v_{ik}), i = 1, 2,…, m, k = 1, 2,…, n.
For a prediction system made up of m objects and n predicting indexes, the corresponding initial data matrix is defined by (Ming *et al*., 2012):

$$V=(v_{ik})_{m\times n}=\begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} \quad (2)$$

- The normalization process of index value, in order to make every index existing dimensional difference is compared with other indexes and the corresponding formation is given as follows:

$$x_{ik}=\frac{v_{ik}-\min_i v_{ik}}{\max_i v_{ik}-\min_i v_{ik}} \quad (3)$$

where, $\min_i v_{ik}$ is the minimum value of predicting object for kth index and $\max_i v_{ik}$ is the maximum value of predicting object for k th index and the matrix after normative procession is expressed as follows (Xu *et al*., 2014):

$$X=(x_{ik})_{m\times n}=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (4)$$

- Compute the relational coefficient, the X_0 = (x_{01}, x_{02}, …., x_{0n}) is defined as the reference sequences, the X_i = (x_{i1}, x_{i2}, …., x_{in}), i = 1, 2, …,m is defined as comparing sequences, the relational coefficient is computed based on the following formulation:

$$\xi_{ik}=\frac{\min_i \min_k |x_{0k}-x_{ik}|+\rho \max_i \max_k |x_{0k}-x_{ik}|}{|x_{0k}-x_{ik}|+\rho \max_i \max_k |x_{0k}-x_{ik}|} \quad (5)$$

where, ρ is the distinguishing factor, $\rho = 0.5$.
The relational coefficient matrix is defined by:

$$E=(\xi_{ik})_{m\times n}=\begin{bmatrix} \xi_{11} & \xi_{12} & \cdots & \xi_{1n} \\ \xi_{21} & \xi_{22} & \cdots & \xi_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \xi_{m1} & \xi_{m2} & \cdots & \xi_{mn} \end{bmatrix} \quad (6)$$

where, ξ_{ik} is the relational coefficient of optimal index.
- The relational degree of single hierarchy is computed, the optimal weight of every index in any layer to top object is expressed by:

$$W=(w_1,w_2,\cdots,w_t) \quad (7)$$

where $\sum_{k=1}^{t} w_k = 1$, t is the number of indexes, the relational degree is computed by the following formulation:

$$R=(r_i)=(r_1,r_2,\cdots,r_m)=W\cdot E^T \quad (8)$$

LEAST SQUARES SUPPORT VECTOR MACHINE PREDICTION MODEL

The support vector machine belongs to a kind of machine learning means, which is superior to the artificial neural network method. The support vector machine uses the performance prediction of small samples, which has good predicting reliability, at the same time it has good performance, then the higher predicting precision is obtained. Therefore, the good predicting effect is obtained depended on least squares support vector machine for grain price (Aiyer *et al*., 2014).

The training samples {(x_i, y_i)} (x_i, $y_i \in R$; i, j = 1, 2, …, n) are known, the least squares support vector machine uses a nonlinear mapping function to transfer the data transfer from low dimensional space to a high dimensional space and then be mapped back to the initial space to get the linear regression of input space, the linear regression model is defined by:

$$f(x)=[\vec{\omega},\phi(x)]+b \quad (9)$$

where,
ω = The weighted vector
$\phi(x)$ = The mapping function
b = The threshold value

