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Selecting dynamic moving average trading rules in the crude oil futures market using a genetic approach ☆

Lijun Wang [a,b], Haizhong An [a,b,c,*], Xiaojia Liu [a,b], Xuan Huang [a,b]

[a] School of Humanities and Economic Management, China University of Geosciences, Beijing 100083, China
[b] Key Laboratory of Carrying Capacity Assessment for Resource and Environment, Ministry of Land and Resources, Beijing 100083, China
[c] Lab of Resources and Environmental Management, China University of Geosciences, Beijing 100083, China

HIGHLIGHTS

- We select trading rules in crude oil futures market using genetic algorithms.
- The rules can be adjusted dynamically based on the performance of reference rules.
- Trading rules generated by this approach can make profits in actual investments.
- They are more favorable for traders than static moving average trading rules.
- Investment advices are given out for traders in applications based on our findings.

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ABSTRACT

Strategies to increase profit from investments in crude oil futures markets are an important issue for investors in energy finance. This paper proposes an approach to generate dynamic moving average trading rules in crude oil futures markets. An adaptive moving average calculation is used to better describe the fluctuations, and trading rules can be adjusted dynamically in the investment period based on the performance of four reference rules. We use genetic algorithms to select optimal dynamic moving average trading rules from a large set of possible parameters. Our results indicate that dynamic trading rules can help traders make profit in the crude oil futures market and are more effective than the BH strategy in the price decrease process. Moreover, dynamic moving average trading rules are more favorable to traders than static trading rules, and the advantage becomes more obvious over long investment cycles. The lengths of the two periods of dynamic moving average trading rules are closely associated with price volatility. The dynamic trading rules will have outstanding performance when market is shocked by significant energy related events. Investment advices are given out and these advices are helpful for traders when choosing technical trading rules in actual investments.

1. Introduction

Crude oil is the foundation of a nation's economic development. With the process of globalization and financialization, crude oil is regarded as an important financial asset, not only a commodity [1]. Crude oil futures market plays an essential role in financial market. Investors normally make investment decisions in crude oil futures market based on their prediction of oil prices fluctuation trends [2]. Scholars use different methods [3], such as neural networks and genetic algorithms [4–6], multiple linear regression [7], support vector machine [8,9], and wavelet analysis [10] to forecast the oil prices in different markets. Integrated intelligent methods combining several algorithms [11–13] are often used. Analyses of the crude oil futures markets are receiving more and more attentions. People try different ways to find some valuable information in the crude oil market by technical analysis to help traders making investment decisions [14,15]. To find useful information for investment, scholars in this field studied the efficiency of the crude oil futures markets [16,17], the correlations between crude oil price and other finical assets [18,19], factors affecting

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* Corresponding author at: School of Humanities and Economic Management, China University of Geosciences, Beijing 100083, China. Tel.: +86 1082323783.
E-mail address: ahz369@163.com (H. An).

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the price changes [20–22], crude oil price movement features [23], and the price discovery in the energy market [24,25]. The results of these exiting studies prove that there are some useful information could be found by technical analysis in the crude oil futures market. A small profit opportunity or useful finding will make significant value because the crude oil futures market is so important and massive. Considering the complexity of the crude oil markets and the high investment risk in futures markets, strategies for increasing profit in the crude oil futures market is no doubt a crucial issue for investors. It is also an important issue to be addressed in academia. This problem has received increasing attention in the energy finance literature in recent years [26,27]. In this paper, we propose a new approach to identify optimal dynamic moving average trading rules to help traders make investment decisions in the crude oil futures market. Technical analysis is a useful tool for price forecasting and decision support in financial markets. Technical indicators have been applied to various financial markets, i.e., stock markets [28,29], exchange markets [30,31], and futures markets [32–34], to describe the price features or to forecast price trends. Among these indicators, moving averages are the most popular indicators widely used in trading strategy optimization for financial markets [35–40] because they can help predict the price changes and are easy to implement with actual investments. Traders use two moving averages of different lengths to forecast the price trends. This paper chooses moving average indicators as the basic indicators to describe the price changes of crude oil futures markets and to inform trading decisions.

Most existing studies in energy finance use static moving average trading rules [27,41–43]. However, static moving average trading rules have some drawbacks. First, the simple average price for a period, which is always used in these studies, cannot describe price fluctuations within a period, and these fluctuations are important to consider when making trading decisions. Furthermore, static moving average trading rules use fixed parameters regardless of price changes during all investment periods. In a continuous investment cycle, the price trends may change significantly and the parameter settings, which are determined in the beginning of the investment period, may be unsuitable as a result. Some studies find that the moving average rules are helpless in actual applications [30,44]. It is most likely caused by the drawbacks mentioned above.

To address these limitations, we designed dynamic moving average trading rules for the crude oil futures markets through improving the static moving average trading rules in two aspects. First, we improved the method used to calculate moving averages. We use adaptive moving averages in this paper, which can reflect differences in price volatilities during the calculation period. Adaptive moving averages can change the weights of prices to reflect price volatility in the calculation period. This calculation method can forecast price more accurately compared with simple moving averages because it will increase the weights of last days of the calculation period when the prices fluctuate more violently [45]. Another improvement is the use of dynamic trading rules in the crude oil futures markets. Dynamic trading rules can change to reflect recent performance, as opposed to fixed parameters, which are set regardless of any changes in price. Similar studies that have considered other financial markets have proven that variable rules can help traders make decisions more scientifically and that dynamic rules are increasingly used in technical analysis [46–50]. In this paper, reference rules are used to modify moving average trading rules during an investment period. The performances of both the current moving average trading rule and the reference rules will be evaluated several times in a continuous investment period and the current trading rules will be improved based on the best reference rules in the subsequent sub period. Thus, the trading rules will adapt to changes in price and offer better investment advice. Through the above two modifications, our dynamic moving average trading rules will have the ability to describe price fluctuations in both the moving average period and the investment period.

The lengths of the two moving average periods, the frequency and extent of dynamic adjustment are important parameters of our dynamic moving average trading rule in the crude oil futures market. There are many options for these parameters, and we have to use some algorithms to determine the best choice. Optimization methods such as artificial neural networks [27,51,52], particle swarm optimization [53–56], and genetic algorithms [32,57–59] have been applied to a selection of technical trading rules in different financial markets in the existing studies. Artificial neural network can be used to find a solution without understanding the inner relationships of the factors totally because it is a black-box approach that is "data-driven and model-free" [60]. Genetic algorithms can identify the optimal solutions among a large set of feasible solutions [61]. In our paper, we want to find out the best parameter settings of the dynamic trading rules. The structure of the trading rules has been determined before the selection process. We just need to find out suitable values of the parameters. For this problem, "one advantage of GAs over NNs is the GA's ability to output comprehensible rules" [62]. Therefore, we use genetic algorithms to select the optimal period lengths, adjustment frequency, and adjustment volume of moving average trading rules in the crude oil futures market. Particle swarm optimization is a method to fine the optimal solution through iteration. Here we reference the evolutionary approach of particle swarm optimization when design the structure of the dynamic trading rules.

To verify whether our dynamic trading rules effectively help traders make profit in crude oil futures markets, we compared our dynamic trading rules with the Buy-and-Hold (BH) strategy and with static moving average trading rules. The performance of each type of rules is analyzed under different market circumstances and the results can inform investment strategies under different price fluctuation patterns.

In summary, this paper focuses on selecting optimal moving average trading rules in the crude oil futures market. We designed a type of "dynamic" moving average trading rules which can adapt market changes through self-adjustment. Genetic algorithms are used to find the best parameter settings of our dynamic trading rules. The results prove that this approach is helpful for investors to make profits in actual applications. Investment advices about when and how to use moving average trading rules in different circumstances are given out for traders according to our findings.

