UNIVERSITY OF TARTU
FACULTY OF MATHEMATICS AND COMPUTER SCIENCE
Institute of Mathematical Statistics
Financial Mathematics

Martynas Trepeka

Development of an algorithmic trading model for intraday trading on stock markets based on technical analysis methods

Master's Thesis (15 ECTS)

Supervisor: Raul Kangro, University of Tartu

Tartu 2014

Development of an algorithmic trading model for intraday trading on stock markets based on technical analysis methods

Abstract:

The theory of technical analysis suggests that future stock price movements can be forecasted by analyzing historical price changes and studying repetitive patterns. In this thesis we aim at implementing technical trading rules in intraday trading. In theoretical part the descriptions and explanations of applying indicators and rules in intraday trading are provided. Three types of approaches – price, volume and market microstructure analysis for determining market changes are researched. A range of trading rules are empirically tested and based on the findings an algorithmic trading model is constructed.

Keywords:

Financial mathematics, Stock market, Investment strategy, Technical analysis, algorithmic trading, intraday trading.

Tehnilise analüüsi meetoditel baseeruva kauplemisalgoritmi väljatöötamine päevasiseseks kauplemiseks aktsiaturgudel

Lühikokkuvõte:

Tehnilise analüüsi teooria tugineb eeldusel, et teatud mustrid lähimineviku hindades võimaldavad ennustada tulevikus toimuvaid aktsiahinna muutuseid. Käesolevas magistritöös kirjeldatakse populaarseimaid tehnilise analüüsi indikaatoreid kohandatuna päevasisese kauplemise olukorrale. Vaadeldakse kolme tüüpi indikaatoreid – hinnaliikumistel põhinevaid, kauplemismahtudel põhinevaid ning turu mikrostruktuuri kirjeldavaid näidikuid. Vaadeldavate näidikute poolt tekitatud signaalidel põhinevate kauplemisstrateegiate efektiivsust analüüsitakse konkreetseid turuandmeid kasutades ning saadud tulemusi arvestades konstrueeritakse mitmeid signaale kombineeriv automaatse kauplemise strateegia.

Võtmesõnad:

Finantsmatemaatika, aktsiaturg, investeerimisstrateegia, tehniline analüüs, algoritmiline kauplemine, päevasisene kauplemine.

Table of Contents

Introduction

The increasing influence of algorithmic trading system in the financial markets calls for deeper studies of the field and more detailed analysis. The very beginning of algorithmic trading was in 1970's - 1980's when investment companies started to write trading rules to computer code in order to develop market signals. With increasing computer power and speed of calculation the algorithmic trading really took off and has seen a significant rise in the use in past decade. With market trade share varying up to 40 - 80% of total trades, and especially high level of trades in most developed markets, the importance of algorithmic trading is forceful (In 2011 according to Reuters and Bloomberg algorithmic trades in equities accounted for ~73%, according to TABB group in 2012 in Europe 40% of all trades were generated by algorithmic trading) .

Algorithmic trading - also called automated trading, algo trading and so on, is a trading system which uses electronic platforms for making market decisions based on predefined set of rules. Algorithmic trading is very broad concept and usually involves learning, dynamic planning, reasoning, and decision taking (Treleaven, Galas, Vidhi, 2013), all done by the algorithmic system itself. The complexity of the systems can vary hugely, from highly mature systems that can scan and read news and respond correspondingly to trading systems that are developed as learning process with abilities to adjust to various changes in the market. Although creating such a system requires large amount of financial and technical support, and for a single investor it is way out of scope. We will be targeting to create a system that would work on predefined set of rules from technical analysis and study of the market data, therefore using the idea of algorithmic trading in theoretical mathematical approach. Depending on the automated trading system it can be created for selected purposes, there are many strategies that algorithmic systems are built for: to hide large orders in the market (iceberging), to read news or scan human sentiment by social media and trade accordingly, or to scan market for arbitrage opportunities and so on. In this work, our aims will be:

- To test performance of technical trading rules in intraday trading;
- To analyze the use order flow information in intra trading;
- To develop an algorithmic trading model that generates profitable trading outcome based on technical analysis and order flow information.

Transaction cost reduction (or as mention, iceberging) is commonly used by investment, mutual funds and other big institutional participants of the market in order to “hide” huge trades and reduce the effect of them in market when needed to enter or liquidate the position. We will be focusing solely on creating an algorithmic trading model that would generate profitable outcome from intraday trading operations. While mostly highly sophisticated algorithmic trading systems are employed by larger investment companies, the use for individual investors is also available in adjusted scope. The model that we are building in this work will rely highly on the concepts of technical analysis.

The work will consist of three main parts. The first part will be theoretical, where we describe technical analysis indicators used and show how we modify them to be able to apply them in intraday trading. Practical part is divided into two: analysis of the technical trading rules in intraday trading and empirical development of algorithmic trading model based on findings from performance of technical trading rules.

1. Background

1. 1. Literature review

The work will be joining two concepts: algorithmic trading and technical analysis to search for meaningful results. While the algorithmic trading is widely used in practice, the assumption that ideas of technical analysis can generate profitable outcome is highly debated. First to mention, the belief that technical analysis works contradicts the efficient market hypothesis (EMH) of Fama that stock prices fully reflect all available information (Fama, 1970). Therefore technical analysis cannot predict market movements. In the scope of weak efficiency form, EMH suggest that only fundamental analysis could result in excess returns and only in short time period. Supporting to Fama's idea, Samuelson (1972) also provided evidence that backed up Fama's theory, questioning the value of technical analysis.

Also there are studies on the use of technical analysis by market participants, which provide information of it being extensively used, contradicting the efficient market hypothesis. Study by Menkhoff (2010) indicates that professional financial market participants rely heavily on technical analysis when constructing their own trading strategies. His research suggests that in practice technical analysis neglects skepticism from academic point of view and is widely used. Several earlier researches, by Lui and Mole (1998) and Menkhoff and Taylor (2007) support the most recent Menkhoff findings. Hence evidence suggests that while contradicting to market efficiency theory, technical analysis is still used in practice.

Additionally opposing to Fama's efficient market hypothesis there are a series of works showing evidence of excess returns in different markets using technical analysis rules. William Brock, Josef Lakonishok, Blake LeBaron, (1992) examined the predictive abilities of moving averages and trading range breakout rules of DJIA index data for period from 1897 to 1986. Their findings indicated that some technical trading rules provided higher returns than buy and hold strategy. The study of Brock et al. (1992) is considered to be an important milestone in the field of technical analysis. Not only because of the evidence found, but also because of technical analysis being widely dismissed by academics before their publication.

Following the findings of Brock et al. there was a real surge in studies of technical trading rules. Research by Parisi and Vasquez (2000) provide evidence that using moving averages and trading range breakout rules results in higher returns on Chile market. Raj and Thurston (1996) tested the same trading rules on Hong Kong Futures exchange market and found that trading range breakout rule, but not moving averages, delivered excess returns. Furthermore, Vasiliou, Eriotis and Papathanasiou (2008) examined various moving averages rules for Athens stock market and discovered that these rules provided significantly higher returns than simple buy and hold trading strategy. Therefore there is variety of research on different markets providing evidence of technical analysis rules giving higher returns than buy and hold strategy. Additionally Yu, Nartea, Gan and Yao (2012) explored approximately 60 technical trading rules in five Southeast Asian markets, their findings suggest that technical trading rules have predictive power and outperform buy and hold strategy. Still, they discover that once the transaction cost would be considered the profitability of technical rules would be eliminated. On the other hand, one rather recent study by Fang, Jacobsen and Qin (2014) perform similar analysis to Brock et al. (1992) on S&P500 and DJIA indexes for various periods. Their findings indicate that for more recent periods (after research by Brock et al.) the excessive returns by technical trading rules disappear. One of their suggestions is that markets have become more efficient with time, removing the possibility for technical trading rules to work. This corresponds to work of (Yu et. al. 2012) as they also noticed that when markets become more efficient the profitability of technical trading rules diminish. Despite of that, it should be mentioned that all of these findings are based on using historical daily stock price data, and while the findings are divided, we will look into intraday data related research next.

While traditionally testing of profitability of technical analysis trading rules is performed on daily data, the research in intraday trading is done in significantly smaller scope. One reason for that, pointed out by Holmberg, Lönnbark, Lundström (2012) is the relative unavailability of intraday trading data. With daily price information being available to everyone usually free of cost, detailed intraday information is not so easily accessible, and can be rather expensive. Same authors test intraday ORB (Open range breakout) strategy for US Crude oil futures and finds that technical trading rules produce remarkable results, (Holmberg et. al.2012). Additionally, (Schulmeister 2009) analyzes S&P 500 index in both daily and intraday time periods. He states that there is a visible shift from profitability of technical trading rules applied to daily data to intraday data (30min period data in his work). His findings confirm that in period from 1983 to 2007 several technical trading rules in intraday outperformed buy and hold strategy for the index. Contrary, (Marshall and Cahan 2007) investigates US equity market, and after testing wide range of technical trading rules on intraday S&P 500 SPDR ETF data find no evidence of any rules being profitable. In addition, Yamamoto (2012) investigates profitability of technical trading rules on Nikkei 225 stocks. Variety of order flow and technical analysis rules fail to outperform in intraday trading period for one year. Therefore, obviously the previous researches have mixed findings, and different outcomes.

In addition to research of profitability of technical trading rules, it would be worthy to note research by (Lin, Yang and Song 2011) which aimed at using technical analysis to create trading system that would learn trading rules from historical prices and provide trading suggestions. By applying their trading system on large number of S&P 500 equities, they managed to receive significantly higher returns than buy and hold strategy. In rising market when buy and hold strategy gains ~20.5% in average, the system profits 41.6%. Furthermore, in decreasing market, when buy and hold strategy losses 20.3%, the trading system still profits 26.5%, outperforming buy and hold strategy in both falling and increasing markets. While these are notable returns, the performance of such model still is far from the top algorithmic trading systems used by institutional traders. According to the Wall Street Journal, Renaissance Technologies hedge fund top performing Medallion fund have average 34% annual return since the 1988. For obvious reasons the trading system used by the hedge fund is unknown publicly and even so for the investors in the fund. What is known is that intensive algorithmic trading system is used, but the mechanism is purely black box for anyone outside company. Surely this is not the only successful hedge fund employing algorithmic trading systems and reaching supreme returns. While development of such system is far out of scope of this work, a simple algorithmic trading system using technical analysis tools will be further analyzed.

1. 2. Data

We will be using intraday trading data on two stocks traded on LSE: Vodafone Group PLC (VOD.L) and AstraZeneca PLC (AZN.L). The data on both stocks is from 2007/01/01 to 2007/05/16. We totally have 94 days of intraday trading data for each stock. In the trading algorithm development part various trading signals and their profitability will be analyzed by using first 60 days data of each stock separately and the other 34 days data will be used to test the performance of the proposed algorithmic trading model. We do this in order to avoid data snooping bias. The data itself is a tick data, meaning that once there is a change in the market microstructure then it is immediately printed in the tick data. Therefore the data itself is comparably large in memory size and by number of observations per trading day. The choice of stocks comes from availability of data and there are no other reasons why these two stocks are selected.