The least squares support vector machine regression uses two times penalty function to transfer the regression problem into two times optimization problem, the corresponding objective function is defined by (Gao and Li, 2015):

$$R_{ref}[f]=R_{emp}[f]+\eta\|\psi\|^2=\sum_{l=1}^{n}C(e_l)+\eta\|\psi\|^2 \quad (10)$$

where,
$C(.)$ = The loss function
η = Regularization factor, $e_l = f(x_l)-y_l$

The calculation of Vapnik ε insensitive loss function is used as the optimal model, which is defined by (Mohsen and Afshid, 2013):

$$\min_{\omega,b,\tau,\tau^*} J=\frac{1}{2}\omega^T\omega+C\sum_{i=1}^{n}(\tau_i+\tau_i^*) \quad (11)$$

$$s.t.\begin{cases} y_i - \omega^T \phi(x_i) - b \le \mu + \tau_i \\ \omega^T \phi(x_i) + b - y_i \le \mu + \tau_i^* \\ \tau_i, \tau_i^* \ge 0 \end{cases} \tag{12}$$

where, τ_i and τ^*_i are the relaxation coefficents, C is the penalty function, $C > 0$, μ is the precision.

The critical function is applied and the dual function of the expression (11) is defined by:

$$\max_{\beta,\beta^*} J = -\frac{1}{2}\sum_{i,j}^{n}(\beta_i - \beta_i^*)(\beta_j - \beta_j^*)\cdot \tag{13}$$

$$K(x_i, x_j) - \mu\sum_{i=1}^{n}(\beta_i + \beta_i^*) + \sum_{i}^{n} y_i(\beta_i - \beta_i^*)$$

$$s.t.\sum_{i=1}^{n}(\beta_i - \beta_i^*), \beta_i, \beta_i^* \in (0, C] \tag{14}$$

where, β_i and β_i^* are also Lagrange operators, $K(x_i, x_j)$ is the core function.

The estimating function of the least squares support vector machine can be defined by:

$$f(x) = \sum_{i=1}^{n}(\beta_i - \beta_i^*)K(x, x_k) + b \tag{15}$$

The parameters optimization of the least squares support vector machine is very important. The critical function always uses the radial function. There is an unknown factor Gamma, improving the value of Gamma can improve the convergence rate of the algorithm. In addition, there is another parameter, which is the parameter of the least squares support vector machine γ, the parameters Gamma and γ decide the learning performance of the least squares support vector machine.

The algorithm procedure of the least squares support vector machine is concludes the following steps:

Step 1: The scope of the two parameters Gamma and γ is established through basic principles of the least squares support vector machine, the scope of the two parameters are chosen as Gamma ∈ [0.01, 0.1], γ ∈ [0.02,10000]。

Step 2: The value of the two parameters Gamma and γ are confirmed in range, then the two dimensional plane ($Gamma_i$, γ_i), i = 1, 2, …, m, 1, 2, …,n can be constructed. The value of Gamma and can be chosen according to the real situation of training samples and relating experiences.

Step 3: The pairs of parameters ($Gamma_i$, γ_i) in different plane grid nodes are exported to the least squares support vector machine, the corresponding training is carried out for the training samples and then the training error is calculated ($Gamma_i$, γ_i) with lest error is the best results.

Step 4: When the training precision of algorithm is not satisfy with the actual requirement, the optimal parameter is the center to establish the new plane grids and choose the close parameter, then the new training is carried out again, then the precision of the algorithm is improved, the procedures mentioned above are carried out repeatedly, then the multi layers parameter optimization plane network can be formed, finally the optimal parameters of the least squares support vector machine can be obtained, then the ideal training precision can be obtained (Mohsen and Afshid, 2013).

COMBINED PREDICTING MODEL

The combined predicting model can apply the information provided by single model comprehensively, which is an effect method for improving predicting precision and confirming the optimal weight coefficients of single prediction model is very important, the fitting error of minimum variance principle is used to decide the weighted coefficients.

There are n kind of prediction models and the combined prediction model is expressed as follows (Özgür, 2011):

$$y_t = \sum_{i=1}^{n} k_i y_{it} \tag{16}$$

where y_t is the prediction value of combined prediction model at t moment (t = 1, 2, …,N), k_i is the weighted coefficient of ith prediction model (t = 1, 2, …,n, $\sum_{i=1}^{n} k_i = 1$), y_{it} is the prediction value of ith prediction method (i = 1, 2, …,n, t =1, 2, …,N).