The remainder of this paper is organized as follows. Section 2 describes the methods and data used to identify optimal moving average trading rules in the crude oil futures market. Section 3 presents the experimental results. Section 4 discusses the experimental results, and Section 5 concludes this paper.

2. Methods

2.1. Structure of dynamic rules

Traders use many types of technical indicators in different financial markets, including maximum price, minimum price, rate of price change, and average price. It is recognized that mathematical indicators of past prices can be used to predict the price trends and help make investment decisions [63,64]. For the crude oil futures market, we also can use technical indicators to help make investment decisions through predict the price trends using history data. In this paper, two moving averages, for two different periods, are used to establish our moving average trading rules. Moving average trading rules inform investment decisions by comparing the average price during a short period with the average price during a long period. Short period averages are more sensitive to price changes than are long period averages, so a long position is taken when the short period average price is higher than the long period average price. A short position is taken when the short period moving average price is lower than that of the long period.

Six calculation methods can be used for moving average trading rules. These include simple moving average (SMA), weighted moving average (WMA), exponential moving average (EMA), typical price moving average (TPMA), triangular moving average (TMA) and adaptive moving average (AMA) [45]. SMA is the mean value of the prices in the calculation period. WMA is a weighted average of the prices, and the weight distribution follows a linear decreasing process from the newest value to the oldest one. EMA is the sum value of weighted price, whose price weights follow exponential distribution. For TPMA, the result is the mean of three typical values: the maximum, the minimum and the last day's price during the calculation period. TMA is the simple moving average of the simple moving average prices, which ignores more information in short time scales. AMA is an improvement of EMA, which can change the weight distribution according to the price changes.

Among the six calculation methods, AMA is the most complex. However, AMA can describe more price features than the other methods can [65,66]. AMA is proposed by Perry Kaufman in its book "Smarter Trading" [67]. The result of AMA is associated with the trends and fluctuations of the price in the calculation period. Two periods having the same mean price may have different AMA values. AMA is similar to EMA, and both methods stress the importance of prices near the decision day. Current value is calculated as the weighted sum of the previous value and the price on the last day in the moving average period. However, EMA uses the same weight distributions, which are always fixed, whereas for AMA, the weight of the last day's price is determined by the fluctuations over the whole calculation period.

Using AMA, the moving average price of an n-day period at time t is

$$\mathrm{AMA}(t) = \mathrm{AMA}(t-1) + \mathrm{SSC}_t^2(p_t - \mathrm{AMA}(t-1)) \tag{1}$$

where

$$\begin{aligned} &\mathrm{SSC}_t = \mathrm{ER}_t(\mathrm{fastSC} - \mathrm{slowSC}) + \mathrm{slowSC}, \\ &\mathrm{fastSC} = 2/(1+2),\ \mathrm{slowSC} = 2/(1+30), \\ &\mathrm{ER}_t = |p_{t-1} - p_{t-n}| \Big/ \sum_{i=t-n+1}^{t-1} |p_i - p_{i-1}|. \end{aligned} \tag{2}$$

where p denotes the daily price. According to Eq. (2), the weight of the last day's price will be higher when the price experiences smaller fluctuations, and when the fluctuation is significant, the weight of the last day's price will be very low. AMA will be more sensitive when price shows certain trend and less sensitive when price experiences obvious shocks. Therefore, AMA performs better in reducing the impact of random fluctuations in the price and discovering price trends than the other methods.

The selection of the two periods influences the performance of moving average trading rules significantly. Therefore, we use genetic algorithms to determine the optimal period selections. In addition to the two moving average periods, our dynamic moving average trading rules contain three other parameters, which are also generated by genetic algorithms. Two of the additional parameters determine the selection of reference rules, and the other one decides the frequency of self-assessment and modification.

We use a 19-binary string to denote dynamic trading rules in this paper, which can define all parameters of the dynamic moving average trading rules. The structure of a single dynamic moving average trading rule is shown in Fig. 1.

Four reference trading rules are used to adjust the length of the moving average period associated with current trading rules. Each reference rule changes the length of one period associated with the current rule, implying a longer or shorter moving average period. At the end of every evaluation cycle during the investment period, the performance of the four reference rules and the current rules will be evaluated. If the best rule is one of the reference rules, the current trading rules will be replaced. Our moving average trading rules can adapt to price changes dynamically through this adjustment mechanism. The idea for the mechanism comes from particle swarm optimization methods [54,68]. Thus, the moving average trading rules can have the adaptability to conduct self-modification during an investment cycle. We do not need to use a large number of reference rules in this case for two reasons. First, the trading rules are selected with genetic algorithms at the beginning of the investment period. Second, the four reference rules lengthen or shorten the two moving average calculation periods. This combination is sufficient to account for short-term price changes, and we therefore choose this method for its simplicity.

Based on the above description, we can obtain the position strategies of a dynamic trading rule on every trading day in the whole investment period. The positions in the first *ADT* days are determined by the initial moving average trading rules and the positions in the following days will be specified by the newest adjusted rules in every *ADT* days.

2.2. Selecting process

We use genetic algorithms to select the parameters of the dynamic moving average trading rules. Genetic algorithms, proposed by Holland [61], use a way that resembles a natural selection to find the optimal solutions among large optional set. The goal is achieved through a series of cyclic operations including evaluation, selection, crossover, mutation and reevaluation. In respect to the trading rules in the crude oil futures markets, the individuals represent the parameters sets of the dynamic trading rules. Through the optimization process based on genetic algorithms, we can find out the optimal trading rules for the crude oil futures market.

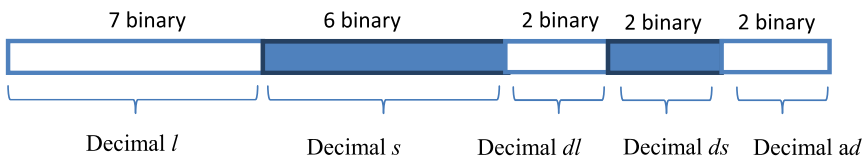
During the optimization process, each rule must be evaluated at the end of every generation to facilitate the selection of the outstanding rules that will comprise the next generation. According to AK's method [69], we use the return rate of the moving average trading rules to evaluate the rules in the generating process. However, we used the rate of return instead of the excess rate of return for the BH strategy, which AK used in their study.

The equation to calculate a trading rule's rate of return in a given investment period is

$$\begin{aligned} &R = R_l + R_s + R_f \\ &R_l = \sum_{i=1}^{n}((P_{\text{out}} - P_{\text{in}})/P_{\text{in}} * (1-c)/(1+c))/R_m \\ &R_s = \sum_{i=1}^{m}((P_{\text{in}} - P_{\text{out}})/P_{\text{in}} * (1-c)/(1+c))/R_m \end{aligned} \tag{3}$$

where R is the rate of return; specifically, it is the sum of the returns for the long positions and short positions in the evaluation period. R_f is the risk free rate of return outside the market. R_m is the margin ratio for 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. P_{begin} is the price on the first day of a period, and P_{end} is the price on the last day.

Through nonlinear conversion, the return rates of moving average trading rules are transformed to a number between 0 and *sp* according to



Short period: N=s+4 (4~67) Long period: M=N+l+10 (14-204)

Change of short period: DM=dl+1 (1, 2, 3, 4) Change of long period: DN=ds+2 (2, 3, 4, 5)

Adjustment frequency: ADT=20+ad*20 (20, 40, 60, 80 days)
Each string represents a dynamic moving average trading rule: *DR* (*M, N, DM, DN, ADT*).
The initial main rule is *SR(M+DM, N)*, which indicates a long moving average period of *M* days and a short period of *N* days. The four reference rules are：*SR*(*M+DM, N*), *SR*(*M-DM, N*), *SR*(*M, N+DN*), *SR*(*M, N-DN*). The initial rule will be replaced by the best reference rule every *ADT* days if it is not the one having the best performance in the last evaluation cycle (*ADT* days), and the reference trading rules will also update according to new main rule.

