Forecasting Soybean Futures Price Using Dynamic Model Averaging and Particle Swarm Optimization

Tao Xiong
Huazhong Agricultural University
China
taoxiong@mail.hzau.edu.cn

ABSTRACT

We develop a model to forecast Chinese soybean futures price with eighteen predictors by integrating the recently proposed dynamic model averaging (DMA) and particle swarm optimization (PSO). Specifically, three important parameters, i.e., two forgetting factors and a decay factor, of DMA are tuned by PSO. The proposed prediction model, named DMA-PSO, not only allow for coefficients to change over time, but also allow for forecasting model to evolve over time. Experimental results show that the proposed DMA-PSO outperforms four counterparts and the best predictors in DMA-PSO for forecasting soybean futures price vary a lot over time[1].

KEYWORDS

Forecasting; swarm optimization; time-varying; soybean futures

1 INTRODUCTION

Soybean futures are the effective channel for market participants to hedge price risks and chase profits. In 2016, the total trading value and volume of Chinese soybean futures was 244.82 billion CNY and 6.51 million contracts, respectively. Accurately measuring and forecasting the dynamics of soybean futures price is inevitably an important component not only in trade risk management but also in price speculation.

Unsurprisingly, there exist a number of studies that include soybean as one of the target agricultural commodities of interest in recent forecast evaluations, adopting various different modeling techniques. However, the most apparent weakness is that none accounts for the parameter and model uncertainty due to, for example, the presence of structural breaks. The presence of structural breaks might be the result of the effect of some specific predictors on futures price changes over time. As such, they may be useful at some points in time but not others.

Against this backdrop, this study applies the dynamic model averaging recently proposed by Raftery, Kárný et al. [1] to forecast monthly Chinese soybean futures price with eighteen exogenous variables. In order to obtain good performance of DMA, two forgetting factors and a decay factor in DMA must be carefully tuned. Different from the previous studies which set values of these three key parameters based on experiences or observance, this study adopts particle swarm optimization (PSO) [2] to tune these parameters totally on the basis of forecasting performance. Given n predictors for crude oil price, $K=2^n$ models could be constructed. The proposed DMA-PSO method considers all K possible model combinations in each time t. To this end, the probability of model $k \in (1,...,K)$ which should be employed as model weights for forecasting at each time needs to be computed [1]. Thus, DMA-PSO method not only allows the regression coefficients in each model to evolve over time, but also the forecasting model to change over time simultaneously.

In summary, our contributions can be outlined as follows. First, we extend the DMA to the scenario of agricultural futures price forecasting. Second, to address the parameters selection problem of the DMA, two forgetting factors and a decay factor in DMA are tuned using PSO.

2 THE PROPOSED DMA-PSO METHOD

The detail formulations of DMA [1] and PSO [2] are not included here to save space. In short, the first forgetting factor λ implies that the observations in past j periods have the weight of λ^j. For example, $\lambda = 0.99$, for monthly data considered in this study, suggests observations ten months ago receive approximately 90% as much weight as last period's observation. The second forgetting factor α with interpretation similar to λ but in terms of model rather than parameter evolution. The decay factor κ concerns on the error evolution. $\kappa = 0.94$ means the prediction error twenty monthly ago receives 30% as much weight as the last period's error. To obtain good performance of DMA, these three parameters mentioned above must be carefully tuned. In view of the remarkable optimization ability, PSO [2] are used for optimization of the parameters of the DMA in this study. There are four major operations, i.e., representation, initialization, evaluation, and update, in the proposed DMA-PSO method.

2.1 Representation and initialization

The position and velocity of one candidate solution (or particle) have only three dimensions that denote the three parameters (two forgetting factors λ and α, a decay factor κ) to be optimized in DMA. A set of particles $\mathbf{P} = \{\mathbf{x}_1^t, ..., \mathbf{x}_M^t\}$ is called a swarm.

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Initially, the particles in the population are randomly generated in the solution space according to Eq.(1) and Eq.(2),

$$x_{id} = x_{\min,d} + r \times (x_{\max,d} - x_{\min,d}) \tag{1}$$

$$v_{id} = v_{\min,d} + r \times (v_{\max,d} - v_{\min,d}) \tag{2}$$

where x_{id} and v_{id} are the position value and velocity in the dth dimension of the ith particle, respectively. r is a random number in the range of [0,1]. $x_{\min,d}$ and $x_{\max,d}$ denotes the search space of the dth dimension (that is, the upper and lower limit of the parameters in DMA), while $v_{\min,d}$ and $v_{\max,d}$ is used to constraint the velocity of the particle to avoid the particle flying outside the search space.

