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Performance of generated moving average strategies in natural gas futures prices at different time scales

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A R T I C L E I N F O

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A B S T R A C T

When analyzing investments based on the moving average strategy in natural gas futures markets, the time scale of the data is a notable factor. Most studies on moving average investment strategies have focused on one specific time scale. In this paper, moving average performances based on data at different time scales are compared and analyzed. Weekly, daily and hourly natural gas futures prices from the New York Mercantile Exchange are used as target data. The types of strategies, the lengths of the time periods and the range parameters are coded into a binary string, and genetic algorithm is used to search for suitable lengths, appropriate calculation methods and other parameters. According to the results of three experiments using data at different time scales, the performances differ in type of moving average strategy selection and adoption of range parameter. Generally, experiments based on daily scale data show better performance than weekly and hourly scales in rate of return, return times and return stability. The results from this study could help in choosing data when using moving average strategy in natural gas futures markets.

1. Introduction

In natural gas futures markets, investment strategy is a research hotspot. Among varieties of investment strategies, moving average strategy is an effective tool when making decisions. Whether the result of moving average strategy is affected by time scale of data is a notable topic. In this paper, we analyze the performances of generated moving average strategies on different time scales in the natural gas futures markets.

In the previous research, the moving average strategy is widely used in financial market such as commodity futures (Szakmary et al., 2010), oil futures (Shambora and Rossiter, 2007) and kinds of stock markets (Zhu and Zhou, 2009; Metghalchi et al., 2012; Rosillo, de la Fuente et al., 2013). As a trend following technical rule, the profitability (Szakmary et al., 2010) and the reason for profit (Friesen et al., 2009) are hot study aspects. However, at present, most studies focus on one specific time scale. In other words, most scholars study the moving average strategies based only on hourly (Cuaresma et al., 2004; Munoz et al., 2013), daily (Wang et al., 2012) or weekly (Ayadi et al., 2009; Davey 2010)data. It is our firmly believe that the performances of moving average strategies based on data at different time scales differ. Therefore, in this paper, we compared the performances of moving average strategies based on data at different time scales.

The principle of moving average strategy is that it attempts to use the moving average line of prices to predict market trends and makes it possible for computers to generate buy and sell signals automatically. Buy signals and sell signals are generated by the moving averages of long-term and short-term price series. The signal to buy occurs when the average of a short-term period exceeds the average of a long-term period, and the signal to sell occurs when the average of a long-term period exceeds the average of a short-term period (Boylan and Johnston, 2003; Andrada-Felix and Fernandez-Rodriguez, 2008). Nevertheless, many different types of moving average strategies are available (Wang et al., 2014) with different methods of calculation. In the calculation process, the selection of various parameters also affects the results of the data analysis. Selection of differentiated parameters will result in changes of strategies, thereby affecting the results of investment decisions. Moreover, there are two vital parameters in the moving average, i.e., the length of the time period (Chiarella et al., 2006; He

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and Zheng, 2010) and the range parameter (Potvin et al., 2004).

Because the price series have different trends, fluctuations and other features, it is not appropriate to use one fixed strategy with a set of fixed parameters no matter in which time scale. To make better choices, most scholars prefer to use optimization algorithms. Neural Network (NN) (Kim, 2006; Chang and Li, 2010; Dunis et al., 2013), Partial Swarm Optimization (PSO) (Zhu et al., 2011; Guo et al., 2013; Bagheri et al., 2014) and Genetic Algorithm (GA) (Wang, 2000; How et al., 2010; Dong and Huang, 2014) are the three most frequently used algorithms. NN is a black box. The decision-making mechanism and the relationship between the variables is not clear. Nevertheless when using the moving average strategy, the basic structure is already known, and what needs to be done is to make a precise comparison regarding the extent to which the lengths of time periods or other parameters affect the results. So NN is not suitable here. PSO is partly similar to GA, but PSO has a higher possibility of local convergence. Therefore, we use GA in this paper.

GA is a computational model used to simulate natural selection and biological evolution. Using the processes of selection, crossover and mutation, genetic algorithm searches for the optimal solution (Roberts, 2005; Creamer, 2012; Behroozsarand and Soltani, 2014). In financial market, GA is mainly used to portfolio optimization (Kabundi and Mwamba, 2012), trading rule modeling (Routledge, 2001; Deng et al., 2015), price forecasting (Deng et al., 2015) and strategy optimization (Wiesinger et al., 2013). It has been provided to be a reliable method to choose the best trading rules (Allen and Karjalainen, 1999; Esfahanipour and Mousavi, 2011; Qu and Li, 2014). In this paper, GA provides a way to optimize variables including methods, lengths of time periods and range parameters when using the moving averages.

The types of strategies, the lengths of the time periods and the range parameters are coded into a binary string, and GA is used to search for suitable lengths, appropriate calculation methods and to judge the range parameter adoption. Therefore, the trading strategy can be represented in fixed structure using genetic individual. In this way, the selection process of the best parameters set becomes the selection progress of best genetic individuals.

In this paper, to compare the performances of moving average strategies on natural gas futures prices at different time scales, we choose three time scales, hourly, daily and weekly, and natural gas futures prices as sample data. By using GA, dynamic moving average strategies are generated and optimized. We then analyze the similarities and differences among these strategies at different time scales. The results from this study could provide additional aid in making investment decisions.

2. Data and methods

2.1. Data

In this paper, we use the natural gas futures data on the New York Mercantile Exchange (NYMEX). Three types of time scales were selected: the weekly futures prices, the daily futures prices and hourly futures prices. The weekly futures prices and daily futures prices were downloaded from the U.S. Energy Information Administration website (http://www.eia.gov/dnav/ng/ng_pri_fut_s1_d.htm, 2014-5-7), and hourly futures prices were derived from Mandarin Financial.

The NYMEX natural gas futures contain 12 contracts, and each contract period is one year. Every contract's last delivery date is the third business day before the expiration month. For example, if Contract 2 matures in February 2013, then its last delivery date is January 29, 2013. If Contract 1 matures in January 2013, then its last delivery date is December 27, 2012 because December 29 and 30 of 2012 are weekend days.

The data for hourly futures prices were also collected by adopting the approach of the EIA and using the most active futures contract prices. The trading time for NYMEX is 6:00 pm to 5:15 pm the next day, and there is a 45-min break every day. On the last delivery day, the market closes 3 h in advance. In the winter, the trading time is 7:00 to 6:15 the next day. Therefore, the hourly futures prices for December 2012 are the trading prices from 7:00 pm November 29, 2012 to 3:00 pm December 28, 2012 of Contract 1; the hourly futures prices for January 2013 are the trading prices from 7:00 pm December 28, 2012 to 3:00 pm January 30, 2013 of Contract 2.

The weekly futures prices are taken from January 14, 1994 to December 27, 2013. The daily futures prices are taken from January 13, 1994 to December 31, 2013. The hourly futures prices are taken from 6:00 March 29, 2012 to 2:00 March 28, 2014. The algorithm used in this paper needed three portions of data, i.e., the training period, selection period and test period every time. The training period is used to evaluate and select the generated trading rules in each generation. The selection period is used to test the best individual in every generation and identify the best trading rule in a trail. The final rate of return is calculated in the test period because the moving average method requires part of the former data. To calculate the moving average price in the training period, a data set of approximately 500 items is chosen as the previous data. In the weekly price experiment, 520 data items, approximately 10 years, from 1994 to 2003, are set as the previous data, and the training period, selection period and test period are all set at 52, which is one year. In the daily price experiment, two years of data (the year of 1994 and 1995) are set as the previous data, and the three periods are all set for 250, which is also one year. In the hourly price experiment, one month of data (April, 2012) are set as the previous data, and the three periods are set for 510, which is about one month. The data groups are shown in Tables 1–3. Because of the data amount requirement, the weekly data and hourly data are divided by year so that we can compare these two experiments in the same period. The hourly data are divided by month. There is an extra experiment on daily data that is also divided by month to compare to the experiment using hourly data. The data groups of the extra experiment are shown in Table 7.

2.2. Methods

Six types of moving average strategies are used in this paper, i.e., the Simple Moving Average (SMA), Weighted Moving Average (WMA), Exponential Moving Average (EMA), Adaptive Moving Average (AMA), Typical Price Moving Average (TPMA) and Triangular Moving Average (TMA). These six strategies use different calculation methods for the average, and the calculation methods are shown from formula (1) to formula (6) (Wang et al., 2014). Every moving average strategy requires a long-period time series and a short-period time series. In general, if the moving average of a long time period exceeds the moving average of the short time period, the market is in a falling trend; if the moving average of a short time period exceeds the moving average of the long time period, the

Table 1
Data groups of weekly futures prices.

Data group	Training period	Selection period	Test period
1	2004	2005	2006
2	2005	2006	2007
3	2006	2007	2008
4	2007	2008	2009
5	2008	2009	2010
6	2009	2010	2011
7	2010	2011	2012
8	2011	2012	2013