Fig. 1. Structure of the dynamic moving average trading rule.

$$\mathrm{Fitn}V(r) = \frac{Pop * X^{r-1}}{\sum_{i=1}^{Pop} X(i)} \quad (4)$$

where X is computed as the root of the polynomial:

$$(sp-1) * X^{Pop-1} + sp * X^{Pop-2} + \cdots + sp * X + sp = 0, \quad (5)$$

Pop is the population size. *sp* is *A* fitness value is then assigned to each individual depending on its ascending order, *r*, in the sorted population [70]. When a nonlinear function is used, the fitness values will display hill-climbing tendencies [71].

To select the best moving average trading rules, a generating process is conducted. Fig. 2 shows the process of using genetic algorithms to select the optimal dynamic trading rules in the crude oil futures market (see Fig. 3 for details about the sample data we used in the select process).

An initial population of 20 individual rules is randomly created, where each rule represents a moving average trading rule.

In each generation, the fitness of every rule is evaluated, and the best rule is selected. To evaluate the rules, the return rate is calculated for each rule, and the fitness value is calculated according to the return rate. The rule with the highest fitness value is selected and evaluated during the selection period. This second evaluation is necessary to avoid over fitting the training data. Only when the selected rule performs well in the selection period can the trading rule be marked as the best rule so far. If the selected rule does not perform well during the selection period, the best rule from the prior generation is retained as the best trading rule.

Then, a new population is generated through selection, crossover, and mutation operations. Ninety percent of the individual rules are selected according to their fitness values; the same rule could be selected more than once. Rules with higher fitness values have higher probabilities of being selected. The remaining two trading rules are randomly generated to avoid rapid convergence of the generation process. With a probability of 0.7, a recombination operation is performed to generate a new population. Finally, all of the recombination rules are mutated with a probability of 0.05.

The evolution process ends with the 60th generation. The best trading rule identified by the above program is then tested in the test period, which determines the rate of return and indicates whether the genetic algorithm is able to identify optimal moving average trading rules in this sample period.

The optimization process described above is implemented into a program using Sheffield's GA toolbox in Matlab [72]. In the selection process, parameter settings affect the result of the optimization. We use a crossover rate of 0.7 and a mutation rate of 0.01 with considering the settings of existing studies [73–75] as well as the optimization problem in this paper. The number of generations is 60 because the algorithm will converge within 60 generations with a population of 20 individuals based on our experiments. The transaction cost rate is set to 0.1%, which is an intermediate value according to previous studies [33,69,76]. The risk free rate of return is 2%, based primarily on the rate of return for short-term treasury bonds [77]. In this paper, we assume the margin ratio to be 0.05. However, the margin ratio has no influence on our experimental results or the selection of the best moving average trading rules because we use a simplified rate of return to evaluate the performance of a trading rule.

2.3. Sample data

We use daily prices of crude oil future contracts from the New York Mercantile Exchange. The original data are available from the website of the U.S. Energy Information Administration: http://www.eia.gov/dnav/pet/pet_pri_fut_s1_d.htm. The data we used in this paper is from 1983 to 2014, which contains all the historical data of the target crude oil futures market. Prices on daily frequency are suitable for conducting technical analysis based on our previous study [78], and they are selected by studies on different financial markets [33,57,77], including the crude oil futures market [27].

We use three periods of daily prices for each experiment. Of the three continuous periods of daily prices, we used the first period to run the trading rules in every generation. Prices from the second period were used to examine the best rule from every generation, and prices from the last series were used to test whether the best rules could help traders earn profit in the crude oil futures market. We also need 250 additional daily prices prior to each sample series to calculate the moving averages for the sample period. The lengths of the three periods were determined by the following experiments. Fig. 3 shows the selection method of the experimental data in this paper.

2.4. Experiments

Three group experiments were conducted to evaluate the performance of our moving average trading rules. The number of individual experiments that can be conducted is determined by the step value. Details of the three group experiments are presented in Table 1.

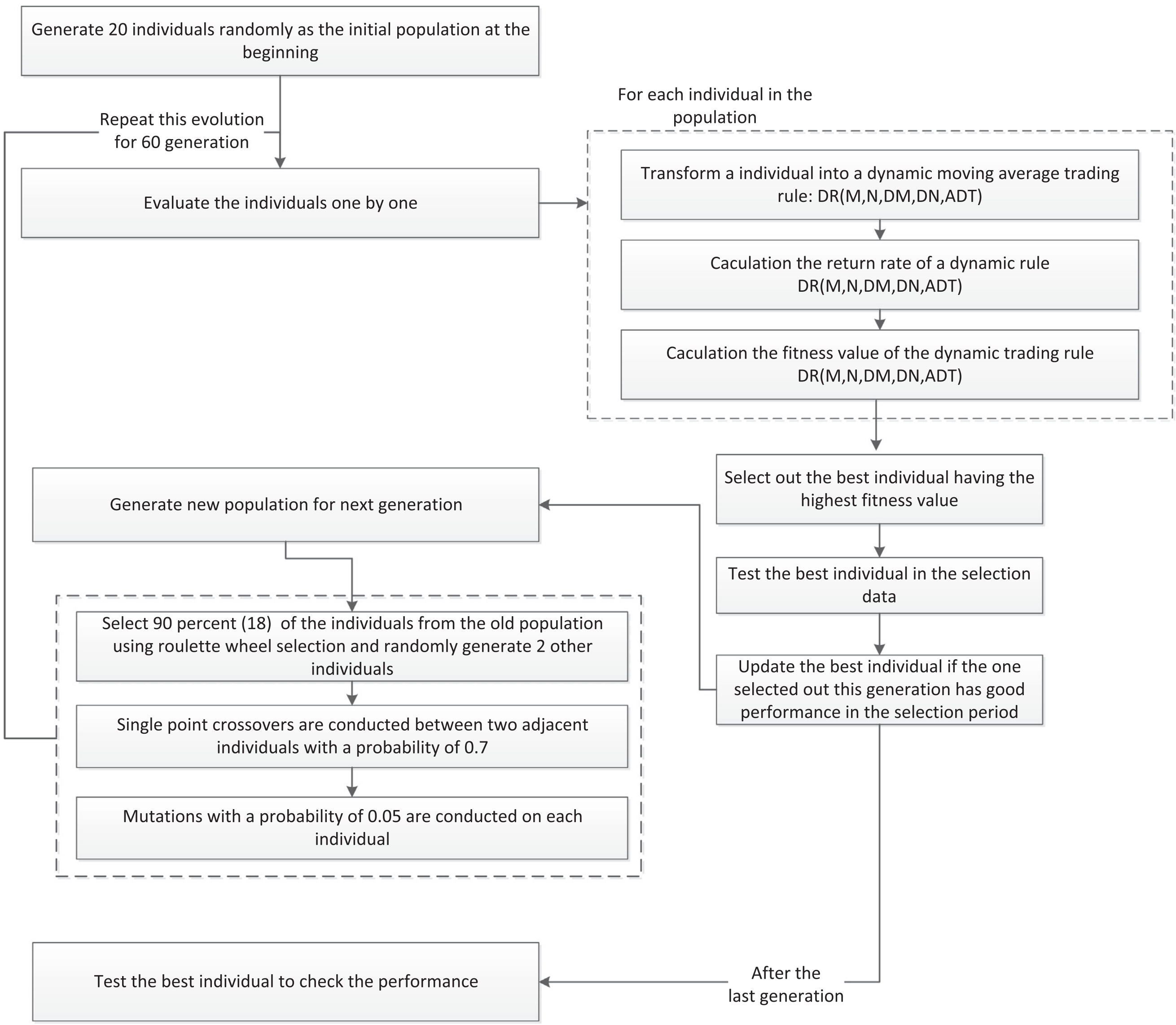


Fig. 2. Implement process of the GA based dynamic trading rules optimization.