2.2 Evaluation and update

The fitness function is defined as the prediction error in terms of the mean squared error (MSE).

To search for the optimal solution, each particle adjusts their flight trajectories by using the following updating equations:

$$v_{id}^{t+1} = w \times v_{id}^{t} + c_1 \times r_1 \times (p_{id} - x_{id}^{t}) + c_2 \times r_2 \times (p_{gd} - x_{id}^{t}) \tag{3}$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \tag{4}$$

where $c_1, c_2 \in \Re$ are acceleration coefficients, w is inertia weight, r_1 and r_2 are random numbers in the range of [0,1]. v_{id}^{t} and x_{id}^{t} denote the velocity and position of the ith particle in dth dimension at tth iteration, respectively. p_{id} is the value in dimension d of the best parameters combination (a particle) found so far by particle i. $\mathbf{p}_i =< p_{i1},..., p_{iD} >$ is called personal best position. p_{gd} is the value in dimension d of the best parameters combination found so far in the swarm ($\mathbf{P}$); $\mathbf{p}_g =< p_{g1},..., p_{gD} >$ is considered as the global best position.

3 EXPERIMENTAL RESULTS

This analysis is based on monthly data. The period of analysis spans from January 2000 to June 2017, with total 210 observations. The first 60 observations are used as in-sample data, which is employed to start Kalman Filter in DMA-PSO. The last 150 observations are reserved as out-of-sample data. The monthly soybean futures price is the explained variable. We use three groups of predictors to forecast soybean futures price. Specifically, global soybean yield, consumption, and ending stock, Chinese soybean spot price and net imports are selected as indicators of fundamentals of soybean. U.S. soybean futures price, volume and turnover rate in Chinese soybean futures contracts are adopted as indicators of soybean futures markets. Shanghai composite index, Shenzhen component index, S&P 500 index, VIX index, WTI crude oil spot price, gold price, exchange rate of USD to CNY, Baltic dry index, China monthly money supply M2, and China CPI are selected as indicators of macroeconomic environment.

The average number of predictors employed by DMA-PSO at each point of time is shown in Fig. 1. The pattern in Fig. 1 indicates that, as time goes by, the expected number of predictors is changing dramatically. Taking into account the 18 predictors, furthermore, Fig. 1 indicates a high degree of parsimony of predictors, and the average number of predictors is only 7.06.

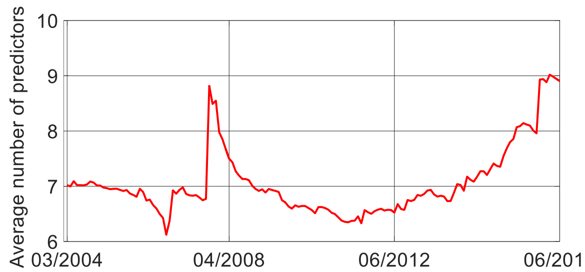

Figure 1: Average number of predictors in each forecasting exercise via DMA-PSO over the out-of-sample data

Here, we present the forecasting performance of the DMA-PSO with four counterparts. In terms of forecasting methods, we present results for DMA-PSO, traditional DMA whose parameters are determined by recommendation [1], time-varying parameter model, linear regression, and random walk.

Table 1 Performance comparison in terms of NMSE and MAPE.

Forecasting methods	NMSE	MAPE
DMA-PSO	0.0582	0.0287
Traditional DMA	0.0686	0.0327
Time-varying parameter model	0.0731	0.0462
linear regression	0.0765	0.0423
Random walk	0.0791	0.0582

According to the results shown in Table 1, the overall story is clear and strong: the DMA-PSO does tend to forecast better than the other counterparts and, in many cases, the forecast improvement are substantial. In addition, the DMA-PSO performs better than tradition DMA in terms of both two accuracy measures. It is conceivable that the reason for the superiority of the DMA-PSO is that the PSO used in DMA. In short, the experimental results show that the integration of DMA and PSO can improve prediction performance in soybean futures price forecasting.

4 CONCLUSIONS

Building on the recent proposed DMA, we propose a swarm intelligence based DMA by using PSO for optimization of the parameters of the model for soybean futures price forecasting with eighteen predictors. Our experimental results show that the proposed method is a promising alternative in soybean futures price forecasting.

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