The intraday data on each stock contains observations of market situation at different time moments t_i from market opening at 08:00:00 GMT to 16:30:00 GMT. Each observation consists of values of 38 variables. In grouped way we can identify that the data contains the following information: (1) 5 top bid and ask prices, (2) size of 5 top bid and ask orders, (3) number of top 5 bid and ask orders, (4) information on trades, including their price and volume (5) time information. Another important thing to be noted is that trade volume q_i at the time moment when trade happened contains additional information:

$$\begin{cases} q_i < 0 \ \rightarrow when\ buyer\ agrees\ to\ sellers\ ask\ price\ (buyer\ initiated\ trade) \\ q_i > 0 \ \rightarrow when\ seller\ agrees\ to\ buyers\ bid\ price\ (seller\ initiated\ trade) \end{cases}$$

This will be important in the section of order flow analysis. Another remark on the data usage is related to testing of trading signals and trading simulation. We will not start trading from 08:00:00 GMT, by the reason of imbalances in data pre trading. Secondly, time period before trading is needed to generate trading signals based on previous time period. Therefore some trading signals, which require more of previous time periods, will be started testing at later time of trading day. Secondly, the trading doesn`t end at the time market closes. We will terminate trading and close all positions some time before market closing. Furthermore, all trading will be done in intraday period, so all positions are opened and closed on the same trading day, no positions are held overnight and only same trading day history is used for producing market signals. Finally for some indicators we will need to compress data for specified periods (e.g. 5min) so notation of *n* number of period will represent *n* number of data specified for some period. (e.g. 14 periods of 5min. data, totally 1h 10min data needed).

1. 3. Properties of Algorithmic trading systems

Before going to a wider explanation on concept of technical analysis and use of it, let's consider what possible positive and negative sides an automatic trading system can have. In order to concentrate on the topic of this work, we will note only the effects on the side of individual investor, and not the qualities or parameters of market influenced by algorithmic trading. Following qualities can be regarded as positive for algorithmic trading system on individual investor level and in general:

- Actions in market follow predefined rules. Since investors usually have their strategy built up into the algorithm, then the actions in the market are taken strictly regarding those rules. The situation when wrong decisions are taken because of personal traits of investor, or something as irrational as bad feelings are completely avoided when algorithms perform trading. “Money drives people to do crazy things…” (Epstein, Garfield 1992) - But for machine the factor of psychology is vanished and it is capable of following strictly the rules that are predefined. Therefore, space for human error in active trading dissolves.

- Decision speed is noticeably higher. Computers can both perform and take decision relying on conditions regarding the market position in milliseconds, at the same time human might not even be able to notice the change in separate parameters. Accordingly for intraday trading the speed of decision can be crucial for profitable outcome. (Martinez and Rosu 2011) argues that speed of algorithms gives an ability to squeeze the possibility of exploiting the information much better than human trader.

- Simple approach to back - test the algorithmic model to historical data and to evaluate performance. Testing of the given model on historical data can give indication which features produce desirable outcome, and which need editing. This testing gives simple approach to find weak and advantageous aspects of strategy without using real investments (Hanif, Smith 2012). Afterwards we can implement our strategy expecting that what worked on historical data will produce anticipated outcome in the future.

- Comparably easy to increase the amount of profit up to a limited point. In case where individual investor develops profitable strategy, he could possibly double the stake in the investments in liquid market without having the effect on market structure (Brockwell, 2010).

On the contrary, one must notice the possible drawbacks of using algorithmic trading system also:

- Mechanical errors. Since the set of rules is predefined, and the trading plan is strictly followed by the model we remove the human factor errors, but the possibility for technical error remains. The algorithms could malfunction, the internet connection could fail, and electricity shortage or something could ruin the trading. The variety for mechanical errors when relying on algorithmic trading remains rather large.

- Misbehavior of trading system itself. There could be no mechanical errors or no failings in the structure of system itself, but it could misbehave because of extreme actions in the market. Also there could be changes in market behavior that make the assumptions built in the system invalid. The best example of that kind of situation is the “Flash crash” of 2010 May 6th, when within minutes market crashed 9% and quickly recovered back. While the event is still highly debated, the automatic trading systems are believed to cause that, where one action of automated trading system was followed by other systems causing fast fall and recovery of prices. (United States SEC and CFTC argue that the flash crash was caused by algorithmic trading).

- Need for monitoring and correction. No matter how good the model behaves regarding historical data, or if it generates the profitable results for some time, the need to check the market parameters and conditions remain. In today's volatile markets and constantly changing environment there is high probability that some extreme market conditions would unfold, where investor would simply prefer to move away from the market or to halt trading. Thus, the automatic trading system still needs supervision and control. Also monitoring the performance of algorithmic trading system could indicate a need for a revision in trading strategy, when returns from automated trading starts to deviate from targeted results (Kendall, 2007)

- High requirements for skills to be able to create a successful and fully functioning algorithmic trading system. It is not only enough to be successful investor on personal level to switch to successful one in algorithmic trading. The programing skills, software and hardware knowledge and ability to build trading strategy are fundamental when creating algorithmic trading system. So the setting up cost can be rather large and demanding.

All of this considered, the increasing use of algorithmic trading suggest that the positive side outweighs the drawbacks. So now after broadly discussing the functioning and sides of algorithmic trading we could move on to reviewing the basics on which we will construct our trading strategy. The aim of the strategy is that it would be built in a way which would avoid weaknesses coming from both algorithmic trading and technical analysis side.

1. 4. Notes on computing averages in unevenly spaced data

Since in this work we will be analyzing intraday trading data, the remark about how the averaging will be implemented is needed before we move on to discuss technical trading tools. We can consider two principal ideas for averaging in unevenly spaced time series. First we could consider calculating moving average of a continuous time process by the following expression:

$$SMA(X,\tau)_t = \frac{1}{\tau}\int_0^{\tau} X(t-s)ds$$

We introduce Δt_i – time difference between trades and replace the integral by following piecewise constant approximation:

$$SMA(X,\tau)_i \approx \sum_{j\in[t_i-\tau,t_i]} X_j \frac{\Delta t_j}{\tau}$$

So we would be dividing time moments according to observations inside the time period and then approximating the value of average. In this case we would take into consideration of time difference between the observations. In case of using exponential moving average we will also take into account time differences and will use following formula:

$$EMA(X,\tau)_i = \frac{2}{\tau}\int_0^{\infty} X(t_i-s)e^{-\frac{2s}{\tau}}ds$$

We introduce Δt_i – time difference between trades. For the period of *EMA* to have same average time delay as in case of simple moving average we take $\frac{2}{\tau}$ in the integral. And in the following we derive formula for *EMA* calculation:

$$EMA(X,\tau)_i = \frac{2}{\tau}\int_0^{\Delta t_i} X(t_i-s)e^{-\frac{2s}{\tau}}ds + \frac{2}{\tau}\int_{\Delta t_i}^{\infty} X(t_i-s)e^{-\frac{2s}{\tau}}ds$$

We consider the first term of equation and we approximate the integral:

$$\frac{2}{\tau}\int_0^{\Delta t_i} X(t_i-s)e^{-\frac{2s}{\tau}}ds \approx \frac{2}{\tau}X(t_i)\int_0^{\Delta t_i} e^{-\frac{2s}{\tau}}ds = \frac{2}{\tau}X(t_i)\left(-\frac{\tau}{2}\left(e^{-\frac{2\Delta t_i}{\tau}}-1\right)\right)$$

$$= X(t_i)\left(-e^{-\frac{2\Delta t_i}{\tau}}+1\right)$$

Now if we consider the second term of equation:

$$\frac{2}{\tau}\int_{\Delta t_i}^{\infty} X(t_i-s)e^{-\frac{2s}{\tau}}ds = \frac{2}{\tau}\int_{\Delta t_i}^{\infty} X((t_i-\Delta t_i)-(s-\Delta t_i))e^{-\frac{2(s-\Delta t_i+\Delta t_i)}{\tau}}ds$$

$$= \frac{2}{\tau}\int_{\Delta t_i}^{\infty} X((t_i-\Delta t_i)-(s-\Delta t_i))e^{-\frac{2(s-\Delta t_i)}{\tau}}e^{\frac{-2\Delta t_i}{\tau}}ds$$

$$= e^{-\frac{2\Delta t_i}{\tau}}\frac{2}{\tau}\int_{\Delta t_i}^{\infty} X\left((t_i-\Delta t_i)-(s-\Delta t_i)\right)e^{-\frac{2(s-\Delta t_i)}{\tau}}ds$$

We can see that this second term can be rewritten as: $e^{-\frac{2\Delta t_i}{\tau}} EMA(X,\tau)_{i-1}$. Now if put approximation from first term and second together we get the following:

$EMA(X,\tau)_i = X(t_i)\left(1 - e^{-\frac{2\Delta t_i}{\tau}}\right) + e^{-\frac{2\Delta t_i}{\tau}} EMA(X,\tau)_{i-1},$

we denote $w_i = e^{-\frac{2\Delta t_i}{\tau}}$, then the final equation for exponential moving average:

$EMA(X,\tau)_i = X_i(1 - w_i) + w_i\, EMA(X,\tau)_{i-1}.$

Second option is to treat our unevenly spaced time moments in the same way the discrete time case. In this case we would simply consider taking simple arithmetic average of observation for the given period τ. This would result in all values of the same time period having exactly the same weight in the average. As a consequence, even the values from the beginning of period would influence the average value equally as most recent observations. In this case we would calculate simple moving average by the following formula:

$$SMA(p,\tau)_i = \frac{\sum_{j:t_j \epsilon [t_i - \tau, t_i]} p_j}{n_{j:t_j \epsilon [t_i - \tau, t_i]}}$$

Exponential average in this case, could be approximated using formula:

$$EMA(p,\tau)_i = \frac{\sum_{j=0}^{i} e^{-\frac{2}{\tau}(t_i - t_j)} p_j}{\sum_{j=0}^{i} e^{-\frac{2}{\tau}(t_i - t_j)}}$$

In this work we will use the first option and we will assume that trades, which occur more frequently, have more importance to the average than those trades, which happen rarely.

2. Price based trading strategies

2. 1. Trading strategy

Trading strategy is defined as a set of rules, or fixed plan, which is designed to perform a trading in market in order to achieve profitable result. Depending on the qualities and complexity of a trading strategy, trading strategy could consist of few features as entry and exit points to the market, portfolio allocation or complicated set of order management and risk exposure control rules. Further on trading strategy will composed by three parts of different section of technical analysis tool, while some might be overlapping and working with each other, the main parts will be: technical analysis price based indicators, volume based indicators analysis, and orders flow analysis. In study of the strategy performance, the various combinations of different strategies will be implemented, in order to find proof that combinations of the different technical indicators can result in profitable trading outcome. Often it is acknowledged, that single indicator can provide not justified indication of buying or selling signals, therefore combinations of several indicators are considered to be effective.

2. 2. Technical indicators

While technical analysis dates back to as early as 17th century, the most significant changes and real surge of technical analysis happened during the past few decades. Due to the increasing use of computers in analysis and technical progress the advances of technical analysis resulted in increased number of tools and different possibilities to implement them. The very fundament of technical analysis is based on the idea that: if A preceded B several times before, B is likely to happen now when A has occurred. As A is an indicator that B will happen. This comes from inductive idea, as humans repeat behavior, patters also tend to repeat, or as well – deterministic machines repeat patterns (Rockfeller, 2002). The key task is to find the blueprint for the repeating patters, to spot that A which will result in B and try to profit from their relationship. An indicator is described as a mathematical calculation that can be applied current asset price or volume fields in order to future changes in that asset's prices.

Obviously the research relies heavily on the belief that technical analysis can be productive and yield in successful trading. While Efficient Market Hypothesis by Fama contradicts the very essence of technical analysis stating that prices in the market already incorporate and reflect all information relevant to the asset. And this means that one is not able to constantly to earn higher returns on the market, as movements of prices are unpredictable as Kendall found in 1953 and follow random walk. Opposing to this, there are recent evidence that using technical analysis provides higher returns and can be effective when constructing trading strategy.