The first group (Group A) contains 540 independent experiments. We use prices from a single year to run, select, and test the rules. With a step of one year, dynamic moving average trading rules identified by our generated approach are tested in 27 years from 1987 and 2013. The experiment is repeated 20 times for stable results. The first group of experiments is conducted to test the overall performance of the dynamic moving average trading rules in the crude oil futures market. Group B is similar to Group A. For Group B, however, we extend the test period from one to two years. This extended test periods enables us to examine the long-term performance of the dynamic moving average trading rules. Only 26 periods can be used for Group B because of the change in test period. Group C contains 661 independent experiments. Unlike the analysis of Group A, for Group C, a step of 10 days was used to analyze the change of moving average trading rules over the entire period.

3. Results

In the 27 years from 1987 to 2013, the dynamic moving average trading rules earn an average return of 2.90. The average rate of return in each of the 27 years is shown in Table 2. From the table, we can see that the dynamic moving average trading rules earned profit in 19 of the 27 years, or in 70% of the years. The dynamic moving average trading rules earn the highest rate of return in 2008 and lowest rate of return in 1996. There are eight years (1989, 1998, 1999, 2001, 2004, 2007, 2008, and 2009) in which all 20 of the experiments earn profit. Overall, the dynamic moving average trading rules can help traders earn some amount of profit in actual crude oil futures markets.

The BH strategy is a traditional benchmark strategy in financial analysis. To test the performance of the dynamic moving average trading rules and identify the suitable market environments in which the dynamic moving average trading rules can be used, the trading rules generated by our optimization process are compared with the BH strategy.

From these results, we found the relative performance of the dynamic trading rules and the BH strategy depends significantly upon price trends and fluctuations. When price decreases in the test period (Fig. 5(1)), the dynamic trading rules perform much better than the BH strategy. Under these circumstances, price experiences an obvious decrease and there is no doubt the BH

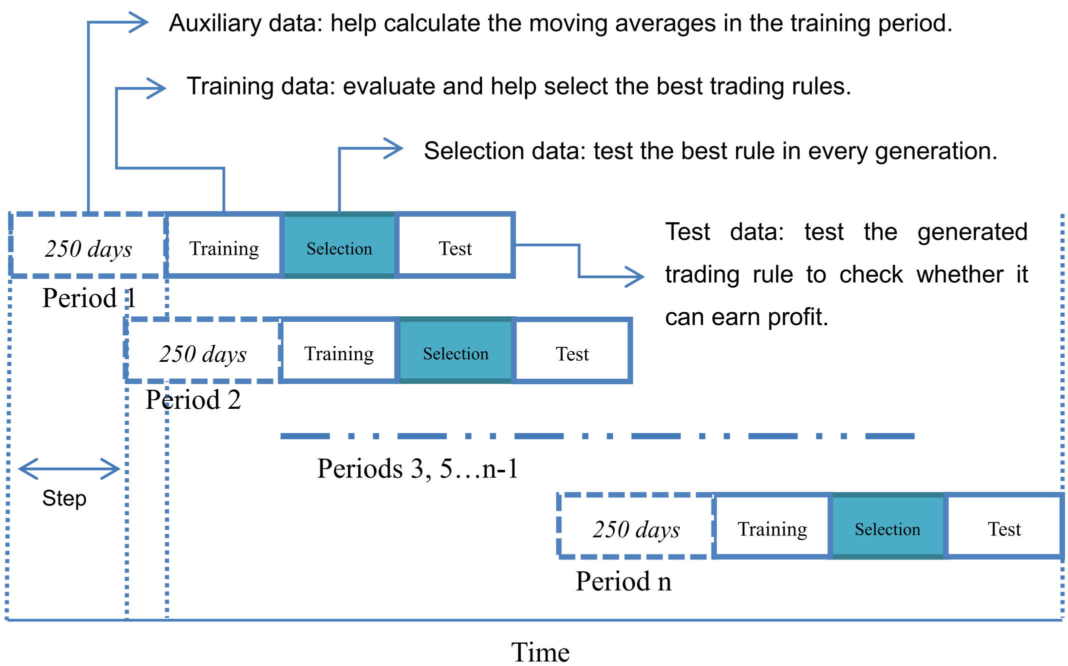


Fig. 3. Sample data.

Table 1
Details of three group experiments.

Group	Training (days)	Selection (days)	Test (days)	Step (days)	Periods	Repetition (s)	Numbers
A	250	250	250	250	27	20	540
B	250	250	500	250	26	20	520
C	250	250	250	10	661	1	661

Table 2
Experimental results of Group A.

Year	*AVR*	*Count*	Year	*AVR*	*Count*
1987	1.48792	17	2001	5.613634	**20**
1988	−2.18863	1	2002	−0.34003	15
1989	3.85482	**20**	2003	1.977476	14
1990	1.399265	14	2004	5.682188	**20**
1991	4.760458	19	2005	8.315967	19
1992	1.450937	18	2006	−1.10354	2
1993	2.611131	19	2007	8.12761	**20**
1994	0.773607	13	2008	13.9974	**20**
1995	−3.60432	0	2009	10.33538	**20**
1996	−3.97467	1	2010	0.176301	9
1997	−0.75597	11	2011	0.407526	14
1998	5.225746	**20**	2012	−0.86027	3
1999	16.24977	**20**	2013	−2.423	2
2000	1.013608	13	Average	2.896678	

Note: *AVR* is the average return rate of the 20 experiments in the same year, and *Count* denotes the number of times the dynamic trading rules earn profit in the 20 trials. The bold numbers are marked to stress the years in which the generated dynamic trading rules performed well and made profits in all the independent experiments.

strategy will lead to a loss. The dynamic moving average trading rules earned an average return rate of 3.73 in the nine years shown in Fig. 4(1).

In contrast, when price experiences significant fluctuations, the dynamic trading rules perform poorly. In other 6 years (Fig. 4(2)), the dynamic trading rules perform worse than BH strategy and earn negative returns. Obvious price fluctuations occur in these years (Fig. 5(2)) and it is too difficult for the dynamic moving average trading rules to discover the price trends under these circumstances. In the remaining 12 periods, the dynamic trading rules earn profits but do not earn higher returns than the BH strategy. This means the dynamic trading rules is not suitable when the markets fluctuate violently and show no tendencies.

The performance of static moving average trading rules and dynamic trading rules are compared in this paper. No rules are suitable for all market circumstances, so it is meaningless to analyze and compare the two types of moving average trading rules in all circumstances. A trader will only use moving average trading rules when they perform better than the BH strategy. Therefore, we compare the profitability of static moving average trading rules and dynamic moving trading rules in the periods in which the moving average trading rules performed better than the BH strategy. For the periods in which the BH strategy is not the optimal choice, the dynamic of moving average trading rules perform better than static trading rules generated by the same process described in this paper for a one-year test period. However, the

Table 3
Rate of return for three investment strategies in 11 periods of Group B.

Periods	Static rules	Dynamic rules	BH strategy
1987–1988	−0.22679	−0.73378	−1.67343
1990–1991	7.651661	2.509302	−1.72506
1991–1992	3.913348	5.820859	−5.52134
1992–1993	2.127767	4.830968	−5.01317
1993–1994	0.327576	1.830109	−2.14873
1997–1998	4.312154	3.234756	−10.1678
1998–1999	9.480217	10.2056	8.542085
2000–2001	−4.86669	3.16072	−5.97583
2001–2002	0.605262	1.697453	−1.32614
2007–2008	14.73163	17.1015	−5.74376
2008–2009	8.219904	8.484867	−4.00089
Average	4.206913	5.285669	−3.15946

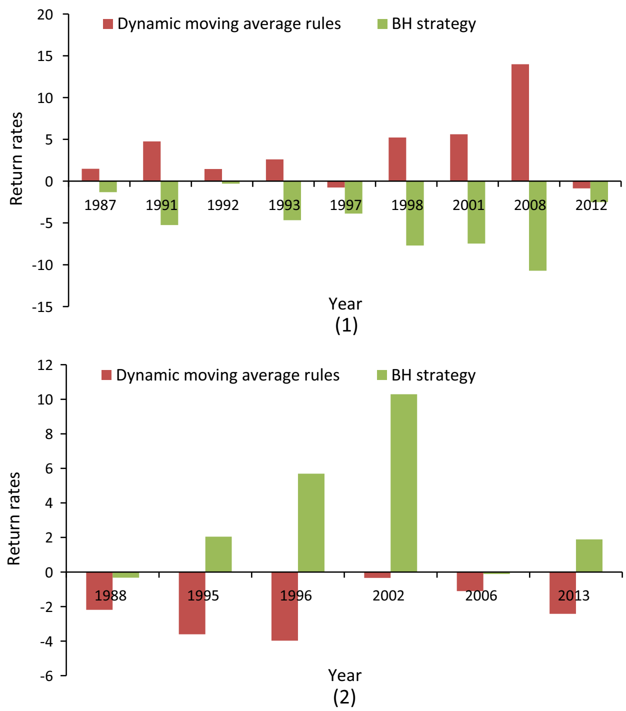


Fig. 4. Comparison of the dynamic trading rules and the BH strategy. (1) The BH strategy failed to earn profit, but the dynamic moving average trading rules performed well. (2) The dynamic moving average trading rules gained negative returns.

advantage of dynamic trading rules is not obvious. In the nine years in which the BH strategy performed worse than the moving average rules (1987, 1991 1992, 1993, 1997, 1998, 2001, 2008, 2012) the dynamic moving average trading rules earn an average rate of return of 3.73, 4.19% higher than the average rate of return of the static moving average trading rules (3.58). This result proves that the dynamic moving average trading rules are better than static ones in actual applications.

The Group B experiments were conducted to evaluate performance of the dynamic moving average trading rules over long investment periods. When the test period is two years, the advantage of the dynamic trading rules becomes obvious. Table 3 shows the return rates for all three strategies for 11 years in which the BH strategy earned the lowest rate of return. For the two years investment cycle, the dynamic rules earn an average return that is 25.6% higher than that of the static trading rules, a much larger difference than was observed in the one year investment cycle. Using dynamic moving average trading rules, the lengths of the two moving average periods could be adjusted dynamically during the investment cycle to adapt new circumstances. Thus, the investors can foresee the prices changes timely, making decisions more scientifically.

From the results of Group C, we can find that the lengths of the moving average periods of the dynamic moving average trading rules are closely related to price volatilities. We use the stand deviation of a processed series, the difference between the current price and the 10-day moving average price, to describe the price volatility. Fig. 6 shows that the values of M (long moving average period) and N (short moving average period) change over time. Fig. 6 shows when market volatility increases, the length of the long moving average period decreases. When market volatility stops increasing or begins decreasing, the length of the long moving average period stops decreasing. If market volatility remains low compared with previous days, the length of the long period will increase. The length of the short moving average period also shows similar features. Its length is greater when price fluctuations are not obvious and lower when market volatility is high. However, the length of the short period is more random than that of the long period. Overall, when price trends are steady, longer moving average periods are selected. Traders prefer to understand the overall trend of the market when the market is stable. When price fluctuations are significant, shorter moving average periods are selected. This is because rapid response to market volatilities is more important for making decisions in these situations.

Apart from the statistical results mentioned above, we also found that the performances of the dynamic trading rules show some correlations with some major energy-related events in history. In the 8 years (see Table 2) dynamic trading rules performed abnormally well, we can see the market prices experience significant changes in these years. Coincidentally, almost all these years just underwent some major energy events. In 1990–1991, the outbreak of the Gulf War volatized the crude oil market. The crude oil price also experienced a decreasing process during the Asian financial crisis. The internet bubble event occurred in 2001 and the crude oil price decreased in this year. After the Iraq war, the crude oil markets increasing rapidly and our results show the generated trading rules also have abnormal performance. During 2007–2009, the crude oil price experienced a roller coaster because of the financial crisis. In these years mentioned above, we found that the dynamic moving average performed excellently. The temporal correlation between these events and the performance of technical trading rules can give investors some information on choosing trading strategies. There will be more profit opportunities using dynamic moving average trading rules when the market is shocked by some external factors and experience obvious changing process.

4. Discussion

We designed dynamic moving average trading rules in the crude oil futures market and use genetic algorithms to identify the optimal parameters for these rules, thereby demonstrating an approach to select moving average trading rules. The results show that the dynamic moving average trading rules generated by our evolution process can help traders earn profit in crude oil futures markets.

According to the experimental results, the dynamic moving averages trading rules perform best when prices trend down without significant fluctuations. When prices decrease the BH strategy will clearly earn negative returns, but dynamic moving average trading rules can discover the downward price trend and earn profit by taking short positions. However, the dynamic trading rules performed poorly during significant price fluctuations with no obvious trends. When price fluctuates quickly, it is difficult for moving average trading rules to discover the price trends. Prediction of price changes from moving averages always lags behind market price changes. Therefore, when moving average trading rules perceive increases or decreases in price, the price has already changed, which may not conform to the prediction. Therefore, dynamic trading rules cannot help traders earn profits during period of high volatility. In fact, during these circumstances, any trading strategy other than the BH strategy cannot reliably earn profit. Although we have no proof that dynamic moving average trading rules can earn more profit than the BH strategy overall, we still believe the dynamic trading rules are helpful for traders in certain circumstances.

The advantage of dynamic moving average trading rules is more obvious for long-term investments. This is true because dynamic trading rules can change the length of moving average periods, adapting to changes in price. For long-term investments, price trends and the level of volatility are likely to change over time. The original static trading rule may be not suitable in the new

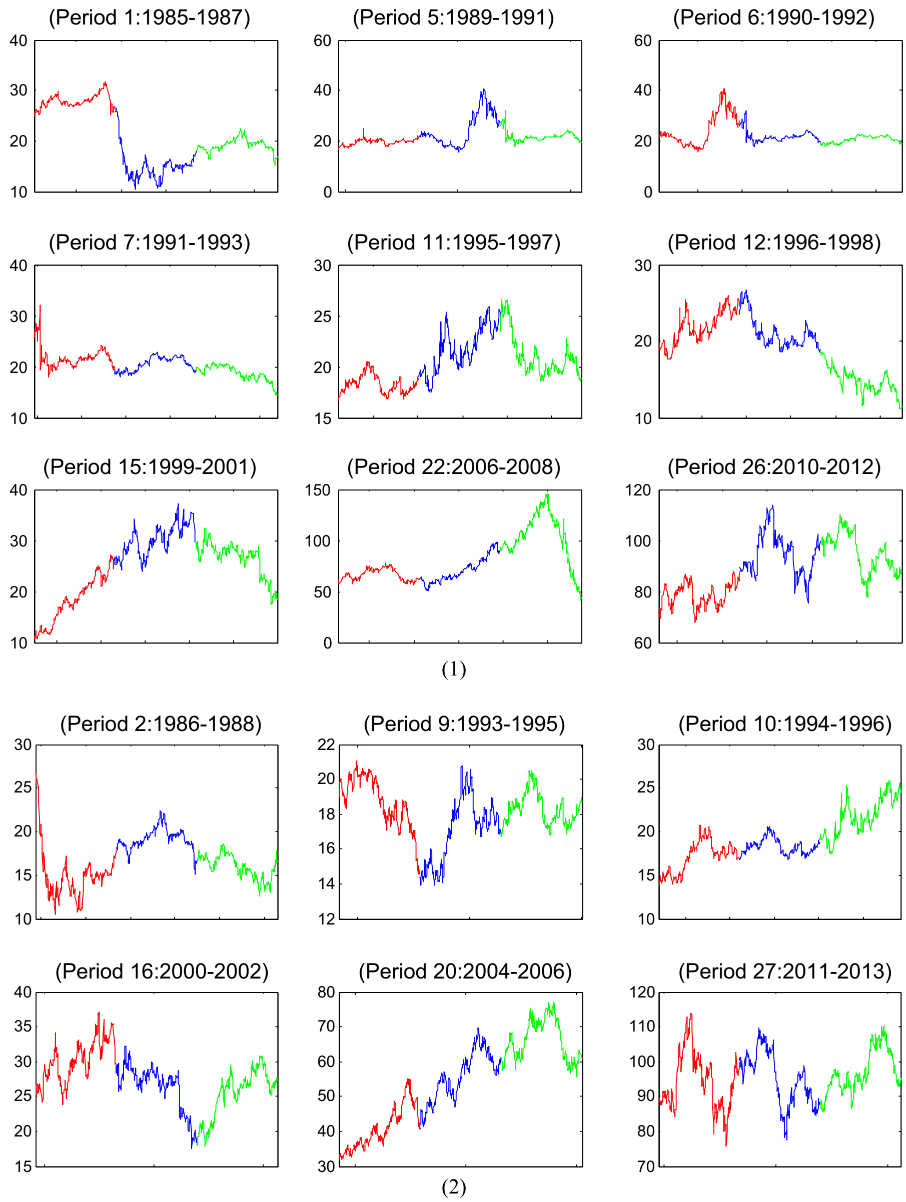


Fig. 5. Price trends. (1) Price trends when dynamic trading rules perform better than BH strategy. (2) Price trends when dynamic trading rules perform poorly.

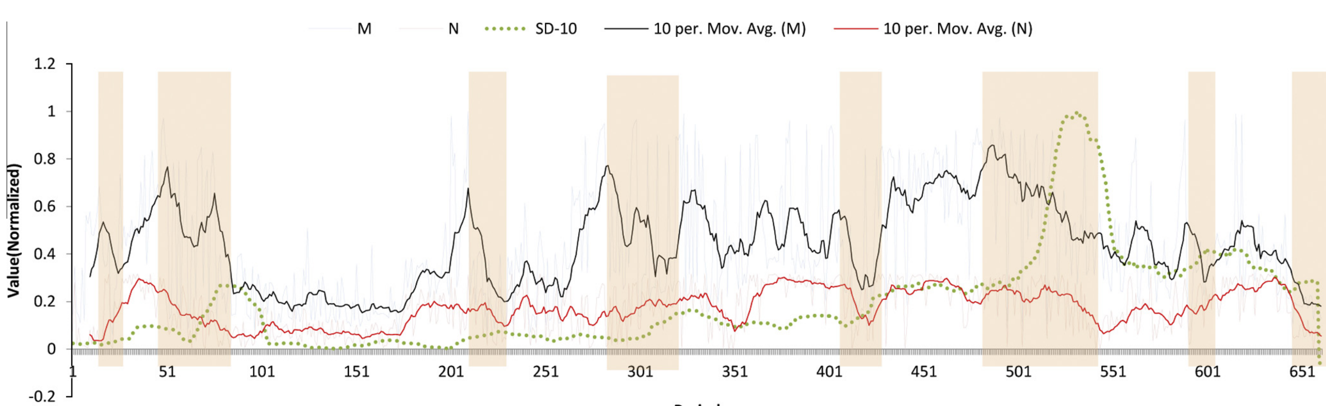


Fig. 6. Evolution of market volatility and periods lengths of the moving average rules. The values in the 661 experiment periods are normalized to compare their trends. *M* shows the trends of the long moving average period and *N* shows the trend of the short moving average period. SD-10 is the stand deviation of a processed price series, which is equal to the difference between the initial price and a 10 day moving average price. In addition, 10 period moving averages of *M* and *N* are used to illustrate the trends of these two parameters.

market environment. Therefore, the dynamic trading rules perform much better than static trading rules in these circumstances.

From the 661 experiments in Group B, we observed that the choice of moving average period length is closely related to market volatility, a fact that may be useful for traders when deciding whether and how to use moving average trading rules in crude oil future markets. In particular, shorter moving average periods are associated with higher market volatility.

From 28 years (1987–2014) of data, a total of 661 different price series were selected to generate the best dynamic moving average trading rules using algorithms. We can see that the lengths of the two moving average period change continuously and have obvious differences in different periods. This indicates that using genetic algorithms to identify the optimal settings of the two periods is necessary. It is impossible and infeasible to use fixed moving average periods in all circumstances, such as by using an average or intermediate value.

We can discern some general rules regarding the lengths selection of the two moving average periods from our results. We found that the lengths of the periods are associated with price volatility. Short moving average periods are always used in periods of high volatility. This is because longer moving average periods will eliminate the short-term price trends and a trader will miss many short-term profit opportunities. The shorter the calculation period, the more sensitive the rule will be. It is suggested that traders use short moving average periods to predict price changes when market volatility increases.

The effectiveness of moving average trading rules in different financial markets is discussed widely in the existing studies. The results from different studies may be totally different and different scholars prefer different ways to do quantitative analysis [39,44,79]. It has always been a controversial topic that whether technical analysis can help traders make profits in actual markets. In fact, it is impossible to prove that technical analysis is helpless in all markets or a technical strategy is suitable for all circumstances [80,81]. All that can be done is to test particular rules in a target market, such as the crude oil futures market. We tested the performance of the dynamic moving average trading rules generated by our optimization approach. The results show that the dynamic moving average trading rules performs better than static moving average rules and is helpful for traders. Dynamic adjusting of the moving average trading rules improves the profitability of our rules. Our result can provide traders some reference in certain circumstances. The relationship between the moving average period lengths and the market volatilities revealed by our results is also meaningful for choosing trading rules in the crude oil futures market.

From the results, we found that there are profit opportunities for dynamic moving average rules users in the crude oil futures market. In addition, we also found that a trader will make more profits using our approach in the circumstances when the crude oil futures markets are shocked by some significant energy-related events. When some external factors affect the crude oil price, the market efficiency will be damaged and the market will use a relative long time to rehabilitate a new harmonious market [81]. In the process, technical investors will have more opportunities to earn returns. In other stable periods, there are still some profits can be gained by our approach, indicating that the crude oil futures market disobedience the efficient market hypothesis. This conclusion is also supported by some other studies about the crude oil markets [82–84]. Because the crude oil market is always affected by many factors such as investor's sentiment [85], market factors [86] as well as seasonality [87]. It cannot become an ideal perfectly competitive market in the actual operation. Therefore, we believe the results of this paper will be helpful for actual applications.

In this paper, we use a fixed method to generated reference trading rules. However, a much better approach would consider the current values of moving average periods and the market volatility when choosing reference trading rules. In addition, considering numerous exogenous factors of the crude oil price would be also necessary in our future research.

5. Concluding remarks

We proposed an approach to generate optimal moving average trading rules for crude oil futures markets. Adaptive moving averages are used to predict price trends. The rules are dynamic to respond quickly to price changes within investment periods. We found that this approach can help traders earn profit in crude oil futures markets. When price decreases, dynamic moving average trading rules perform extremely well in comparison to the BH strategy. However, this approach is not applicable during periods of obvious price volatility, when the market is moving sideways.

