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A PSO Approach to Search for Adaptive Trading Rules in the EUA Futures Market

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Abstract

The carbon emission futures markets become more and more important in worldwide. More and more counties begin to emphasize environmental protection in the economic development. Carbon emission trading has become an important part of the energy finance. How to make more profits in the carbon emission futures market is concern by more and more traders and scholars. This paper proposed an approach to search for optimal trading rules in the CO2 allowance futures markets. A group of different moving average trading rules with different weights are used to constitute an integrated trading rule. This is better than a single fixed moving average trading rule. Similarity of trading rules, a parameter we designed, is used to help select basic rules. The authors use static particle swarm optimization process to find the best weights distributions of the selected basic trading rules. After the initial weight distribution is determined, the weights of the basic trading rules will adjusted dynamically every day in the trading process using particle swarm optimization algorithms. Experiments using the EUA Futures Market price data were conducted to find out best adaptive trading rules in the carbon emission futures market. According to our results, it is not necessary to use two moving average trading rules that making same investment advice at a probability higher than 70%. The results show this approach have good performance in adjusting the weights according to the price changes. We found that the adaptive trading rules can help traders make profit in the EUA Futures Market except extreme special circumstances after price change significantly. This approach might be helpful for traders to make scientific decision in actual investments.

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Keywords: Carbon emission trading; Futures markets; Technical trading rules; Particle Swarm Optimization

1. Introduction

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Carbon emission is a hot topic in the energy world. Most of the energy related industries have to face the carbon emission problem. Companies exchange CO_2 allowance for higher capacity or more profits. Carbon emission trading is becoming an important role in the field of energy finance. Carbon emission futures markets can help companies store CO_2 allowance or reduce the risk of carbon emissions trading in the spot markets. Analyzing the features of price change and price trends of the carbon emission futures markets and using appropriate investment strategy is very important for a company or an investor to make decision. How to make more profits in the carbon emission futures markets is a crucial issue for traders and scholars. This paper focus on the CO_2 allowance futures markets and attempt to find out profitable technical trading rules in the carbon emission futures markets using moving average trading rules and particle swarm optimization algorithms.

Moving average trading rules are popular technical trading rules widely used in stock markets, exchange markets and different kinds of futures markets. Moving average trading rules are effective to describe price trends and are easy conducted. What's more, using different moving average lengths, they can have good performance in different price fluctuation status. We use different moving average trading rules to establish a trading rules group to help traders make decision in this paper. This is because it is impossible to find a fixed moving average trading rule suitable for all markets circumstances. A combination of different moving average trading rules with different moving average periods can describe different market circumstances. In this paper, we use the result, which is a weighted sum of all the rules considered, of a group of moving average trading rules to help make decision. We make the moving average rules group to be adaptive through adjusting the weights of each trading rules dynamically based on their performance in the past.

To find out the best weights distributions and adjust them dynamically to adapt the price changes in the trading process. A particle swarm optimization algorithm is used to regulate the weights of the moving average trading rule in the trading rules group. Because selecting the weight distributions of the trading rules is complex and there is no absolute optimal solution, it is impossible to find out the best trading rule through strict mathematical calculation. Exiting research projects always use some optimization algorithms to find out optimal solutions, such as ANFIS [1], GAs [2], and PSO [3] algorithms. These algorithms are all used to find the most suitable solutions through a training and selection process. The core idea of PSO process is that the entire individuals will move to the best individual in every evolutionary generation. Considering the sum of the weights of different moving average trading rules are fixed during the whole trading process, it is suitable to use particle swarm optimization algorithm to select the best weight distributions of different.

2. Data and Methods

2.1. Data

We use the ECX EUA Futures prices from 2008 to 2014 as sample data to search for optimal adaptive trading rules. ECX EUA Futures are traded on the Intercontinental Exchange. Each contract is for 1,000 CO2 EU Allowances. For each complete selection process, three periods of price data are needed. The first 250 days are used to calculate the moving average prices used in the following training and evolution process. The second 250 days are used to select the best weight distributions of the all the moving average trading rules. At last, a 500 days price series is used to test the adaptive trading rules. For more detail results, we divided the last period into several sub periods to check the return rate of the generated adaptive trading rules in different investment cycle. Therefore, one single complete experiment will need 1000 days (about 4 years) CO2 allowance prices. According the length of all the price data we have, 8 group independent experiments were conducted to analysis the performance the adaptive trading rules in the EUA Futures market. The Fig. 1 shows the details of the data selection and experiment design.