With wide range of various technical analysis devices available it might be rather complicated to select the most suitable ones. While all of them are aimed at the same goal - indication of profitable opportunities to take preferred actions in the market, the difference and purpose of each has to be considered while building a trading strategy. Since each tool alters in its purpose for which it is designed, the abilities and usage also has to be carefully checked when adding them to the strategy. Generally indicators are divided according to the market data that they are using, usually its prices of assets and trading volume. Since the data which was available and used in this work provides not only information about prices and volume, but also material about the market micro structure in the intraday trading, the analysis of the order flow will be examined as well later on. Starting with price related indicators, further on briefly will define all the analysis tools that are going to be used in the trading strategy.

One important thing to be mentioned is the way the trading signals will be executed. After the indicator provides a buying (selling) signal the trade will happen immediately at the best ask (bid) price available. Once the trade is executed, the position in the asset is held until a time moment when the opposite trading signal is developed. During the period until the opposite signal emerges no trading is done, all the other signals in that period are ignored.

2. 3. Relative strength index (RSI)

The Relative Strength Index was developed by J. Welles Wilder in the 1970′s. It is considered to be useful and gained its popularity for the ease of understanding and implementation. *RSI* compares the magnitude of assets recent gains to the magnitude of its recent losses, giving indication whether the asset is considered to be overbought, or oversold. Increasing value of *RSI* reflects increasing momentum in stock price, proving the uptrend until the levels when asset is considered overbought, and vice versa. Momentum in the stock price is the empirically observed tendency for rising stock prices to rise further, and falling prices to keep falling. Relative Strength index is measured on a scale from 0 to 100, with bound from 0 - 30 considered as an oversold levels, generating buy signal. And contrary levels from 70 to 100 are considered overbought levels, providing signal to sell. Other bounds for signal indication can be also used, and in empirical study we will test several of them. Commonly *RSI* is used on a 14 day timeframe (Achelis, 2013), while in this work it will be concentrated on using 10, 20 and 30 min period. We will be also testing results regarding shorter, 7min period, which is considered to be more effective for the intraday trading. *RSI* is a tool used to provide both market entry or exit signals, and to indicate strength of the trend. Though the description and from the sight it appears quite simple, the mathematical part of *RSI* is a bit more complicated. General formula for *RSI*:

$$RSI_i = 100 - \frac{100}{1 + RS_i},$$

where RS stands for:

$$RS_i = \frac{EMA(U,\tau)_i}{EMA(D,\tau)_i},$$

and *EMA*, here stands for Exponential moving average, of U - upward change in asset price, D - downward changes in asset price and τ is so called period for *RSI* chosen (corresponds to the period of exponential average). The increase / decrease in the asset price are reflected in the following values for U and D:

$$\begin{cases} if\ p_i > p_{i-1} \rightarrow U_i = p_i - p_{i-1};\ D_i = 0 \\ if\ p_i < p_{i-1} \rightarrow D_i = p_{i-1} - p_i;\ U_i = 0 \end{cases}$$

We evaluate these values of U_i and D_i for all observations, and then we calculate values of exponential moving average for specified period τ and after that compute the value of *RSI*. In later combinations with several other strategies will be also considered.

2. 4. Simple moving average (SMA)

Simple moving average arguably is one of the most popular technical analysis indicators used by traders (Ming, 2006). Simple moving average calculated as simple mean of *n* number of values of previous asset prices. Basically it is arithmetical average applied for previous n values of asset prices, which have no weight factors applied. That formulation holds for *SMA* in uniformly distributed time. In our model we will have *SMA* for specified period in minutes, and we compute the average by formula described in section “Notes on computing averages in unevenly spaced data”.

SMA is used to eliminate volatility from the stock price movements and as an indicator *SMA* is used to identify the trend and to give entry / exit points on an asset. For trend indication *SMA* is trivial to use, while *SMA* is pointing up, the price of asset is trending higher, and vice versa when we have a down pointing *SMA*. Usually the *SMA* is used in combination, of few, most commonly two options of different period’s averages. According to (Lento 2007) study about profitability of technical trading rules on main United States indexes (S&P, NASDAQ and DJIA), moving averages crossover strategy consistently outperform the buy-and-hold trading method.

Moving averages crossover consists of setting one moving average for longer, and one for shorter period, their intersections are assumed to be market action indicators. When shorter period *SMA* crosses longer period *SMA* from below - buy signal is generated, and when from the top of it - sell signal is set up. For intraday trading the advised and common combination is 10 and 20 periods *SMA’s* (Droke, 2002), while the different combinations can be adjusted by each trader preferences. Since reducing time period of shorter period *SMA* will increase the quantity of signals, invoking increased number of trades the profitability of that must be inspected. As *SMA* is lagging indicator signals are delivered already after the trend have changed, so the signal is rarely generated at the most profitable point for market entry. If the data is measured at equally space time moments then the formula for calculation of *SMA* is following:

$$SMA(p,n)_t = \frac{p_t + p_{t-1} + \ldots + p_{t-(n-1)}}{n}$$

Where *p* is price of asset, *t* is time period and *n* is the number of periods for the required *SMA*. This formula is usually used for calculations when daily stock price information is analyzed. Since we are working with intraday data we will be using the following formula:

$$SMA(X,\tau)_i \approx \sum_{j\in[t_i-\tau,t_i]} X_j \frac{\Delta t_j}{\tau},$$

where τ is the length of time period (e.g. 10min) and n stands for number of price observations in give time period τ.

2. 5. Trading range breakout (TRB)

Trading range breakout *TRB* is a rather different technical analysis tool compared to the previously discussed two. *TRB* being more a rule than an indicator is widely tested when analyzing technical trading and proved to return more profitable outcome than simple buy – and hold strategy in US index market according to Brock, Lakonishok, and LeBaron (1992). Also the predictive power of *TRB* was found in Southeast Asian stock markets by Hao Yu, Gilbert V. Nartea (2012), therefore the rule will be included in the work for testing as well. Trading range breakout works as a rule when to enter the market or to liquidate the position regarding the value of the price in respect to predefined range.

Support and resistance levels of the asset price trading range to indicate whether a trade should be done. Trading range of the price can be defined as spread between high and low prices for a period of time. With support level being a historical level for which price was able to "bounce back" in downward trend, and resistance level being exact opposite of support. The resistance (support) level is defined as a local maximum (minimum) price over a given period of time, with a buy (sell) signal generated when the price moves through the resistance (support) level. Situation when trend breaks the previous support level is considered by investors to result in indication for an upcoming uptrend and is used as buying signal. Conversely, the selling signal is generated when price crosses the resistance level. Local maximum and minimum points are defined based on chosen past period, in daily data (50, 150, 200) days periods are used commonly (Yu, et. al. 2013). In our intraday trading system we will try (10, 30, 60, 120) minutes ranges for deciding on support and resistance levels, since in different works the wide range of intervals from 30min to 3h are used. Brock, Lakonishok, and LeBaron (1992) also suggest using band technique, where price must fall behind (exceed) the local minimum (maximum) point by 1% in order to produce market action signal. Since the trading rule requires no index calculation, the signals for action will be generated accordingly:

$$\begin{cases} p_i > (1+c)\cdot max\{p_j, t_j \epsilon [t_i-\tau, t_i]\} \rightarrow buy\ signal \\ p_i < (1-c)\cdot min\{p_j, t_j \epsilon [t_i-\tau, t_i]\} \rightarrow sell\ signal \end{cases},$$

where c – percentage of the band and m – chosen period for resistance (support) level range.

2. 6. Moving Average Convergence / Divergence (MACD)

Moving Average Convergence / Divergence, or shortly *MACD*, is an indicator developed by famous market technician Gerald Appel in 1970s. It is described as one of the simplest and most effective momentum indicators available. In literature mixed results can be found by implementing *MACD,* some stating *MACD* to outperform buy and hold strategy, while other findings does not find any evidence in profitable use of indicator. Used for several things, such as strength, direction, momentum and duration of trend of assets price. In principle, *MACD* uses same idea as earlier described *SMA*, different length moving averages are used to generate the signals, but *MACD* construction is more complicated.

In most common cases, indicator is consisting of three parts: *MACD* line, signal line and divergence, or simply bar chart. *MACD* line is a difference between to different length exponential moving averages. The longer term exponential moving average is subtracted from shorter one to produce *MACD* line. Traditional the length of the longer term average is taken as 26 periods, and the shorter one is set to 12. Then, the signal line is a product of *MACD* line, since it is taken as exponential moving average, with length of 9 periods, of it. Commonly the *MACD* histogram is also added to the chart, and it is plotted as difference between the *MACD* line and signal line. In the analysis we will concentrate only on signals generated by *MACD* and signal lines. The settings of *MACD* (12, 26, 9) where originally suggested by Appel and we will not be testing different combinations. In our case these will be periods of minutes that are used.

The signals can be produced by *MACD* in several ways, by one line, or crossovers of theirs. Firstly, using only *MACD* line, the market trend signal is generated when *MACD* line crosses the zero line, which is also known as center line. Since *MACD* oscillates in areas above or below the center line, the market trend can be spotted rather easily, and mathematically, positive *MACD* corresponds to uptrend, or increasing upside momentum. Conversely, the negative *MACD* corresponds to downtrend and increasing downside momentum; therefore crossings of zero line are used as momentum indicators. Another way to get market signal, is to use combination of *MACD* and signal line crossovers. Similarly to simple moving averages, the buying signal is generated when *MACD* line crosses signal line from below, indicating recent increase in uptrend momentum. And vice versa, when the *MACD* line crosses signal line from above, goes under it - the downward momentum occurs indicating to sell the asset. As all indicators *MACD* possess its drawbacks - when price graph is flat for a period of time and doesn't have trend, the *MACD* is unreliable and doesn't give decisive signals. Furthermore, the different lengths of averages used might produce better signals when adjusted to separate assets, and traditional options may not provide most efficient results. The calculation of *MACD* consists of three computations:

1. $MACD_{line_i} = EMA(p, 12)_i - EMA(p, 26)_i$
2. $Signal_{line_i} = EMA(MACD_{line}, 9)_i$
3. $MACD_{histogram_i} = MACD_{line_i} - Signal_{line_i}$

So *MACD* line is composed from difference of *EMA* of asset prices for 12 days and *EMA* of asset prices for 26 days. Signal line is *EMA* of *MACD* line for 9 days and *MACD* Histogram is found by subtracting signal line from *MACD* line. The time intervals to be used in *MACD* calculation have effect on the number of trade signals generated and also profitability results, therefore they must be considered with cautiousness.

2. 7. Stochastic oscillator (SO)

Stochastic oscillator is very different momentum indicator from the ones that are described earlier. Being developed by George Lane in late 1950s the indicator refers to the position of the current price in relation of the set period price range. What distance *SO* from other indicators, is the fact that indicator does not follow prices, or volumes directly, instead, it follows only the momentum of price. In a simple approach, one could say that stochastic oscillator delivers information about how close the current price of an asset is relation to the highs and lows of the price range of that asset in given period. The basic concept behind the stochastic oscillator is the concept that prices of the assets tend to reach near recent range extreme values, before the reversal of the trend appears. Since the oscillator varies from value of 0 to 100, the bounds of 80 and 20 are frequently taken as overbought and oversold levels, respectively, since these bounds were initially suggested by Lane. Same margins will be used in our trading strategy.

The signals from *SO* are generated in two separate lines - *%K* and *%D*, construction described below. While *%D* line is an average of *%K* line its value is tracked for the signal related to overbought and oversold levels of underlying asset. The crossings of both lines, *%K* and *%D* produces signals equivalently: when *%K* line crosses *%D* line from below the buy signal is produced, and when *%K* line crosses *%D* line from above, sell signal is generated. One shortcoming of the indicator could be noted as the sensitivity to adjustment of parameters for the length of the averages and period considered. The following are original formulas of *%K* and *%D* lines developed by George Lane:

$$\%K_i = \frac{Current\ price\ -\ Lowest\ low\ of\ period\ (14)}{Highest\ high\ of\ period\ (14)\ -\ Lowest\ low\ of\ period\ (14)}$$

$$\%D_i = SMA(\%K, 3)_i$$

In our work we will be using following formulation for *%K*:

$$\%K_i = \frac{p_i - min\{p_j : t_j \epsilon [t_i - \tau, t_i]\}}{max\{p_j : t_j \epsilon [t_i - \tau, t_i]\} - min\{p_j : t_j \epsilon [t_i - \tau, t_i]\}},$$

here t_i stands for time of current observation and τ – length of period for estimating minimum and maximum values. (Originally 14 was look - back period (trading days, weeks, or intraday trading period)). Calculation of *%D* we will use simple moving average of %K with time period 3min.

2. 8. Commodity Channel Index (CCI)

Commodity Channel Index was introduced by Donald Lambert in 1980 for identifying cyclical trends in commodities market. Since that time, the oscillator gain substantial amount of popularity among investors, and can is used not only for trading commodities but equities, and other securities. *CCI* have the same target as Stochastic Oscillator, it is designed to measure current price value relatively to the average price value in the given period. As well as *SO*, the *CCI* reaches high value when the prices are far above from their average, and low value when the price is far below its average value. As most of oscillators, *CCI* have its ranges to identify buying and selling signals, with levels above 100 assumed to be levels of overbought, and delivering market exit indication, and levels below -100 regarded as oversold levels, giving market entry signal. The slight difference in construction of *CCI* is that it takes into account the deviation of the mean of the price. And also instead of highest or lowest price, the typical is used in assessment. Construction of the oscillator is the following:

$$CCI_i = \frac{TP_i - SMA(TP, 14)_i}{0.015 * MD_i}$$

$$Where: TP_i = \frac{\max\{p_j: t_j \epsilon [t_i - \tau, t_i]\} + \min\{p_j: t_j \epsilon [t_i - \tau, t_i]\} + p_i}{3};$$

$$MD_i = \frac{1}{n} \sum\nolimits_{j: t_j \epsilon [t-\tau, t]} \left| TP_j - SMA(TP, 14)_i \right|$$

The value of 0.015 is constant set by Lambert to provide that about 70 to 80 percent of *CCI* values would fall between −100 and +100 intervals. MD_i - stands for mean deviation.

A default setting for the *CCI* is 14 periods. In our empirical study we will hold to that setting, and we will be considering 14 periods of 5 min time intervals. We will not be testing other period settings for *CCI*, while smaller number of periods would produce more sensitive indicator giving more trading signals, and conversely longer – less signals.

To sum up all technical indicators based mainly on asset prices that we will be using in trading strategy, the table below gives full information when “buy” or “sell” signals are generated according to each indicator:

Table 1. Technical analysis, price based indicators

Indicator	Value range	Notable levels	Signals
RSI	0 – 100	< 30 – oversold	Buy
		> 70 – overbought	Sell
		Increasing value – uptrend, decreasing – downtrend.	
SMA (e.g. SMA(10), SMA (20))	No specific range, follows price of asset	SMA (10) crosses SMA (20) from above.	Sell
		SMA (10) crosses SMA (20) from below.	Buy
		Asset prices above SMA confirm uptrend. Asset prices below SMA confirm downtrend	
MACD	No specific ranges, differs according to asset	MACD line below 0	Sell, downtrend
		MACD line above 0	Buy, uptrend
		MACD line crosses signal line from below	Buy
		MACD line crosses signal line from above	Sell
		Center line crossovers are also considered start of uptrend when from negative to positive and vice versa for downtrend.	
SO	No specific ranges, differs according to asset 0 – 100	< 20 – oversold	Buy
		> 80 – overbought	Sell
		%K line crosses %D line from below - buy signal %K line crosses %D line from above - sell signal.	
CCI	80% of values in -100 - + 100	< -100 – oversold	Buy
		>100 – overbought	Sell

3. Volume based indicators

After discussing price based indicators, we are now turning to indicators related to volume. In general, volume is the number of shares or contracts traded in a security or in an entire market during a given period of time. In this work, volume will be related to the number of shares traded on a single security during specified period. Since our trades will be happening only with one security within one day, it is not the entire market, and the period will be not given in days or weeks, but selected number of minutes, depending on indicator used. Volume is without doubt important element of technical trading. Following the prices and combining indications from their movements and volume movements can provide anticipated security's price changes. In the case of a strong and healthy trend increasing prices are expected to be accompanied by increasing volume. Otherwise, increasing prices, but decreasing volume signals that the trend is not strong and there might be possible reversal in a security movement. The heavier the volume appears in a security, the more likely it is in continuation of reaching new price levels, and proceeding movements in existing trend (Baiynd, 2011). To put it shortly, volume provides clues as to the intensity of a given price movement (Achelis, 2013). Very often without significant volume levels stock prices remain directionless and new trends do not appear. Later we are focusing on following three patterns in volume: increasing volume, declining volume, and volume spikes. Further on we discuss several volume based indicators that we will use in the trading strategy.

3. 1. Volume weighted Moving Average (VMA)

The Volume weighted Moving Average differs from the previously described simple moving average by adding volumes of trades as weighting factor to the calculations. The purpose of such use is to put more importance on the days, or trades (in intraday trading) which have heavier volume. *VMA* computes the average price per share while *SMA* computes the average price per trade, so in the case of *VMA* trades with larger volume receive more weight in the average. Trading signal for *VMA* is generated in the same way as for earlier mentioned *SMA*. The moving averages crossovers are one of indications to be considered, where we take two different time period length averages. When shorter period *VMA* crosses longer period *VMA* from below - buy signal is generated, and when from the top of it - sell signal is produced. And increasing *VMA* will confirm uptrend, and conversely decreasing – down trend. The formula for calculating *VMA* at time moment t that we will be using is given by:

$$VMA(p,\tau)_i = \frac{\sum_{j:t_j \epsilon [t_i-\tau, t_i]} p_j \cdot q_j}{\sum_{j:t_j \epsilon [t_i-\tau, t_i]} q_j},$$

where τ is the length of time period (e.g. 10min) and p_j and q_j represents price and volume correspondingly.

3. 2. Volume Weighted Average Price (VWAP)

The Volume Weighted Average Price (*VWAP*) is very similar to volume weighted moving average mentioned above, except the fact that the period τ whole trading day up to the current time moment. By using *VWAP* strategy to enter or leave the position market participants agree to receive average price of *VWAP* in some time period, buy splitting their huge trade into smaller pieces that are spread over decided time period, and performed at average *VWAP*. In 2005 according to research ordered by Bank of America, approximately in 50% of institutional participant's orders the *WVAP* strategy was used. *VWAP* is calculated by intraday trade data only, and is applied mainly for intraday trading.

In practice *VWAP* can be used as indicator when the ability to enter position under the value of *VWAP* price can be assumed to be a "buy" signal and in reverse for a "sell" signal. While in literature there are evidence that *VWAP* doesn't produce higher returns than using only *SMA* (Makwana and Kohli, 2012), in foreign exchange market *VWAP* can be used to predict levels of support and resistance, therefore same logic will be applied to our model. We will consider situations when price available to buy asset under *VWAP* value as market entry points, and when price will be above *VWAP* we will judge it as a signal for liquidating the position. Not to forget, that market prices above *VWAP* value serves as upward trend indication, and in a long uptrend prices can remain above *VWAP* values for extended period of time. Volume Weighted Average Price is only visible at intraday time frames and is calculated from the beginning of trading day till the market closes. Calculations of VWAP are the following:

$$VWAP_i = \frac{\sum_{j:t_j\epsilon[t_o,t_i]} p_j \cdot q_j}{\sum_{j:t_j\epsilon[t_o,t_i]} q_j}$$

Where p_j - stock prices at t_j – th time moment, and q_j – volume of trade. And since the indicator is calculated from the beginning of the trading day, the calculation starts from one chosen time point and ends at another. This is related to the idea, that in trading strategy we will consider starting trading not at the very beginning or ending at the time market close, but sometime after market opens, and some time before it closes, in order to avoid higher volatility in times after opening and closing of the market.

3. 3. On Balance Volume (OBV)

On Balance Volume is a momentum indicator that relates price change to volume. *OBV* was developed by Joe Granville in 1963, introduced in his book "New Strategy of Daily Stock Market Timing for Maximum Profits". *OBV* measures buying and selling pressure as a cumulative indicator that adds up volume on the days the stock price increases and subtracts volume on the day prices decreases. This results in *OBV* showing whether the volume is flowing into the security (accumulation) or out of it (distribution). In Granville's theory it is stated that volume precedes price, therefore *OBV* rises when volume on increased price days is higher than volume on decreased price days, and vice versa when *OBV* is decreasing. An increasing *OBV* reflects a positive pressure on the volume, which tends to result in higher prices. When the *OBV* and price moves in the same direction, then the signal of continuing up trend and higher prices is generated, and conversely, when direction of *OBV* and prices is opposite it indicates possible reversal in a trend. Traditional calculation of *OBV* is the following:

$$OBV = OBV_{prev} + \begin{cases} q, & if\ close > close_{prev} \\ 0, & if\ close = close_{prev} \\ -q, & if\ close > close_{prev} \end{cases}$$

Where OBV_{prev} is and *OBV* value at previous period, traditionally - a day and q is a volume on current period. At the starting day of calculation the *OBV* value is determined by the initial value. The absolute value of *OBV* is not of the interest, and the focus is on trend and direction of *OBV*. Since in this work we are dealing with intraday trading, the construction for *OBV* values will be such:

$$OBV_i = OBV_{i-1} + \begin{cases} q_i, & if\ p_i > p_{i-1} \\ 0, & if\ p_i = p_{i-1} \\ -q_i, & if\ p_i < p_{i-1} \end{cases}$$

To test the trading using *OBV* we will use the indicator alone and with combination with price related technical indicators. For trading based solely on *OBV*, we will use two different time length *SMA`s* of *OBV* and will consider their crossovers as trading signals.

3. 4. Money flow index (MFI)

Money flow index (MFI) is similar to the earlier described *RSI* index, since it is calculated as RSI but includes volume in calculations as well. *MFI* is an oscillator that is calculated over n – time periods in order to measure buying or selling pressure. The purpose of using this oscillator is to evaluate if the money are flowing into the security or out of it. Positive money flow into the security typically results in increasing prices and momentum with buying pressure, conversely money flow is negative when there is selling pressure. In original description for the oscillator by Gene Quong and Avrum Soudack the indicator uses concept of typical price, where typical prices is constructed by high, low, and close price of the corresponding day. Since we are implementing the indicator for intraday trading the construction of typical price will be adjusted. The oscillator values ranges from 0 to 100, as *RSI* does, but the levels of overbought and oversold are considered differently. The levels of *MFI* from 0 to 20 are considered oversold, and identify unsustainable extreme in falling prices, similarly levels from 80 to 100 correspond to overbought areas and indicate possible reversal in uptrend. Quang and Soundack suggest that these levels have to be taken under consideration, when in strong trends; the indicator could maintain value in extreme regions for extended period of time, also generating false market action signals. Identically for *RSI*, the increasing *MFI* confirms the uptrend and decreasing – downtrend. The divergence between movements in *MFI* values and price usually indicate upcoming reversal in the trend, coming from the situation where increasing prices are accompanied by decreasing volume. As earlier noticed, *MFI* have similar, but slightly different calculation from RSI. After we find price differences, then we find money flow, and from that positive and negative money flows:

$$MF_i = p_i \cdot q_i,\ \Delta_i = p_i - p_{i-1}$$

$$\begin{cases} PMF_i = \sum_{j:t_j \epsilon [t_i - \tau, t_i]} MF_i I_{\{\Delta_i > 0\}} \\ NMF_i = \sum_{j:t_j \epsilon [t_i - \tau, t_i]} MF_i I_{\{\Delta_j < 0\}} \end{cases}$$

This way we find the positive and negative money flows for period τ, in our case we test same periods as for *RSI*. Now we can find *MFI* value:

$$MFI_i = 100 - \frac{100}{1 + MR_i},$$

where *MR* is money ratio, found by:

$$MR_i = \frac{PMF_i}{NMF_i}.$$

Parameters for long term trading using the indicator are suggested by Gene Quong and Avrum Soudack as 14 day look back period to get the value of MFI, and trading day information for TP value. The research on other works about feasibility to implement this indicator to intraday trading does not yield in any significant suggestions. Therefore testing for parameters will be done during development process of algorithmic trading model to see if any reasonable results can be found.

Table 2. Technical analysis, volume based indicators

Indicator	Value range	Notable levels	Signals
VMA (e.g. VMA(10), VMA(20))	No specific range	VMA (10) crosses VMA (20) from above	Sell
		VMA (10) crosses VMA (20) from below	Buy
		Asset prices above VMA confirm uptrend. Asset prices below VMA confirm downtrend	
VWAP	No specific range	Price below VWAP level	Buy
		Price above VWAP level	Sell
		Prices staying above VWAP correspond to continuing uptrend, conversely, below VWAP to downtrend.	
OBV	No specific range	OBV crosses SMA(OBV) from below	Buy
		OBV crosses SMA(OBV) from above	Sell
		Rising OBV value confirms uptrend, decreasing – downtrend. Divergence between OBV value and price movements indicates possible reversal in a trend.	
MFI	0 – 100	< 20 – oversold	Buy
		> 80 – overbought	Sell
		Rising MFI value confirms uptrend, decreasing – downtrend. Divergence between MFI and price movements indicates possible reversal in a trend.	

4. Order flow analysis

The last part of analysis to consider will be order flow analysis. First thing to mention is the concept of order flow analysis and how it is different from what was described before. Contrarily from technical and fundamental analysis, order flow is based on the idea of studying market microstructure in the interest of understanding existing positions on buyers and sellers side. The target is information on bid – ask prices and quantities of securities offered. (Love and Payne 2008) suggest describing order flow as the difference between buyer – initiated and seller – initiated trading activity in a given market, and this correspond to what is in practice described as aggressive buying or selling pressure. Order flow in a broad sense and liquidity is described as the foundation of every market, since market movements and price changes are results of actions in orders.

So the essence of order flow analysis is in market microstructure. The order flow analysis, starts from analyzing order book. Order book (also known as Depth of Market (DOM)) in a simplistic way is a two column of listing of the entire bid and ask orders at different prices and quantities. The orders in the market or specified exchange that shown up on the order book are limit orders. Since the market orders (to buy or sell security on current best available market price) are executed immediately, the only orders that are available on order book are limit orders. The limit order is an order to buy (sell) a defined number of shares at a specified price or more favorable price for buyer (seller). Since investors are interested in buying and selling the securities at different price levels - the depth of the market provides that information. And following the changes in order book, which appear due to new orders coming, old cancelled or some fulfilled because of trades is considered as order flow analysis. One could consider this being similar to volume and its analysis, while (Evans 2008) states that order flow is different from volume because of information it conveys: it provides the overview on levels at which market participants are willing to enter or liquidate the position. Because information about market microstructure provides different levels of bid – ask prices, quantities of shares offered and also number of orders, the possibilities for analysis are rather wide. While order flow analysis can be implemented on any market, there vast majority of findings are done on foreign exchange market, and earlier mentioned (Love and Payne, 2008) checked several currency pairs and found that in average one third of price relevant information is impounded into the prices via the order flow. Therefore, it could be possible to test if order flow analysis might be successful in predicting price movements in securities market as well.

Since order flow analysis can consist of a large number of different elements, we will have to specify few areas that we will check for market signals. Findings of (Chordia and Roll 2005) on NYSE suggest that short-horizon returns can be predicted from order flow imbalance. Order flow imbalance is usually defined as number of sellers initiated trades subtracted from the number of buyers initiated trades. Alternatively, one can also use difference between amounts of money for trades received by buyers and sellers. Positive momentum and pressure from buyers side is considered when the order flow imbalance is positive, resulting in expectation for prices to go up, and a signal to enter market. Conversely the signal for selling is generated when order flow imbalance is negative. This will be the first trading rule to consider from order flow analysis. As we did before for other indicators, we will be calculating order flow imbalances for period of 5min; this is also suggested by Yamamoto (2012). First version of order flow imbalance will use number trades to get the indication, and we will denote that by *OFIB#*. We will find it using the following formula:

$$OFIB\#_i = \frac{\sum_{j:t_j\epsilon[t_i-\tau,t_i]} n_{b\,j} - \sum_{j:t_j\epsilon[t_i-\tau,t_i]} n_{s\,j}}{\sum_{j:t_j\epsilon[t_i-\tau,t_i]}(n_{b\,j} + n_{s\,j})}$$

Where *n_b* and *n_s* is a number of buyers and sellers initiated trades correspondingly, in the look back period of τ minutes. Second version of order flow imbalances uses the amount of money which is exchanged between buyers and sellers. To make it more clear, the trades initiated by buyers will result in providing amount of money paid by buyers, and trades that are initiated by sellers will contribute to amount of money received by sellers. The calculation will be:

$$OFIB£_i = \frac{\sum_{j:t_j\epsilon[t_i-\tau,t_i]} p_j q_{j_{\{B\}}} - \sum_{j:t_j\epsilon[t_i-\tau,t_i]} p_j q_{j_{\{S\}}}}{\sum_{j:t_j\epsilon[t_i-\tau,t_i]} p_j q_j}$$

Where $p_j\, q_j$ – represents total amount of money exchanged (in our model the data is in GBP, £, therefore it is denoted as *OFIB£*), and {B}, {S} represents buyers, sellers initiated trades respectively. The understanding of initiation of the trade comes from data or following bid – ask prices and noticing on which price the trade appears. Our data provides information which side initiated the trade, since volume of buyers initiated trade is negative, and sellers initiated trade is reported as positive, so the need to follow bid – ask prices to judge initiating side is unnecessary. For both indicators the market signals will be done accordingly:

$$\begin{cases} OFIB\#_i \text{ } or \text{ } OFIB£_i > \alpha & \rightarrow buy \text{ } signal \\ OFIB\#_i \text{ } or \text{ } OFIB£_i < -\alpha & \rightarrow sell \text{ } signal \end{cases}$$

Since both indicators vary from [-1,1] we will test different α values for trading signal. Since the trading activity in different stocks can vary significantly, the constant tested will be provided in practical part of the work.

The second concept to consider in order flow analysis part comes from the work of Handa (2003) and focuses on order book imbalance. Order book was defined at the beginning of this section, and now we will consider imbalances between different sides of order book. The idea behind order book imbalances comes from the different amount of orders from buying and selling side. The trading strategy consists of observing which side of order book becomes heavier, or also called thicker – with more orders on one side indicating market pressure from that side. It means that if for example the ask side becomes thicker than the bid side, then more sell orders are observed, pushing the prices down and making future price movement predictable from this imbalance. It could be noted that Osler (2003) found predictive power of order book imbalances in exchange rate short term movements. Therefore we will try to apply order book imbalances analysis in our work on selected securities.

We will denote order book imbalance as *OBIB* and as suggested by Yamamoto (2012) we will calculate it at time of each observation:

$$OBIB_i = \frac{\sum_{j=1}^{n} q\_bid_j - \sum_{j=1}^{n} q\_ask_j}{\sum_{j=1}^{n}(q\_bid_j + q\_ask_j)}$$

Here *q* is size of different orders, and we sum them up for the available information, bid and ask sides accordingly. In our data we can observe 5 bid and 5 ask order levels, therefore *n* will be equal to 5. Obviously indicator will can het values from interval [-1,1], with negative values indicating more shares offered on ask side and positive – more shares in bid orders. The trading signal will be done accordingly:

$$\begin{cases} OBIB_i > \alpha & \rightarrow buy\ signal \\ OBIB_i < -\alpha & \rightarrow sell\ signal \end{cases}$$

In paper of Kempf and Korn (1999) it is suggested that more information is conveyed by large orders, this advice that one reasonable idea would be to analyze be large orders appearing and price change following the appearance of large order. Intuitively, we can assume that large orders appearing on bid side should generate buying pressure resulting in increasing prices, and otherwise for ask side. On the other hand, we mentioned in the introduction, that same algorithmic trading systems are developed with the goal of splitting the huge orders in to smaller ones, in order to hide the real demand or supply. In that way big institutional investors are able to reduce impact on the market price when taking or liquidating big positions. This suggests that it might be useful to consider average order size. It should be mentioned, that this type of order analysis is not backed by any previous research and it's purely authors choice. Although the concept itself could be confirmed by the evidence of Kumar, Mamidi, Marisetty (2011) research on NYSE in which they observe that traders react positively into the increased size of orders, and negatively to the increased number of orders. So we will base our indicator on a belief that increasing average order size on the bid side, weighted by the price would indicate actions of institutional participants or increased positive buying pressure. We will denote average order by *AOS*. In order for indicator to have more meaning, we should consider giving higher weights in average calculation for the higher bid prices. Logic behind that is the idea of higher bid prices correspond to more buying pressure, and as well the fact that higher bid price orders are executed before the lower one in normal market conditions. Reverse logic should be applied to ask prices, where lower ask prices indicate more willingness to sell. We will calculate the *AOS* in this way:

$$AOS_i = \sum_{j=1}^{5} \bar{o}_j w_j\ , where: \bar{o}_j = \frac{o_j}{n_j};\ w_{bid_j} = e^{c(p_j - p_1)}\ and\ w_{ask_j} = e^{c(p_1 - p_j)}\ ,$$

where w_{bid} ask and and w_{ask} are weights for bid and ask prices accordingly. In the formula *o* represents order size, *n* stands for number of orders at j-*th* price *p* and *i* here goes from 1 to 5, since we have 5 different levels of bid – ask prices available. And the constant c could be specified by investor for weighting. In our work we will find c by following equation:

$$c = -\frac{\log(a)}{tick\_size}\ ,$$

where is $0 < a < 1$. To use the *AOS* in the trading to generate signals, we will use two periods *SMA* of *AOS*, and consider crossovers as trading signals, similarly as we did in simple moving average section.

And the last part of order flow we would like to analyze in this work is order cancelation. Without doubt it could be stated that cancelation of orders plays an important role in intraday trading activity and one would consider that a meaningful part of order book activity. This comes from the market micro structure itself, when let's say highest bid or lowest ask price order is cancelled, then the spread and market balance changes immediately. Observing cancelation of orders could mean that investors decided to change their position because of the some recent news or development in the market. While this seems to be rather interesting topic and might produce some substantial information how it effects price changes, there is only few studies of the cancellation effects available and they are not purely targeted to researching influence on price levels. One research by Eisler (2009) found evidence on NASDAQ traded stocks that cancelation of orders have an impact to future price movements. Intuitively thinking, we could come to the conclusion, that if arrival of the new bid (ask) order puts additional buying (selling) pressure, consequently, cancellation of corresponding order would reduce this pressure. It would be logical to consider cancelation of bid order as selling signal, and contrary for buying, but judging each cancelation as a signal might be too extreme and would generate too many trading signals. Therefore, and once again it should be noted that this is purely experimental authors concept, we will compare number of cancelation between bid – ask order book sides and then take the market action decision. We will denote cancelation of orders as *CO* and we will calculate it as:

$$CO_i = \frac{\sum_{j:t_j\epsilon[t-\tau,t]} AoC_j - \sum_{j:t_j\epsilon[t-\tau,t]} BoC_j}{\sum_{j:t_j\epsilon[t-\tau,t]}(AoC_j + BoC_j)}$$

Where *AoC* stands for ask orders canceled, *BoC* corresponds to bid orders canceled, and τ is the interval of time for which we calculate orders canceled. The indicator would be in interval from [-1,1], with -1 indicating that all orders that were cancelled in the period τ where bid orders. This would correspond to selling decision. Reverse logic should be applied for buying decisions. If indicator reaches 1, showing that all of the orders canceled where ask orders, buying signal would be generated. Since indicator would be varying from [-1, 1] it might be reasonable to test several different values of parameter λ (specified in testing part), similarly to the method we used in *OFIB#* calculation. So in the trading part we will check and generate signals accordingly:

$$\begin{cases} CO_i > \lambda & \rightarrow buy\ signal \\ CO_i < -\lambda & \rightarrow sell\ signal \end{cases},$$

where different λ values should be tested to explore the strategy.

5. Empirical study of technical analysis indicators returns in intraday trading

5. 1. Technical remarks

We start the study of the returns of technical trading, by indicating our comparison basis. We will be using simple buy and hold strategy to provide benchmark for technical trading results. Buy and hold strategy for both stocks used in analysis will be the following:

- We buy the asset at the starting time of the trading day. We take starting time as 08:30:00, same time we start analysis for most of indicators, later denoted as t_0.
- We sell the asset at the end of the day at time 16:30:00, later denoted as *T*.
- The prices of buying and selling are considered as the prices of ask1 for buying at time t_0 and as bid1 for selling at time *T*.
- Costs of transactions are considered neither for buy and hold, nor for technical trading strategies.

Table 3. Buy and hold returns for AZN, VOD descriptive statistics

	AZN_L	*VOD_L*
Mean	0,00089	-0,00209
Median	0,00139	-0,00174
Standard Deviation	0,00922	0,00967
Minimum	-0,02672	-0,02452
Maximum	0,02411	0,02068
Profitable days	36	24
Unprofitable days	24	33
Observations	60	60

The Table 3., above provides the descriptive statistics of simple buy and hold strategy. The obvious difference is that the AZN have positive mean and more profitable days, while VOD have contrary negative mean and more unprofitable days.

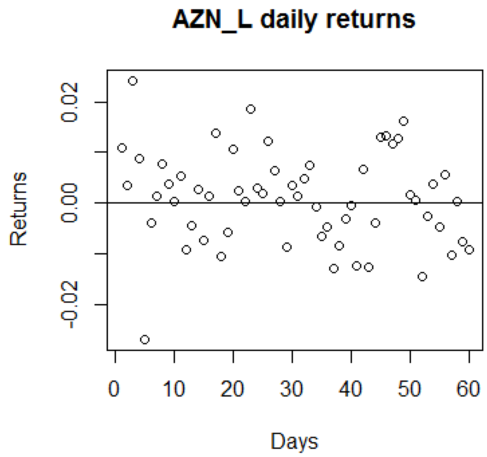

Figure 1. AZN daily returns - Buy&Hold

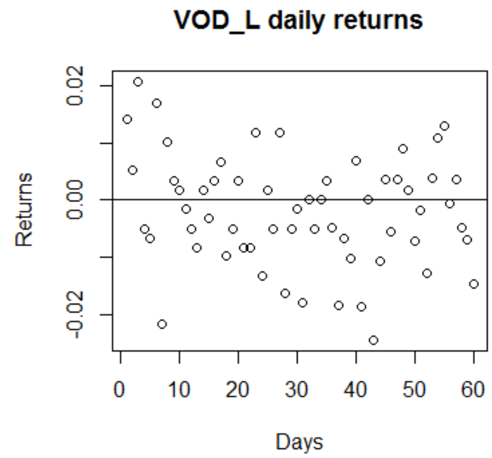

Figure 2. VOD daily returns - Buy&Hold

Returns that are used in the work, here and everywhere further on, are simple returns, calculated by formula:

$$R = \frac{p_T - p_{t_o}}{p_{t_o}},$$

and for the trading strategies the time moment t_0 corresponds to the time of buying, and T to time of selling, that concludes one trade. In most of the tables further on in the work we represent return per trade, but in cases when we need to find intraday return for whole trading day we will be compounding the returns. In those situations when we have multiple numbers of trades per trading day, we compound all of the returns for the strategies using the following formula:

$$R_k = \prod_{j=1}^{n} (1 + R_j)\ ,$$

where R_k is the total return for trading day k and there are n trades during k – th trading. This corresponds to assumption, that we start trading with some amount of initial capital, and we reinvest it all after each trade, not depending on the outcome of the trade. When we represent data for intraday returns we will exclusively specify, not to confuse with return per trade.

First of all, let's look at some examples about how signals are generated in the case of actual intraday trading data. Since all the indicators discussed above have similar formulation, we will not provide charts for all of them. Main two ways that the signal is generated is either an overbought / oversold level, or crossover of two different time length parameters. The charts below provide view how the signal is generated:

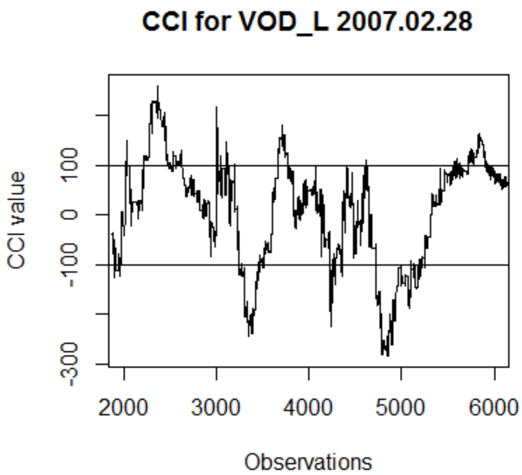

Figure 3. CCI Indicator

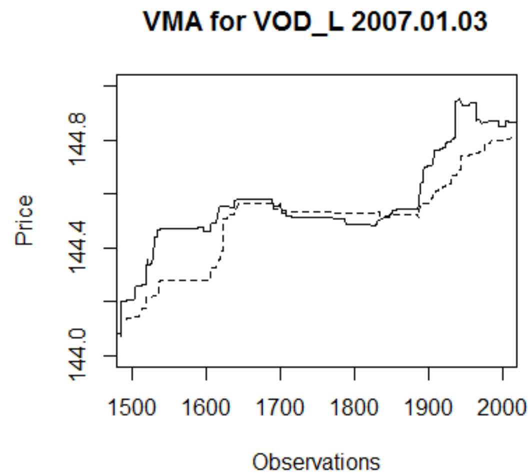

Figure 4. VMA crossover

Figure 3 shows the oscillation of *CCI* indicator. As it has two signal levels -100 and 100 for oversold / overbought levels correspondingly, the signal is generated once the indicator crosses the level. In the Figure 4 there are plotted two time periods *VMA*, the solid line corresponds to *VMA*(p,10) and dotted line for *VMA*(p,20). Signal is generated at each crossover of two averages. In the coding part, the value for buying signal is defined as 1, holding signal as 0 (in some indicators there is only buy and sell signals, no value in between) and selling signal as -1.

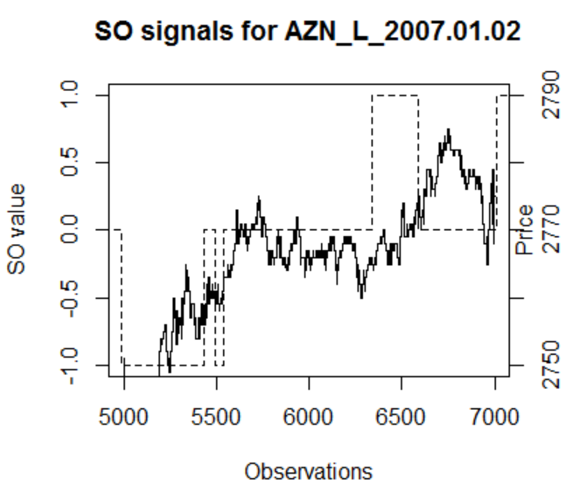

Figure 5. SO trading signals

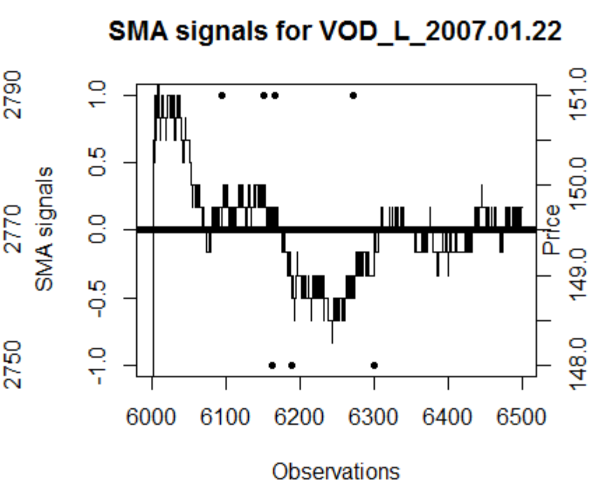

Figure 6. SMA trading signals

The Figure 5 and Figure 6 show signals in relation to price movements. In the first chart signal is dashed line, reaching values of -1 for selling signal, and 1 for buying signal. The Figure 5 corresponds to *SO* indicator reaching overbought/oversold levels and then generating trading signals expressed as either -1 or 1. Figure 6 correspond to signals generated from crossovers; here signal comes from *SMA* of price, for two different periods 10 and 20min. crossing each other. Dot at the level of 1 indicates buying signal, and conversely dot at -1 corresponds to selling signal at time of t_i observation.

Since we just have explained how the indicators are represented and used in trading strategy, a brief explanation of how analysis was carried out in technical terms using R statistical package will be provided. There are three most important structural parts in computations which can be described separately as:

1. Loading of data and time correction. Appendix 1. Time adjustment and loading of *.csv files. One of important things is time correction. Original data is in HH:MM:SS time format, which is not suitable to work with directly. Therefore, time at every observation is converted into time in seconds totally.
2. Computation of a selected indicator. Appendix 2. Calculation of *SMA.* We provide an example of computation for simple moving average. In this case we compute two different period's simple moving averages and generate a signal using the crossovers of averages.
3. Procedure of getting prices that we buy and sell at, as well as return calculation. Appendix 3. Calculation of returns for a given strategy. This is a code for getting the prices of trades and returns. It is directly connected to signals generated at part2. Logic provided in the example is the same logic for all of indicators.

The parts of code that remains almost unchanged with majority of indicators are 1^{st} and 3^{rd}, while the second part – calculation of indicator is different for every technical trading tool.

One last remark to be made before we present results is that in the theoretical part we mentioned that some indicators require adjustments regarding signal generating levels, like *RSI* and *MFI*. For that we do some prior testing on different 10 randomly chosen days for both stocks in order to see which levels provides better performance for the strategy. This suggests that because of activity in trading of different stocks we might want to adjust parameters for them separately. In Appendix 4., results of performed testing for different RSI and MFI signal bounds are represented. They suggest using different levels of bands for both stocks. For AZN stock, which is traded more actively than VOD, we will choose bounds of 10 and 90 for RSI to make market decisions, while those bounds generate highest average return. For VOD on the other hand, the bounds of 30 and 70 appear to work best in terms of average return. Similarly, in the same Appendix 4., we provide information for same type of test carried out for different bounds of MFI indicator. Findings suggest that the highest % of profitable trades for both stocks happened when we consider 10 and 90 bounds. Testing for both indicators was performed using shortest length average of 7min that we are using in the work, in order to get the majority of signals. For other indicators that consider overbought and oversold levels we use signal bounds originally suggested by their creators.

5. 2. Single indicator based strategies

Now we will consider results from all the technical trading strategies tested and their performance comparing to the benchmark. First we overview all the single indicator based strategies. All the results are provided in the Appendix 5, and here we present only the highest performing strategies from each approach. Important conclusion that should be drawn from the test of single strategies is that results from both stocks are rather different, and the main differences are:

- From price approach strategies, for AZN only 35% of strategies outperform buy and hold strategy for more than half of period tested. Same number for is 30%. While if we consider average returns, the differences are more significant. Only 1 strategy (RSI with period 30) was generated higher average return per trade than a buy and hold strategy for AZN share, and also has smaller standard deviation than benchmark strategy. On the other hand, all of the price approach strategies on VOD stock generated higher return than buy and hold strategy. Of course one must mention, that VOD have negative average return for buy and hold strategy, therefore even smaller negative returns from strategy appear to be higher returns than benchmark strategy. This means that we lose less in case of using some strategy, but we still are losing invested capital. The ratio between negative and positive returns for AZN 0,6, and for VOD is only 0.3. So whilst all of VOD strategies generate higher return than buy and hold strategy only 30% of trades result in actually profit. But also, all of price approach strategies applied on VOD share have smaller standard deviation than buy and hold, and higher mean, making them simply better strategies.
- Shortly it could be said that all of volume approach strategies perform worse than buy and hold strategy for AZN stock. In case of AZN 58% of strategies have positive average return per trade, but all of them are smaller than average return from buy and hold strategy. While two type of *VMA* manages outperform buy and hold strategy in more than half of trading period, the amount of profitable trades is only 30%. Considering VOD share, situation is similar as in price approach indicators. All of the strategies have higher average return and smaller standard deviation, making them preferable strategies to buy and hold strategy, but all of them are still negative in average return. And if we consider the fact that none of the trading strategies outperforms buy and hold strategy in more than half of period of trading, then there is very little practical use for all of them in this case.
- Looking at the results of order flow approach, we could notice that once again, for AZN share, there is only one strategy that have higher average return than buy and hold (OBIB, α =0.3), an also smaller standard deviation. Furthermore, situation is better if we consider the fact, that 53% of tested strategies outperform buy and hold strategy in more than half of days in trading period. If to look at the VOD share, once again all of the strategies have higher average return than buy and hold strategy. Otherwise, more than half of strategies results in actually losing invested money. But also, all of order flow strategies for VOD share can be considered better strategies than benchmark strategy, since they possess smaller risk measure of volatility for all of them and higher average return.

Now we will present three most profitable and best performing strategies in comparison to buy and hold strategy for each of the share.

Table 4. Best performing single strategies for AZN

Indicator	Average	Standard deviation	Profitable trades	Unprofitable trades	Buy and hold outperformed	Buy and hold underperformed
OBIB 0.8	0,001219	0,006200	59%	36%	58%	42%
RSI (30)	0,000896	0,005284	37%	15%	68%	32%
SO Sig.1	0,000411	0,003027	69%	26%	57%	43%

In Table 4., the best performing strategies for AZN stock are presented. Order book imbalance strategy, with parameter α set to 0.8 gives the best results of all tested strategies, and together with *RSI*, with time period of 30min are two sole strategies that have higher average return per trade than buy and hold strategies. While *RSI* generates only 37% of profitable trades, it still manages to outperform buy and hold strategy in 68% of days in testing period. That is a result of low level of unprofitable trades, and compounding effect of multiple trades per day. Stochastic oscillator on the other hand, has the highest percentage of profitable trades, but the average return per trade is approximately three times smaller than *OBIB* strategy. And yet still, the average return per day is higher than buy and hold strategy (1.00152 for SO Signal1).

If we would now consider VOD share, in the Table 5., below we can notice that first two best performing strategies have higher return comparing to strategies in AZN case, and in the same time they have smaller standard deviation. This means that applying SO sig.1 and RSI (10) strategy on VOD share we would be getting higher returns, than with first two top strategies in AZN case. One reason for that could be the activity behind trading of each stock. It could be assumed AZN to have properties of higher market efficiency, since it is traded more actively. Therefore applying same strategy on VOD, which is traded less actively, could result in better results, which are the case here.

Table 5. Best performing single strategies for VOD

Indicator	Average	Standard deviation	Profitable trades	Unprofitable trades	Buy and hold outperformed	Buy and hold underperformed
SO Sig. 1	0,0016208	0,002497	86%	9%	88%	12%
RSI(10)	0,0011187	0,003714	55%	19%	88%	12%
OBIB 0.3	0,0007983	0,005513	54%	35%	63%	37%

And in the Table 6., below, we show the most profitable single strategies in case we consider average daily returns and standard deviation of daily returns. Obviously, all of strategies that are above benchmark strategy can be referred as better ones. On the other hand, if we consider these strategies in general, the ratio between standard deviation and average might not make them so attractive, but these are not consideration that we are focusing on in this work. So we will continue on using buy and hold strategy to evaluate the performance of our technical trading strategies. Furthermore, if we check the Appendix 5, we can see that for both securities *RSI* strategy behaves rather differently with changing parameters. For AZN increasing the time period for *RSI* results in higher returns, while *RSI* for VOD works better with shorter time period average.

Table 6. Intraday returns comparison for single indicator strategies

AZN			VOD		
Strategy	Average intraday return	Standard deviation	Strategy	Average intraday return	Standard deviation
OBIB 08	0,0018416	0,0064163	SO Signal 1	0,0131804	0,0169823
SO Signal 1	0,0015166	0,0060432	RSI 7	0,0065540	0,0073378
RSI 30	0,0014039	0,0065739	RSI 10	0,0044457	0,0075935
RSI 20	0,0012671	0,0066881	CCI	0,0042042	0,0075334
RSI 10	0,0011041	0,0060462	OBIB 03	0,0009438	0,0058668
Benchmark	**0,0008957**	**0,0092272**	RSI 20	0,0007876	0,0072338
CCI	0,0008212	0,0064538	RSI 30	0,0003114	0,0076641
MFI 7	0,0003743	0,0060052	MFI 30	-0,0001694	0,0058646
RSI 7	0,0003569	0,0069650	**Benchmark**	**-0,0020896**	**0,0096743**

In the same Appendix 5., we can see the rest of results for price approach strategies. Quite unexpectedly, all different *SMA* strategies fail to outperform benchmark strategy, and at the same time the percentage of unprofitable trades for both securities are too high to consider them as useful trading strategies to apply solely. Also *TRB* have no significant power for both of stocks. We also tested the *TRB* strategy with different bounds, so called band technique suggested in theoretical part, but with constant c values 0.01 or 0.0025 the strategy did not provide any signals. This indicates that there were no extreme level price changes in both stocks tested. Another thing to mention for the reader, the results for indicator *CO* are not provided in the tables, since the development of efficiently functioning order cancelation algorithm was not implemented due to time shortage. Analysis of order cancelation is indeed an interesting one, but the mechanism needed for successful study has to be very sophisticated. To conclude this part, we can say that there are some single indicator based trading strategies which are performing better than buy and hold strategy, but for each stock the adjustment of parameters for trading tool is necessary.

5. 3. Combined strategies

Combined strategies will be the next step towards developing and algorithmic trading model. From single indicator based strategies we saw that there are some strategies that perform relatively well, while others quite poorly. The logic in construction, when combining the strategies, will be to get the signal when both strategies coincide. This should lead to better signals, and at the same time, decreased amount of signals. We will be combining strategies mainly from different approaches to analyze market movements.

One reason to combine strategies could be the aim to avoid early exists of a trend. For example, if we are using indicator which provides signal in case of overbought or oversold levels, then these type of indicators can and they do provide signals when the trend is lasting still and have not reversed yet. In case of *RSI*, after analyzing some days closely, we could notice that *RSI* provides selling signal, but after that the price continues to rise. This was also indicated in theory, that increasing value of *RSI* and indicator in signal levels can remain for continuous periods of time in case of strong trend. In order to avoid leaving still increasing price movement, we can consider using overbought / oversold level indicator together with some type of moving average, in that way, we could expect to get the signal a bit after the reversal of trend, avoiding early exits from strong trends.

Another thing to consider is combining not only different type of indicators, but tools from different approaches. If we combine indicators which rely on different approaches, we can expect to get better signals. This comes from logic, that if we observe increasing prices, and they are supported by increasing volume, we can assume that the trend is healthy and is set to continue. Furthermore, if we see that the prices are increasing and we have order flow imbalance, which clearly indicates strong buying pressure, we can also expect the trend to continue. Therefore, there are many ways, how we can create different combined strategies, and the number of combinations can be rather large. One more thing to notice is that in combined strategies, we will try to find predictive power of strategies, like *WVAP* and *MACD*, that solely did not performed well. So we study the following combined strategies: *MACD* and *MFI*, *MFI* and *RSI*, *OBV* and *RSI*, *OFIB* and *RSI*, *VWAP* and *SO*, *VMA* and *CCI*, *SMA* and *RSI*, and finally *SMA*, *VWAP* and *SO* together. As previously, all of the results are provided in the Appendix 6., and here we will discuss the top performing strategies and some important remarks.

The Table 7., below presents results for combined strategies of AZN share. Comparing to the results of single strategies, the first positive thing to notice is the number of strategies that outperform buy and hold strategy both in terms of average return and in smaller standard deviation. While in single strategy case we had only two strategies that have better estimates for average return and standard deviation, from combined strategies 9 of those have these qualities.

Table 7. Prefered combined strategies for AZN in comparison to benchmark strategy

Strategy	Average	Standard deviation	Profitable trades	Unprofitable trades	Buy and hold outperformed	Buy and hold underperformed
VWAP SO	0,001758	0,006309	50%	48%	58%	42%
MFI RSI (10 & 10)	0,000725	0,004516	60%	35%	58%	42%
OBV(03 & 05) RSI (10)	0,000808	0,005007	61%	36%	57%	43%
OBV(05 & 15) RSI (15)	0,000954	0,007091	50%	45%	53%	47%
MFI RSI (5 & 5)	0,000107	0,002561	53%	38%	53%	47%

The trading strategy of *VWAP* and *SO* combined appears to be most successful in outperforming buy and hold strategy. The average return per trade is higher than average return in buy and hold strategy already and if we consider comparing daily returns, the results of this strategy are also better than benchmark (average daily returns for this strategy 0.0014062 and standard deviation 0.0056916). Other strategies in the Table 7., may not present much higher returns per trade as *VWAP* and *SO* strategy, but if we consider the daily returns, then all of them outperform benchmark strategy, and that could be judged from the last two columns, where we see the percentage of days when strategy outperforms or underperforms. From all the data gathered by testing information of AZN share movements we could see that some strategies, that did not perform well when used singly, performed well combined. For example *MFI* and *MACD* with parameter of 15min average for *MFI* resulted in returns higher then benchmark, and smaller standard deviation, making it preferable strategy against buy and hold. Additionally, combination of three strategies – *SO*, *WVAP* and *SMA* resulted in highest number of profitable trades – 70.59%, highest average return per trade compared to the rest - 0,003993 and smaller standard deviation than benchmark strategy. But due to the low number of signals, only 19 buying signals per testing period, was left out from further considerations, while it still can be considered as relatively profitable strategy.

Below we provide Table 8., reflecting information which combined strategies could be considered as better performing for VOD share. The most significant performance from all of the strategies tested was delivered by combination of *MFI* and *RSI* strategy, with both of them set at 5min time parameter for average. And from all combined strategies for both stocks, this one could be referred as most successful one. While it resulted in 367 trades, highest number of trades from combined strategies, it also provided highest number of profitable trades, and in same time smallest number of unprofitable trades – 14,44%. Also it should be noted, that all but one of combined strategies, for VOD security, have higher average return per trade, and smaller standard deviation, which makes application of combined strategies for VOD share more promising in terms of results. Same remark could be made as in AZN case, some strategies that performed poorly when used singly, in combination resulted in acceptable results comparing to benchmark strategy. And examples include *VMA*, *OBV*, *OFIB* and *MFI*, which in combination performed better.

Table 8. Preferred combined strategies for AZN in comparison to benchmark strategy

Strategy	Average	Standard deviation	Profitable trades	Unprofitable trades	Buy and hold outperformed	Buy and hold underperformed
MFI RSI (5 & 5)	0,001278	0,002624	65,40%	14,44%	88,33%	11,67%
OBV(03 & 10) RSI (10)	0,001018	0,006088	59,26%	35,19%	63,33%	36,67%
OBV(05 & 10) RSI (10)	0,001325	0,005966	59,02%	36,07%	68,33%	31,67%
OFIB(0.6) RSI(10)	0,001546	0,006168	58,82%	31,37%	66,67%	33,33%
VMA (05&10) CCI	0,000186	0,004877	57,55%	29,25%	66,67%	33,33%

The results from combined strategies provide the suggestion what to use in our proposed model. For AZN share we will proceed with implementing trading model of *SO* and *WVAP* strategies together, and for VOD we will use combination of *MFI* and *RSI* strategies.

5. 4. Proposed algorithmic trading model

The choice of algorithmic trading model comes from the results of tests performed on historical data for both stocks. The application of model for the new data, which was not included in the work so far, does not use any information of unfolding market situation to change the parameters of model so it would improve performance or adjust. We are applying same algorithm of indicators calculation and trading decisions as we did previously. Therefore we hold to the assumption that trading strategy which worked for tested days will continue to perform similarly in the future.

We start from analyzing results on AZN share. The Figure 7., below shows returns of our trading model together with buy and hold strategy. Returns from our suggested trading model are represented by bars and returns from benchmark strategy by dots. From graphical observation we can say that our strategy does not yield in systematic outperformance of benchmark strategy. Since cases when the bars are higher than dots, representing benchmark strategy, are few. The strategy in total executes 23 trades, of which 11 are profitable, and for 11 trading days the strategy does not execute trades, making total number of profitable days 32.35%. In the graph, lines represent average return for the period from beginning of testing at *k* –th day. Solid line represents returns from trading model, and dashed line – returns from benchmark. One can notice that both averages converge almost to zero. While at the end our strategy have higher average return, which is negative in size, and smaller standard variation, we cannot state that it outperforms the benchmark strategy. Investing in this strategy would still result in loss of capital, as it would in case of choosing buy and hold strategy.

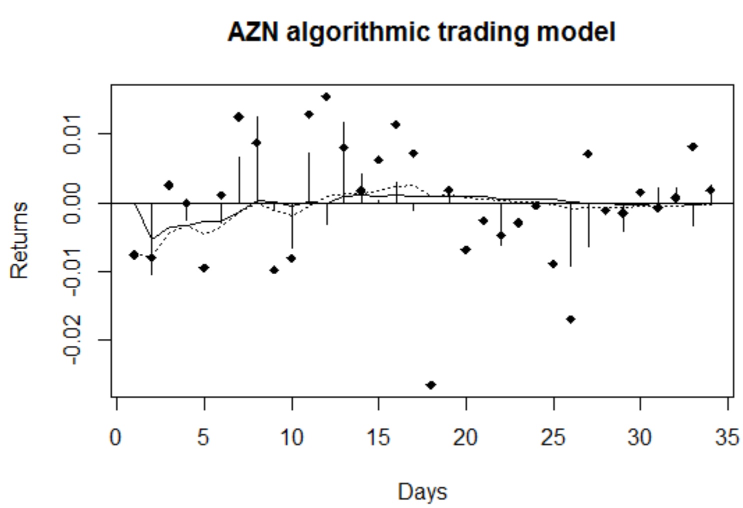

Figure 7. Returns of suggested model for AZN and benchmark strategy

So results from simulating chosen trading strategy on AZN stock suggest that our proposed trading model does not yield in any profitable outcome in the future. We could consider going back and looking over other combined trading strategies and then explore if any of them have predictive power for this period, but that is not our initial assumption. Therefore we have to conclude that for AZN we failed to construct an algorithmic trading model based on technical analysis which would significantly outperform buy and hold strategy.

Now let's analyze the situation with VOD share and our suggested trading model using *MFI* and *RSI* trading strategy. In the same way as we did with AZN share, we provide graphical representation of returns using our algorithmic trading model for the share, and the returns of simple buy and hold strategy. The Figure 8., below shows rather different picture from the one we discussed earlier. Once again, bars in the chart represent returns of our trading model, dots – benchmark strategy and from observation we can say that the results are better than in AZN case.

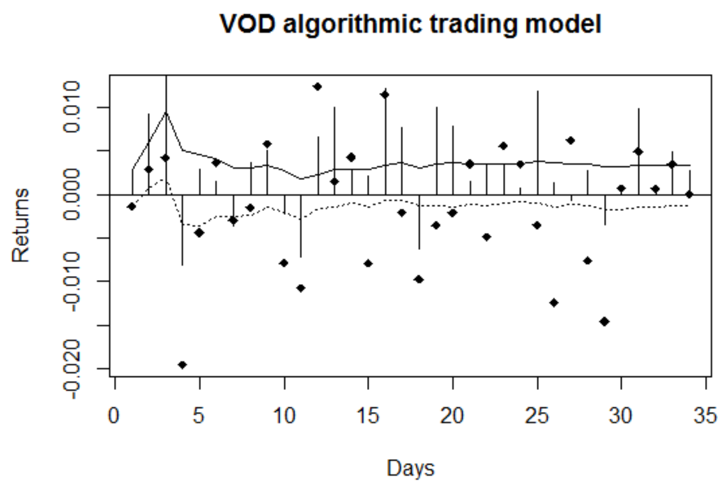

Figure 8. Returns of suggested model for VOD and benchmark strategy

In case of parameters of statistical measures, suggested trading strategy has mean daily return of 0.0033502, when buy and hold strategy in average returns -0,0012259. It the Figure 8., it is represented by solid line for average return of model and dashed line for average return of benchmark strategy up to that day. Additionally, standard deviation is smaller than in buy and hold strategy by 0.0015042 and is equal to 0.005657. Model executes 232 trades, from which 58.18% are profitable and 26.29% are unprofitable. Those numbers are smaller, than in testing period for the development of the model, and the ratio between profitable and unprofitable trades is decreased. But we can observe that this type of trading system has some predictive power over benchmark strategy.

So finally our findings from simulating trading using developed algorithmic models are mixed. In the case of one share – AZN, we failed to construct model that would perform well based on development process using historical results. On the other side, model developed for VOD stock continued to outperform benchmark strategy and suggests that we were able to construct applicable model.

Conclusions

Application of technical analysis in trading historically has been highly debated and argued topic. Algorithmic trading on the other hand has seen it is rise in use with development of technology and mechanical computing power. The aim of this thesis was to consider these two concepts in order to create a profitable trading model.

In the first chapter provides brief background information on important concepts used in thesis. Overview of literature in the field provides knowledge about mixed findings on different markets and trading strategies. Properties of algorithmic trading present the argument for reasons to use algorithmic trading model. Notes on computing averages explain the computations of averages in the thesis. In that part, essential remark about the way we treat observations in unevenly spaced time in accordance to their weight for the average is explained. In the following three chapters the basis of technical trading tools is introduce and the logic behind separate instruments is discussed. Three types of approaches are considered in the work in order to forecast future market actions. Starting with price related trading instruments afterwards volume related tools are considered. Subsequently, the third approach of analyzing order flow is introduced. Explanations for computing indicators in intraday trading are provided and corresponding mechanism for decision making based on changes of indicators is discussed. After that the empirical study is conducted for simulating trading with number of strategies. Empirical study consisted of creating trading simulating algorithms for majority of discussed indicators in statistical package R, and performing testing of strategies on historical intraday trading data.

Results of the empirical study are diverse and not homogenous. Firstly, only limited predictive power of singly used strategies can be remarked. With price and order flow approach performing relatively above the level of benchmark strategy for VOD share, on AZN share there are only few strategies that generate meaningful results. The situation improves in case of applying combined strategies, in those situations significantly higher amount of strategies generate higher average return both per trade, and whole intraday period. Additionally, the number of strategies that would be considered as preferable against benchmark strategy buy and hold is also higher. Final step of simulating trading using proposed model on previously unconsidered data provide split outcome. Regarding the AZN stock proposed algorithmic model does not yield in significantly better performance comparing to benchmark strategy. On the other hand, for VOD security the proposed model generates comparably better outcome than buy and hold strategy.

In final conclusions it can be stated, that evidence of algorithmic trading models based on technical analysis performing better than simple buy and hold strategy, were found. On the other side, some areas of thesis suggest that further analysis in order flow area, extensive research in combining different strategies and building of more sophisticated algorithms could lead to even to greater findings. Empirical study shows that there are stocks and conditions in market when technical analysis provide beneficial outcomes, the next step would be to elaborate the ideas discussed here and elevate trading algorithm.

References

Achelis, S., 2013, ‘Technical Analysis from A to Z’, McGraw-Hill.

Appel, G. & Appel M., ‘A Quick Tutorial in MACD: Basic concepts’, viewed on 23 March 2014 from, http://www.signalert.com/MACD%20tutorial.pdf

Baiynd, A. M., 2011, ‘The Trading Book: A Complete Solution to Mastering Technical Systems and Trading Psychology’, McGraw-Hill.

Brock, W., Lakonishok, J. & LeBaron, B., 1992, ‘ Simple Technical Trading Rules and the Stochastic Properties of Stock Returns’, *Journal of Finance*, 47(5), pages 1731–1764.

Brockwell, A., 2010, ‘Algorithmic Trading: A Brief Introduction’, viewed on 23 March 2014, from http://www.stat.cmu.edu/~abrock/algotrading/

Chordia, T. & Roll, R., 2008, ