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HIGH-FREQUENCY TRADING OF AGRICULTURAL COMMODITIES AS A SOURCE OF ADDITIONAL INCOME IN AGRICULTURE[1]

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ABSTRACT

The paper verifies usefulness of the high frequency trading model developed by Marco Avellaneda and Sasha Stoikov, used in simulation of turnover with futures contract securities of one of agricultural commodities on the selected commodity stock exchange. Accuracy of provided signals of purchase and sale signals was verified on authentic quotations – the futures contract for coffee prices of the London Stock Exchange. Results of ten subsequent session days was analysed in detail. Quality of the assumed investment algorithm was determined with the use of stock exchange ratios: Information Ratio and Maximum Drawdown. A short discussion was conducted, which compared a standard investing method and the analysed model of algorithmic trading. In conclusion, all most important statements and conclusions were made, which confirmed usefulness of the HFT model developed by Marco Avellaneda and Sasha Stoikov for turnover of futures contract securities for agricultural commodities.

Introduction

Algorithmic trading originates in non-complex applications which allow division of big orders into few smaller ones and to perform them optimally. Development of this technique was possible only when the internet stock exchange market with orders sent through e-mails got popular and transaction applications became widely available. At the beginning it was a program, which realized strictly determined orders, in situations, when specific conditions for their conclusion were met. Present programs use complex algorithms, which include mathematical tools, in particular for statistics, optimization or calculus of probability. Transaction programs following quotations and other information sources, which have direct impact on stock exchange markets, give suitable investment signals.

Presently, as a result of dynamic development of IT services and easy access to the internet, access to algorithmic trading is not reserved only to big and significant inventors but is also available for individual investors. The newest solutions for persons, who want to invest in the stock exchange without acquainting with its complexity of functioning, is

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offered by some economic subjects investing through financing robots. These robots operate on algorithmic trading models, without disclosing their operations and only informing the investor on the worked out profit. Moreover, companies, which make such type of software available, compete between each other on many planes. First of all, they try to work out as high profits for clients as possible (and thus increase its nominal provision through the increase of the number of licenses and capital). Secondly, they try to indicate improper conduct of competition automatons. Finally, probably the most important, they modify operation of their algorithms on account of moves and assumed strategy through alternative algorithms. Thus, details of algorithms used by robots may be rarely used in literature. If yes, then in decisive majority, these are publications concerning the use of artificial intelligence, the so-called "black boxes", Thus, Chang et al. (2011) used artificial neural networks for detecting signals of purchase and sale on the securities market. Technical analysis combined with tracing plots of prices/volume of sale was presented by Chavarnakul and Enke (2008), where artificial neural networks were used to the moment of purchase and sale. Gradojevic and Gencay (2013) adapted fuzzy logic for assessment of the investment risk and selection of strategy. Fuzzy sets were also used by Tan et al. (2011) for cyclic stock investments. Analysis of clusters with Support Vector Machine (SVM – machine teaching method) was, on the other hand, the subject of research carried out by Choudaury et al. (2014). Indications for genetic algorithmic (GA) which support strategies based on the technical analysis were presented by Esfahanipour and Mousavi (2011). Genetic algorithms were also the subject of research by Mabu et al. (2013) but papers of this team were guided towards the use of GA for the needs of decision trees. On the other hand, Kluger and McBride (2011) showed implementation of the agent system for discovering investment patterns in intraday investments. The transaction model with high frequency analysed in the paper (High Frequency Trading) is also one of examples of using solutions of algorithmic trading.

Rising requirements of investors, who more often use programmes of algorithmic trading, on the Polish stock exchange market in 2013 forced Warsaw Stock Exchange to change the transaction system WARSET, operating since 2000 into UTP system – Universal Trading Platform. The present system meets the most excessive requirements of investors ensuring suitable environment for concluding transactions, where milliseconds count.

In the world literature one may find publications concerning the use of algorithmic trading models on the securities market (shares, bonds) – Aragon and Dieckmann (2011), Li et al. (2009) – or FOREX stock exchanges (currencies) – Evans et al. (2013), Kozhan and Salmon (2012). There is no common knowledge on analogous models on commodity markets, which decisively differ in its characteristic (liquidity and percentage differences in quotations). Commodity exchanges are characterized with low liquidity and more stable securities prices. It is conditioned by more fixed prices of commodities, quotations of which do not drop drastically or do not increase to few dozen percent during one session as in case of shares of smaller companies. Thus, verification of the algorithmic trading model on the agricultural commodities market is justified.

The objective and the scope of the study

The objective of the paper is to verify usefulness of the high frequency trading model developed by Marco Avellaneda and Sasha Stoikov, used in simulation of turnovers with futures contract securities of one of agricultural goods on the selected commodity stock exchange.

Accuracy of signals to perform alternatively respectively transactions of purchase and sale on authentic quotations of futures contract was investigated. A number of simulations at various values of parameters which influence calculation of threshold values of purchase and sale prices were carried out. Possibility of working out income and the rate of return with engaged capital and the condition of a wallet within subsequent 10 session days was calculated and imaged in the form of plots.

Financial instrument in the form of futures contract for agricultural goods is an object of the research. Selection of contract commodity was guided with high liquidity i.e. number of transactions in a session, necessary for the analysed model. After analysis of available futures contract, futures contract for coffee was selected from data of London Stock Exchange, the type of quotations of which is constant and is characterized with liquidity at the level of approx. 542 quotations during one session. The quotation unit is GBP·tonne-1, i.e. value of one tonne of a commodity expressed in pound sterling. A tick, that is a minimal jump in quotation for this contract is 1.00 GBP.

Data to simulations, which were carried out concerning quoting from subsequent 10 session days (number of session days selected arbitrary), were downloaded from London Stock Exchange through OpenQuant application with IQFeed. Session days included constant period of session days 14 – 17, 22 – 25 and 28-29 April 2014. Additionally it was assumed that 15 minutes before the end of session, conclusion of purchase transaction is not possible. This solution aimed at avoiding the situation of freezing capital to the following session day.

Methodology of work

Stochastic model of investment

It was assumed that the price of a particular commodity S (t) is subject to decomposition Ito

$$dS(t) = b\big(t, S(t)\big)dt + \sigma\big(t, S(t)\big)dW(t), \tag{1}$$

where: W(t) is a standard Brownian motion.

Additionally through $p^b(t)$ and $p^a(t)$ respectively the price of purchase and sale, for which the investor is prone to conclude a transaction, has been determined. At these symbols, price spread for purchase and sale was described as:

$$\delta^b = p^b(t) - S(t) \tag{2}$$

and

$$\delta^a = S(t) - p^a(t) \tag{3}$$

Moreover, two dynamic processes Q (t) were considered – number of securities in a particular moment in time possessed by an investor and X (t) – cash available after transaction.

The investor aims at maximization of the expected value of a portfolio

$$u(t,s,q,x) = \max_{\delta^a,\delta^b} E_{t,s,q,x}\left[-exp[-\gamma(X(T) + Q(T)\cdot S(T))]\right] \quad (4)$$

where:

$t \in [0,T]$ – time,

$s = S(t)$ – present price of a given good,

$x = X(t)$ – cash designed for investment,

$q = Q(t)$ – present level of engagement in a given security.

Parameter γ is a feature, which characterizes the market (liquidity) whereas δ^a and $\delta^b$are the only sizes, which can be influenced by an investor.

Optimization of offered purchase and sale prices of commodities

For determination of a strategy, optimal from the point of view of an investor, Hamilton-Jacob-Bellman equation was used. According to Ho and Stoll (1981) function u meets the following relations:

$$u_t + \frac{1}{2}\sigma^2 u_{xx} + \max_{\delta^b} \lambda^b(\delta^b)[u(s,x-s+\delta^b,q+1,t) - u(s,x,q,t)] + \max_{\delta^a} \lambda^a(\delta^a)[u(s,x+s+\delta^a,q-1,t) - u(s,x,q,t)] = 0 \quad (5)$$

$$u(s,x,q,T) = -exp[-\gamma(x+qs)] \quad (6)$$

It allowed determination of purchase and sale offer of a particular security in any moment in time:

$$r^a(s,q,t) = \theta_1 + 2q\theta_2 + \frac{1}{\lambda}\log\left(1+\frac{\lambda}{k}\right) - 2\theta_2 \quad (7)$$

$$r^b(s,q,t) = \theta_1 + 2q\theta_2 - \frac{1}{\lambda}\log\left(1+\frac{\lambda}{k}\right) + 2\theta_2 \quad (8)$$

The above calculations decisively simplify assuming the final time horizon. Then, the best investment strategy is reserving cash under the purchase sale order respectively as:

$$r^a(s,q,t) = s + (1-2q)\cdot\frac{\gamma\sigma^2(T-t)}{2} \quad (9)$$

$$r^b(s,q,t) = s + (-1-2q)\cdot\frac{\gamma\sigma^2(T-t)}{2} \quad (10)$$

Research results and discussion

In order to better present effects of operation of the investment algorithm, results were divided into two parts

I. effect of operation for single session day,
II. effect of operation for the whole considered period

First session day

Data which characterize the first session day were presented in table 1, whereas on plot 1-3 respectively quotations of the futures contract for coffee, portfolio condition and the condition of possessing securities by an investor, were presented.

Table 1
First session day – summary

Property	Values
Date:	14-04-2014
Time of first quoting	10:00:36
Time of last quoting	18:29:48
Opening price	2 135.00
Closing price	2 136.00
High	2 154.00
Low	2 119.00
Change of the opening price in comparison to the closing price of the previous session	- 10.00 i.e. -0.47%
Change of the closing price in comparison to the opening price	1.00 i.e. 0.05%
Number of quotations	613
Number of signals / Number of purchase transactions according to the model	115/69
Number of signals / Number of sale transactions according to the model	131/69
Number of signals for sale in the period of purchase blocking	8
Condition of a portfolio at the opening of the session day	100 000.00
Condition of a portfolio at the closing of the session day	101 595.00
Daily return rate of the invested funds	1.60%

Comparing quotations of the contract on fig. 1 and the condition of a portfolio on fig. 2, it should be stated that although the quotation has dropped from opening the session to 2:26:52 p.m. by 0.755 the condition of a portfolio gradually increased. Transactions carried out at slight fluctuations of quotation allowed working out the increase of the portfolio value by 0.66%. The reported sudden decrease of quotation between 4:33:39 – 4:53:58 p.m. by -0.79 influenced the decrease of a portfolio by -0.46%. Whereas, quite fast increase of the quotation between 4:53:58-5:55:53 by 0.94% caused the increase of a portfolio by 0.75%. The condition of a portfolio presented in fig. 3 at the beginning of a session allowed purchase of 46 securities at 10:17:16 through the increase of its value to £ 100 138.00 and decrease of securities quotation by £ 6.00 allowed purchase on a one-off basis as much as 47 securities, which allowed more effective use of possessed funds on a hypothetically owned brokerage account.

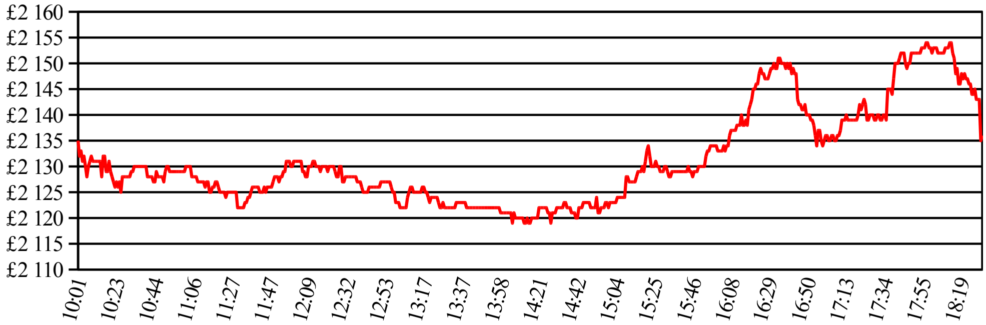

Figure 1. Quotation of the futures contract on the first session day

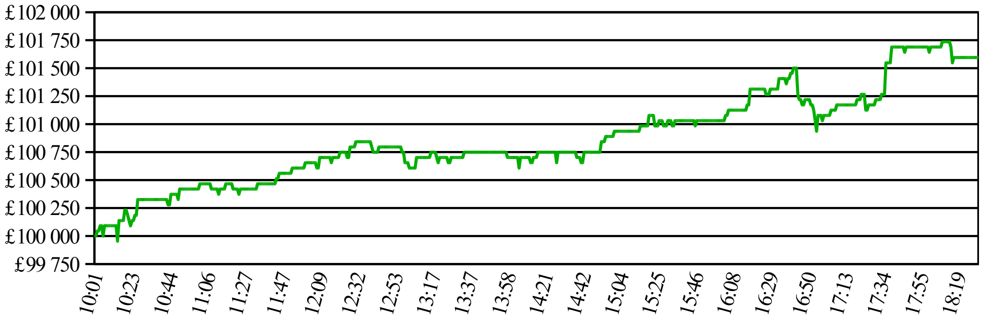

Figure 2. Condition of a portfolio on the first session day

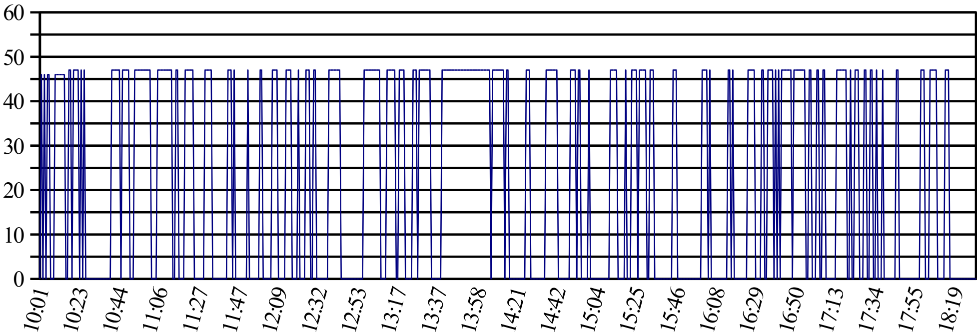

Figure 3. Condition of possessing securities on the first session day

Full analysed period of investment

In order to better reflect differences of quotations and the condition of a portfolio of subsequent ten session days, they were presented in tables 2 and 3.

Table 2
Differences of opening and closing prices and the value of a portfolio of ten session days

Session day	Price		Portfolio		Differences	
	of opening	of closing	at the opening	at the closing	in prices	of a portfolio
1	2 135.00	2 136.00	100 000.00	101 595.00	0.05%	1.60%
2	2 142.00	2 126.00	101 595.00	101 972.00	-0.75%	0.37%
3	2 097.00	2 068.00	101 972.00	103 759.00	-1.38%	1.75%
4	2 069.00	2 124.00	103 759.00	105 603.00	2.66%	1.78%
5	2 136.00	2 161.00	105 603.00	107 699.00	1.17%	1.98%
6	2 179.00	2 178.00	107 699.00	107 993.00	-0.05%	0.27%
7	2 164.00	2 171.00	107 993.00	109 139.00	0.32%	1.06%
8	2 174.00	2 155.00	109 139.00	109 189.00	-0.87%	0.05%
9	2 117.00	2 132.00	109 189.00	109 550.00	0.71%	0.33%
10	2 118.00	2 145.00	109 550.00	110 213.00	1.27%	0.61%

When analysing difference of the portfolio values in table 2 one may observe that the analysed model did not cause any loss within ten years. In seven cases out of ten, the model of algorithmic trading gave better results than quotation differences. It should be emphasised that calculations were made without including price fluctuations between subsequent sessions, that is the so-called reference price.

For the assessment of the accepted investment algorithm, Information Ration (IR) – of one of the most popular ratios for comparison of the level of risk of various investment strategies was additionally determined.

$$IR = \frac{\sum_{i=1}^{m} \frac{R_i - R_m}{n}}{\sqrt{\sum_{i=1}^{m} \frac{(R_i - R_m)^2}{n-1}}}, \tag{20}$$

where:

R_i – rate of return from the analysed model in the period i

R_m – rate of return from benchmark (reference rate) in this case it concerns quotations

n – length of the analysed period.

IR values lower than 0.5 should be recognized as unfavourable. IR values within $[0.50; 0.75]$ are recognized as good. After exceeding the level of 0.75 the investment should be recognized as particularly favourable. The value of ratio was calculated at the level of 0.52 which proves that the analysed model brought good results.

Maximum Drawdown was the second ratio, determined by authors; size, which describes the highest percentage loss in the analysed period.

$$MD = \min_{i=1,\ldots,t;t=1,\ldots,N} \sum_{j=1}^{t} R_j \ , \tag{21}$$

Upon the data analysis of this ratio for two variants of investing (traditional model - HFT model), it proved that HFT model characterizes with considerably lower risk of drawdown. It is reflected in data in table 3.

Table 3
Maximum Drawdown rates and accompanying data for two investing variants

Property	Describing data	
	Standard manner of investment	Analysed HFT model
Moment of purchasing securities	18:12:38 14-04-2014	11:35:41 23-04-2014
Moment of selling securities	14:54:40 17-04-2014	15:22:24 23-04-2014
Capital up	100 000.00	108 385.00
Capital down	95 400.00	106 621.00
Drawdown	- 4 600.00	- 1 764.00
Value of ratio	-4.60%	-1.63%

Comparison of effects and some features of two methods within 10 session days is presented by data in table 4. The analysed HFT model did not cause loss in the entire period as well as on any particular day.

Table 4
Differences between a standard investing model and the analysed model of algorithmic trading

Property	Standard manner	Acc. to the analysed model
Invested funds	100 000.00	100 000.00
Profit	460.00 or 3174.00	10 213.00
Loss	- 3 726.00 or - 4 600.00	Not reported
Rate of return	0.46% or 3.17% or -3.73% or -4.60%	10.21%
Number of transactions made	2	1.454
Price risk	High	Minimized
Availability of funds out of session	Lack	Available

Investor using the standard method may sell securities in the moment, when he/she finds it appropriate. A human factor, in the form of emotions, has a great impact on the possibility of great loss in the standard investing. The investor, who incurs losses, still hopes that quotations will come back to the level, at which, at least, he bought securities. Usually, it is not like that and further adjournment of selling securities deepens the loss. There is a great probability that the investor might decide on the sale of securities only when they reach the most unfavourable price. Model of algorithmic trading eliminates the factor of emotions which accompanies taking up decisions on a transaction, which mainly allows limiting losses. It is very important from a clearly arithmetic point of view, because the amount, which should be made up, rises considerably faster than the incurred loss (Zaremba, 2010).

Conclusions and statements

As it was presented in the paper, the model of algorithmic trading suggested by Avellaneda and Stoikov based on High Frequency Trading, may be successfully used in the agricultural and derivative commodities trading assuming considerably high market liquidity. It may cause obtaining additional profits by farmers, who may thus get advantage over competition.

At the use of stock ratios Information Ratio and Maximum Drawdown, it was confirmed that the analysed model of algorithmic trading is a good tool for investing in comparison to standard methods and is characterised with lesser risk of drawdown.

Analysis of particular days proved that in seven out of ten cases this model is a better method and, what is more important, did not cause any loss on any particular day. The calculated theoretical profit at the level of 10.21% worked out within ten session days at a low risk, as proved by the model, even after including provision of the brokerage house for carrying out a transaction, it would be satisfactory for each investor.

Through the use of author's blocking of securities purchase15 minutes before the end of the session, funds, out of session hours, may be invested on other stock exchanges, FOREX markets, which operate 24 hours a day or on overnight deposits, where they are invested in countries with other time zone. Thus, due to this blocking, the value of a portfolio was made non-dependent of the price fluctuations between sessions.

In order to improve the model suggested in the paper, sensitivity analysis of strategy on arbitrally assumed parameters such as e.g. liquidity and considerably extend time interval included in the research. Investigation of execution of orders is an open problem, which was not discussed, i.e. verification of the time from the moment of confirmation of an order to its execution and how it influences the summary volume of orders on shaping the sale price. Verification of behaviour of the described algorithm, which would have to compete with other investment robots, would also be an interesting cognition aspect.

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HIGH FREQUENCY TRADING W HANDLU TOWARAMI POCHODZENIA ROLNICZEGO JAKO ŹRÓDŁO DODATKOWEGO DOCHODU W ROLNICTWIE

Streszczenie. W pracy sprawdzono przydatność modelu szybkiego kupna i sprzedaży (High Frequency Trading) Marco Avellanedy i Sashy Stoikov'a, użytego w symulacji obrotu walorami kontraktu terminowego na towar pochodzenia rolniczego na wybranej giełdzie towarowej. Zbadano trafność podawanych sygnałów transakcji kupna i sprzedaży na autentycznych notowaniach - kontrakt terminowy na ceny kawy londyńskiej giełdy papierów wartościowych (London Stock Exchange). Szczegółowo zanalizowano wyniki dziesięciu kolejnych dni sesyjnych. Jakość przyjętego algorytmu inwestycyjnego określono za pomocą wskaźników giełdowych: Information Ratio oraz Maximum Drawdown. Przeprowadzono krótką dyskusję porównującą standardową metodę inwestowania oraz analizowany model handlu algorytmicznego. Na zakończenie zebrano najważniejsze stwierdzenia i wyciągnięto wnioski potwierdzające przydatność modelu HFT Marco Avellanedy i Sashy Stoikov'a do obrotu walorami kontraktów terminowych na towary pochodzenia rolniczego o dużej płynności oraz możliwość jego praktycznego zastosowania.

Słowa kluczowe: arbitraż statystyczny, High Frequency Trading, giełda towarowa, handel algorytmiczny.