Dynamic trading rules performed better than static ones. In circumstances when the BH strategy is ineffective, however, we found the dynamic moving average trading rules perform better than static moving average trading rules. Furthermore, the advantage of dynamic moving average trading rules in long investment periods is more dramatic than in short periods. We advocate dynamic trading rules rather than static ones in the crude oil futures markets.

The lengths of the two moving average periods are closely associated with market volatility. The lengths of the moving average periods decrease when price volatility increases. This trend is particularly evident in the long moving average period. Based on this result, we advocate that traders begin using longer moving average trading rules when the market enters a steady period and continue using longer moving average period until market volatility increases. When fluctuations become increasingly significant compared with previous days, shorter moving average periods are more appropriate. Apart from the information of the price trends and fluctuations, attentions to significant external crude-oil-related events are also necessary and helpful for applying technical trading rules.

Above all, we can have the conclusions of this paper. Dynamic trading rules are profitable and perform better than static ones in the crude oil futures market, and adjusting of the moving average periods is necessary for investors to make more profits. We recommend long moving average periods in stable periods and short moving average periods when there are obvious fluctuations in the market. In addition, technical trading rules will have outstanding performance when there are some significant external market shocks. These conclusions could be used for choosing trading strategies in the crude oil futures market.

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References

[1] Kolodziej M, Kaufmann RK, Kulatilaka N, Bicchetti D, Maystre N. Crude oil: commodity or financial asset? Energy Econom 2014;46:216–23.
[2] Gabralla LA, Abraham A. Computational modeling of crude oil price forecasting: a review of two decades of research 2013.
[3] Chiroma H, Abdulkareem S, Abubakar A, Mohammed JU. Computational intelligence techniques with application to crude oil price projection: a literature survey from 2001–2012. Neural Network World 2013;23:523–51.
[4] Panella M, Barcellona F, D'Ecclesia RL. Forecasting energy commodity prices using neural networks. Adv Decis Sci 2012;2012.
[5] Panella M, D'Ecclesia RL, Stack DG, Barcellona F. Crude oil prices and kernel-based models. Int J Financial Eng Risk Manage 2014;1:214–38.
[6] Chiroma H, Abdulkareem S, Herawan T. Evolutionary Neural Network model for West Texas Intermediate crude oil price prediction. Appl Energy 2015;142:266–73.
[7] Shabri A, Samsudin R. Crude oil price forecasting based on hybridizing wavelet multiple linear regression model, particle swarm optimization techniques, and principal component analysis. Sci World J 2014.
[8] Chiroma H, Abdulkareem S, Abubakar AI, Herawan T. Kernel functions for the support vector machine: comparing performances on crude oil price data. In: Recent advances on soft computing and data mining. Springer; 2014. p. 273–81.
[9] Arima GAC. Daily crude oil price forecasting model using arima, generalized autoregressive conditional heteroscedastic and support vector machines. Am J Appl Sci 2014;11:425–32.
[10] Chiroma H, Abdul-Kareem S, Abubakar A, Zeki AM, Usman MJ. Orthogonal wavelet support vector machine for predicting crude oil prices. In: Proceedings of the first international conference on advanced data and information engineering (DaEng-2013). Springer; 2014. p. 193–201.
[11] Shabri A, Samsudin R. Daily crude oil price forecasting using hybridizing wavelet and artificial neural network model. Math Problems Eng 2014.
[12] Gabralla LA, Jammazi R, Abraham A. Oil price prediction using ensemble machine learning 2013.
[13] Chiroma H, Abdulkareem S, Abubakar A, Zeki A, Gital AYu, Usman MJ, et al. Co—Active neuro-fuzzy inference systems model for predicting crude oil price based on OECD inventories. In: 2013 International conference on research and innovation in information systems (Icriis); 2013. p. 232–5.
[14] D'Ecclesia RL, Magrini E, Montalbano P, Triulzi U. Understanding recent oil price dynamics: a novel empirical approach. Energy Econom 2014;46:S7–S11.
[15] Fattouh B, Kilian L, Mahadeva L. The role of speculation in oil markets: what have we learned so far? Energy J 2013;34:7–33.
[16] Wang YD, Wu CF. Efficiency of crude oil futures markets: new evidence from multifractal detrending moving average analysis. Comput Econ 2013;42:393–414.
[17] Zhang B, Li XM, He F. Testing the evolution of crude oil market efficiency: data have the conn. Energy Policy 2014;68:39–52.
[18] Nazlioglu S, Soytas U, Gupta R. Oil prices and financial stress: a volatility spillover analysis. Energy Policy 2015;82:278–88.
[19] Jammazi R. Cross dynamics of oil-stock interactions: a redundant wavelet analysis. Energy 2012;44:750–77.
[20] Kaufmann RK. The role of market fundamentals and speculation in recent price changes for crude oil. Energy Policy 2011;39:105–15.
[21] Kilian L, Murphy DP. The role of inventories and speculative trading in the global market for crude oil. J Appl Economet 2014;29:454–78.
[22] Zhang Y-J. Speculative trading and WTI crude oil futures price movement: an empirical analysis. Appl Energy 2013;107:394–402.
[23] Zhang YJ, Zhang L. Interpreting the crude oil price movements: evidence from the Markov regime switching model. Appl Energy 2015;143:96–109.
[24] Elder J, Miao H, Ramchander S. Price discovery in crude oil futures. Energy Econom 2014;46:S18–27.
[25] Zhang Y-J, Wang Z-Y. Investigating the price discovery and risk transfer functions in the crude oil and gasoline futures markets: some empirical evidence. Appl Energy 2013;104:220–8.
[26] Tehrani R, Khodayar F. A hybrid optimized artificial intelligent model to forecast crude oil using genetic algorithm. Afr J Business Manage 2011;5:13130–5.
[27] Shambora WE, Rossiter R. Are there exploitable inefficiencies in the futures market for oil? Energy Econom 2007;29:18–27.
[28] Zhang YD, Wu LN. Stock market prediction of S&P 500 via combination of improved BCO approach and BP neural network. Expert Syst Appl 2009;36:8849–54.
[29] Mitra SK. How rewarding is technical analysis in the Indian stock market? Quant Finan 2011;11:287–97.
[30] Cialenco I, Protopapadakis A. Do technical trading profits remain in the foreign exchange market? Evidence from 14 currencies. J Int Finan Markets Institutions Money 2011;21:176–206.
[31] Serban AF. Combining mean reversion and momentum trading strategies in foreign exchange markets. J Bank Finance 2010;34:2720–7.
[32] Nakashima T, Yokota Y, Shoji Y, Ishibuchi H. A genetic approach to the design of autonomous agents for futures trading. Artif Life Rob 2007;11:145–8.
[33] Wang J. Trading and hedging in S&P 500 spot and futures markets using genetic programming. J Futures Markets 2000;20:911–42.
[34] Bikbov R, Chernov M. Yield curve and volatility: lessons from eurodollar futures and options. J Finan Econometrics 2011;9:66–105.
[35] Boboc IA, Dinica MC. An algorithm for testing the efficient market hypothesis. PLoS ONE 2013;8:11.
[36] Cheung W, Lam KSK, Yeung HF. Intertemporal profitability and the stability of technical analysis: evidences from the Hong Kong stock exchange. Appl Econ 2011;43:1945–63.
[37] Dewachter H, Lyrio M. The economic value of technical trading rules: a nonparametric utility-based approach. Int J Finan Econom 2005;10:41–62.
[38] Fernandez-Perez A, Fernandez-Rodriguez F, Sosvilla-Rivero S. Exploiting trends in the foreign exchange markets. Appl Econom Lett 2012;19:591–7.
[39] Metghalchi M, Marcucci J, Chang YH. Are moving average trading rules profitable? Evidence from the European stock markets. Appl Econ 2012;44:1539–59.
[40] Neely CJ, Weller PA, Ulrich JM. The adaptive markets hypothesis: evidence from the foreign exchange market. J Finan Quant Anal 2009;44:467–88.
[41] Pavlov V, Hurn S. Testing the profitability of moving-average rules as a portfolio selection strategy. Pacific-Basin Finan J 2012;20:825–42.
[42] Milionis AE, Papanagiotou E. Decomposing the predictive performance of the moving average trading rule of technical analysis: the contribution of linear and non-linear dependencies in stock returns. J Appl Statist 2013;40:2480–94.
[43] Wu Y, Hui X. Research on nonspecific time dynamic VaRModel based on simple moving average trading system. Oper Res Manage Sci 2013;22:177–83.
[44] Nuñez L. Do moving average rules make profits? A study using the Madrid stock market. In: A study using the Madrid stock market (January 26, 2004); 2004.
[45] Wang LJ, An HZ, Xia XH, Liu XJ, Sun XQ, Huang X. Generating moving average trading rules on the oil futures market with genetic algorithms. Math Problems Eng 2014;10.
[46] He XZ, Zheng M. Dynamics of moving average rules in a continuous-time financial market model. J Econ Behav Organ 2010;76:615–34.
[47] Ni YS, Lee JT, Liao YC. Do variable length moving average trading rules matter during a financial crisis period? Appl Econom Lett 2013;20:135–41.
[48] Chiarella C, He XZ, Hommes C. A dynamic analysis of moving average rules. J Econom Dyn Control 2006;30:1729–53.
[49] Chiarella C, He XZ, Pellizzari P. A dynamic analysis of the microstructure of moving average rules in a double auction market. Macroeconom Dyn 2012;16:556–75.
[50] Xiong J, Wang Q, Wan J, Ye B, Xu W, Liu J. Detection of outliers in sensor data based on adaptive moving average fitting. Sens Lett 2013;11:877–82.
[51] Chavarnakul T, Enke D. Intelligent technical analysis based equivolume charting for stock trading using neural networks. Expert Syst Appl 2008;34:1004–17.
[52] Bahrammirzaee A. A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems. Neural Comput Appl 2010;19:1165–95.
[53] Wang F, Yu PLH, Cheung DW. Combining technical trading rules using particle swarm optimization. Expert Syst Appl 2014;41:3016–26.
[54] Zhu HH, Wang Y, Wang KS, Chen Y. Particle Swarm Optimization (PSO) for the constrained portfolio optimization problem. Expert Syst Appl 2011;38:10161–9.
[55] Zhang T, Brorsen BW. Particle swarm optimization algorithm for agent-based artificial markets. Comput Econ 2009;34:399–417.
[56] Yucekaya AD, Valenzuela J, Dozier G. Strategic bidding in electricity markets using particle swarm optimization. Electr Power Syst Res 2009;79:335–45.
[57] Potvin JY, Soriano P, Vallee M. Generating trading rules on the stock markets with genetic programming. Comput Oper Res 2004;31:1033–47.
[58] Shin K-s, Kim K-j. Evolving profitable trading rules with genetic algorithms. Inf – Int Interdisciplinary J 2012;15:3313–21.
[59] Stein RM, Bernard RN, Data mining the future: genetic discovery of good trading rules in agent-based financial market simulations. Ieee; 1998.
[60] Zhang G, Patuwo BE, Hu MY. Forecasting with artificial neural networks: the state of the art. Int J Forecast 1998;14:35–62.
[61] Holland JH. Genetic algorithms. Sci Am 1992;267:66–72.
[62] Mahfoud S, Mani G. Financial forecasting using genetic algorithms. Appl Artif Intell 1996;10:543–66.
[63] Rosillo R, de la Fuente D, Brugos JAL. Technical analysis and the Spanish stock exchange: testing the RSI, MACD, momentum and stochastic rules using Spanish market companies. Appl Econ 2013;45:1541–50.
[64] Yu H, Nartea GV, Gan C, Yao LJ. Predictive ability and profitability of simple technical trading rules: recent evidence from Southeast Asian stock markets. Int Rev Econom Finan 2013;25:356–71.
[65] Rakićević A, Končarević R, Petrović B. Comparison of moving averages for trading trends: the case of the belgrade stock exchange. Of Macedonia 568; 2014. p. 688.
[66] de Gois LA, da Borelli WC. Optimization of procedures for discovery and information of idle resources in distributed systems. ACM SIGOPS Operating Syst Rev 2010;44:103–9.
[67] Kaufman PJ. Smarter trading. Mcgraw-Hill Professional; 2010.
[68] Bagheri A, Peyhani HM, Akbari M. Financial forecasting using ANFIS networks with quantum-behaved particle swarm optimization. Expert Syst Appl 2014;41:6235–50.
[69] Allen F, Karjalainen R. Using genetic algorithms to find technical trading rules. J Financ Econ 1999;51:245–71.
[70] Chipperfield AJ, Fleming P, Pohlheim H. Genetic algorithm toolbox: for use with MATLAB; user's guide (version 1.2). University of Sheffield, Department of Automatic Control and Systems Engineering; 1994.

[71] Whitley LD. The GENITOR algorithm and selection pressure: why rank-based allocation of reproductive trials is best. ICGA 1989:116–23.
[72] Chipperfield A, Fleming P. The MATLAB genetic algorithm toolbox. Applied control techniques using MATLAB, IEE Colloquium on: IET; 1995. p. 10/1–4.
[73] Srinivas M, Patnaik LM. Adaptive probabilities of crossover and mutation in genetic algorithms. Syst, Man Cyber, IEEE Trans 1994;24:656–67.
[74] Kim K-j, Han I. Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index. Expert Syst Appl 2000;19:125–32.
[75] Keung K, Ip W-H, Lee T. A genetic algorithm approach to the multiple machine tool selection problem. J Intell Manuf 2001;12:331–42.
[76] Neely C, Weller P, Dittmar R. Is technical analysis in the foreign exchange market profitable? A genetic programming approach. Cambridge Univ Press; 1997.
[77] How J, Ling M, Verhoeven P. Does size matter? A genetic programming approach to technical trading. Quant Finan 2010;10:131–40.
[78] Liu X, An H, Wang L. Performance of generated moving average strategies in natural gas futures prices at different time scales. J Nat Gas Sci Eng 2015;24:337–45.
[79] Baumeister C, Kilian L. A general approach to recovering market expectations from futures prices with an application to crude oil 2014.
[80] Elton EJ, Gruber MJ, Brown SJ, Goetzmann WN. Modern portfolio theory and investment analysis. John Wiley & Sons; 2009.
[81] Jiang Z-Q, Xie W-J, Zhou W-X. Testing the weak-form efficiency of the WTI crude oil futures market. Physica A 2014;405:235–44.
[82] Lubnau T, Todorova N. Trading on mean-reversion in energy futures markets. Energy Econom 2015.
[83] Holmberg U, Lonnbark C, Lundstrom C. Assessing the profitability of intraday opening range breakout strategies. Finan Res Lett 2013;10:27–33.
[84] Cotter J, Hanly J. Performance of utility based hedges. Energy Econom 2015;49:718–26.
[85] Choi S. Causality test between investor's sentiment and price movements: a case study of the NYMEX crude oil futures market. Int J Oil Gas Coal Technol 2014;7:229–43.
[86] Bjursell J, Gentle JE, Wang GHK. Inventory announcements, jump dynamics, volatility and trading volume in US energy futures markets. Energy Econom 2015;48:336–49.
[87] Auer BR. Daily seasonality in crude oil returns and volatilities. Energy Econom 2014;43:82–8.