The sum of square for combined prediction error is calculated based on the following expression:

$$S = \sum_{i=1}^{N} e_t^2 \tag{17}$$

Then the following expression can be got (Mohsen and Zohreh, 2014):

$$S = \sum_{t=1}^{N}\sum_{j=1}^{n}[k_i k_j (\sum_{i=1}^{N}) e_{it} e_{jt}] = \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix} \begin{bmatrix} \sum_{t=1}^{N} e_{1t}^2 & \sum_{t=1}^{N} e_{1t}e_{2t} & \cdots & \sum_{t=1}^{N} e_{1t}e_{nt} \\ \sum_{t=1}^{N} e_{2t}e_{1t} & \sum_{t=1}^{N} e_{2t}^2 & \cdots & \sum_{t=1}^{N} e_{1t}e_{nt} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{t=1}^{N} e_{nt}e_{1t} & \sum_{t=1}^{N} e_{nt}e_{2t} & \cdots & \sum_{t=1}^{N} e_{nt}^2 \end{bmatrix} \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix}^T \tag{18}$$

Table 1: Prediction results of grain price based on combined prediction algorithm

Year	Flour		Yellow corn		Soybean	
	Prediction value/(Yuan/kg)	Error/%	Prediction value /(Yuan)	Error/%	Prediction value /(Yuan/kg)	Error/%
2009	2.56	0.32	0.78	0.22	1.73	0.40
2011	2.65	0.43	0.79	0.36	1.86	0.34
2012	2.78	0.28	0.82	0.36	1.92	0.23
2013	2.86	0.30	0.84	0.26	1.95	0.44
2014	2.92	0.36	0.88	0.32	1.99	0.41

where, k_j (j = 1, 2, …,n) is the weighted coefficient of j th prediction model, e_{jt} (j = 1, 2, …,n, t = 1, 2, …,N) is the prediction error of j th prediction model.

Let $K = [k_1, k_2,\ldots,k_n]^T$, the error matrix can be expressed as follows:

$$E_{(n)} = \begin{bmatrix} E_{11} & E_{12} & \cdots & E_{1n} \\ E_{21} & E_{21} & \cdots & E_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ E_{n1} & E_{n2} & \cdots & E_{nn} \end{bmatrix} \quad (19)$$

where,

$$E_{ij} = E_{ji} = \sum_{t=1}^{N} e_{it} e_{jt}\ ,\ E_{ii} = \sum_{t=1}^{N} e_{it}^2 \cdot S = KE_{(n)}K^T \quad (20)$$

In order to minimize square sum of error of combined model, the minimal value is calculated under boundary condition $\sum_{i=1}^{n} k_i = 1$, the following expression can be get:

$$S = KE_{(n)}K^T + \lambda(C^T K - 1) \quad (21)$$

where $\lambda \neq 0$.

The partial derivative is calculated for the expression (21) and the value of K can be obtained when the error sum of square is minimum.

CASE STUDY

In order to verify the correctness of combined prediction model, the price of flour, yellow corn, soybean in from 2009-2014 is used as example, the corresponding prediction analysis is carried out based on combined prediction model and the weighted coefficients of grey prediction and least square support vector machine are 0.35 and 0.68 respectively and the corresponding prediction results are listed in Table 1.

As seen from prediction results, the prediction value of flour, yellow corn and soybean is in accord with the actual value and the prediction error is every little, therefore the combined prediction algorithm can improve the prediction precision of grain effectively.

CONCLUSION

With the further deepen of grain circulation system reform, the grain price has achieved the transform from plan to market, the fluctuation of grain price has self distinct personality traits. The combined prediction model is used to predict the trends of grain price and the prediction results can offer effective theoretical basis for putting forward the corresponding measurements. The prediction simulation of grain price is carried out based on combined prediction model and results show that combined prediction model can improve the prediction precision of grain effectively.

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