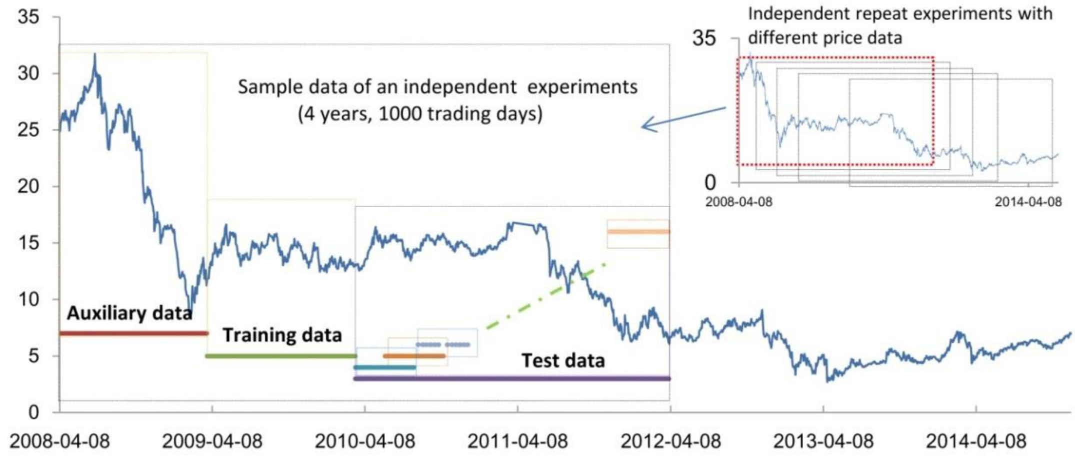

Fig. 1 Sample data selection and experiment design. **Auxiliary data**: help to calculate the moving average prices of different moving average trading rules in the training period. **Training data**: 1) choose the moving average rules from the basic moving average rules set. 2) evaluate different weights of selected moving average rules and help select the best weight distributions through PSO process. **Test data:** 1) test the adaptive combined trading rules to see whether they can make profits in the CO2 emission futures markets. 2) An average return rate of fixed days in the test period was calculated to analysis the profitability of the adaptive combined trading rules.

2.2. Methods

This paper use a group of moving average trading rules to constitute a type of integrated adaptive moving average trading rules in the EUA Futures market. We selected the moving average trading rules from a large number of candidate set. Only one of two moving average trading rules that give the same investment advice in most instances will be selected. A whole year price series will be used to determine the best initial weight distributions of the moving average trading rules before the adaptive trading rule is used. The weights of every moving average trading rule will also be changed through PSO process during the trading period. Therefore, the integrated trading rules will have the ability to adapt the price changes dynamically.

The first step is to select basic moving average trading rules. We must decide the moving average calculation method and the moving average lengths of the basic rules. We use AMA (adaptive moving averages) in this paper to calculate the average prices because this method is proved to be more effective than other calculation methods [4]. How many basic moving average trading rules need to be selected? In most exiting studies, the basic moving average trading rules set is given by experience. In this paper, we choose the basic moving average trading rules by comparing the similarity of the candidate rules. We use MAR(m,n) and MAR(p,q) to represent two moving average trading rules. Their similarity can be calculated according to

$$Sr = daysame / daywhole, \tag{1}$$

where *daysame* is the number of days in which the two moving average trading rules give same advice in a period, and the *daywhole* is the length of the period. We choose the basic moving average trading rules set according to a threshold in our experiments (see below).

After the basic moving average trading rules are selected, we can establish the initial adaptive trading rules through a static PSO process using the training data. Each single moving average trading rule will give out an investment advice and the final result will be calculated with the weights distribution given by

PSO process. The decision process of an integrated adaptive trading rule is presented in Fig. 2.

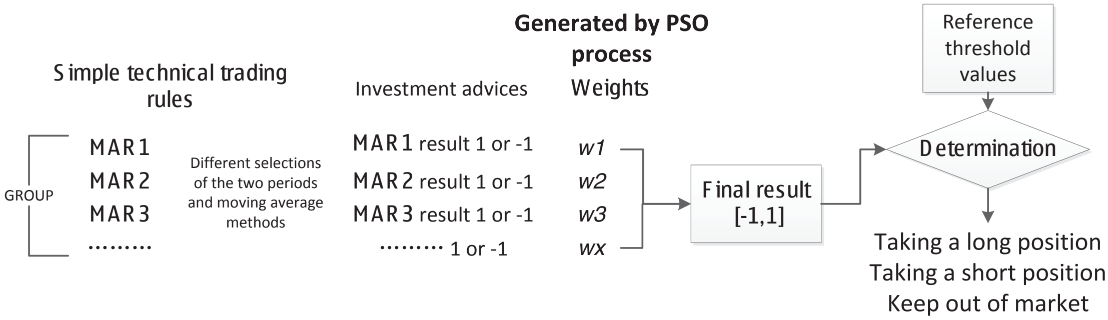

Fig. 2 Decision process of the integrated adaptive rule

We use PSO algorithms [5] to select the optimal initial weight distributions and adjust the weights in the whole trading process. For static PSO process, we use a population of 100 different individuals and evolve the population for 60 generations to find out the best initial weights setting in the 250 days training price series. We use the return rate of a trading rule make in a period to evaluate the performance of the individual. The return rate of a rule is calculated through

$$R = R_l + R_s + R_f$$
$$R_l = \sum_{i=1}^{n}((P_{out} - P_{in}) / P_{in} * (1-c) / (1+c)) / R_m \quad (2)$$
$$R_s = \sum_{i=1}^{m}((P_{in} - P_{out}) / P_{in} * (1-c) / (1+c)) / R_m$$

where R is the return rate of a combined trading rule in the sample period. R_l and R_s are the return rate of the long positions and short positions respectively. R_f is the risk free return when out of market. R_m is the margin ratio of the futures market. The parameter c denotes the one-way transaction cost rate. P_{in} and P_{out} represent the opening price and closing price of a position (long or short) respectively.

In every optimization step, the best individual with the best performance will be selected out and all the other individuals are adjusted towards the best one. We use $BT_t(w1,w2,w3,\ldots wx)$ to represent the best one and $OT_t(u1,u2,u3,\ldots ux)$ to represent an individual need to be adjusted. The new OT is

$$OT_{t+1} = OT_t(u_1,u_2,u_3,\ldots u_x) + \alpha * (BT_t(w_1,w_2,w_3,\ldots w_x) - OT_t(u_1,u_2,u_3,\ldots u_x)), \quad (3)$$

where α is a parameter controlling the convergence rate of the process. To avoid the process convergence at a local optimal solution, 20 percent of all the individuals will be randomly created in every generation.

When the trading rule is used in the test period, the initial weight distribution will be used at the beginning. And a dynamic PSO process will be conducted every day to see whether the weight distributions need to be adjusted. The last generation of the static PSO process will be used as the initial population and the generated best weight distribution in every step will be used to make investment by traders. Through this process, we can make the trading rules adaptive and make predict more scientifically.

3. Results

In this paper, the transaction cost rate is set at 0.1%, which is an intermediate value. The risk free return rate is 2%, which is based primarily on the short-term treasury bond rate [6]. We assume the margin ratio to be 0.05. The long position threshold is 0.3 and the short position threshold is -0.3 when making finial investment decision. The PSO parameter is 0.36, which is proved to be suitable for the EUA futures markets based on our experiments.

As mentioned above, we use a similarity of moving average trading rules to delete the unnecessary basic trading rules. We conducted different experiments with different similarity threshold value from 0.55 to 0.95. To find out the best threshold setting, the average return rate in the training period is compared in different conditions. We use the return rate the generated rules got in the training periods instead of the return of the test period to select the best threshold. This is because the return rate of test period will be affected by the price trends and the target here is to find out how many basic trading rules is optimal for describe the price information. Fig. 3 shows that the return rate will increase with the threshold form 0.55 to 0.69 and begin to decrease when the threshold is bigger than 0.7. Therefore, the best choice of the threshold of the trading rules similarity is 0.69.

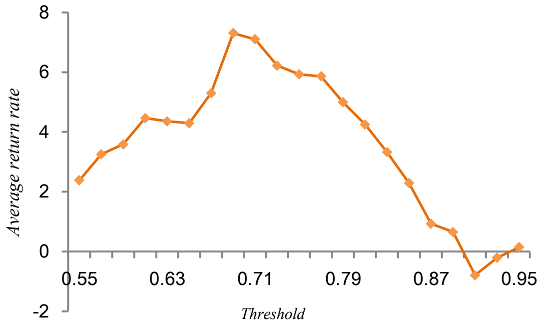

Fig. 3 Average return rates in dynamic training process in different threshold settings. The return rate is the average return rate of best individuals in every step of the dynamic training process in the 8 group of independent experiments. We use this value to check how many basic moving average trading rules to use is better for making more profits.

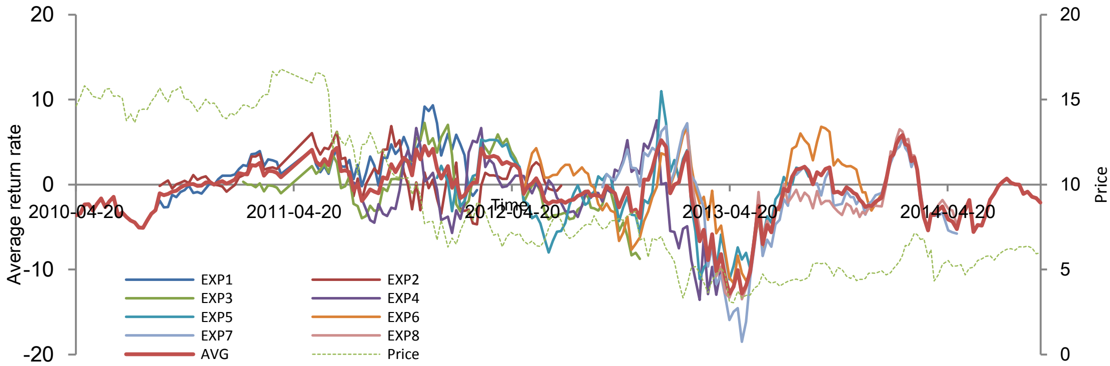

Fig. 4 Trends of return rates in different experiments and the futures price in the same period. We can see that the difference of different experiments is significant from April, 2011 to April 2012. In this year, the futures prices decrease significantly and the trends of price was changed, so it is difficult for the adaptive rules to adjust the weight distributions based on past performance of the basic rules. However, we can see that in other period except this year, the trends of return rates are very consistent and the correlation of return rates in the last two experiments reached 0.94. This proved the trading rules can adjust with the trading process and have adaptability as long as the price doesn't fluctuate significantly.

We compare the average test return rate of two independent experiments. Because the step of choose data is 100 day, two adjacent experiments will have 400 communal test days. We found that adaptive rules in two adjacent experiments with different training data will gain analogous return although the first one is initialed 100 trading days earlier, apart from the special period when price drop significantly. The trends of return rate from different experiments are consistent in long term. This means the trading rules we found have good adaptability to adapt the price changes and can be useful for a relative long time.

We calculated the 50 days average return rate of the generated adaptive in the whole investment cycle. We found that the adaptive rules can help traders make profits when the price is relative stable but will lose effectiveness when price experience significant fluctuations. When price decrease significantly, the return rate of our adaptive trading rules will decrease soon afterwards. When the price experiences a stable period after decreasing, the return rate will stop declining and begin to increase. So decreases of price will be important messages to help traders to reduce risk. They should prepare to close or change positions.

4. Conclusion

In this paper, we proposed an approach to search for adaptive technical trading rules using PSO process in the EUA Futures Market. We designed a new method to select basic trading rules when making decision with the results of a group rules. We have the conclusion that it is better not to use two basic trading rules giving the same investment advice at more than 70 percent of the trading days. This result can help choosing trading rules sets. Based on our results, the generated adaptive trading rules can adapt to price change and can make profits when the price is relative stable. This approach is helpful for traders in making decision although we have no enough evidence to prove the technical analysis can always help traders make profits in long term.

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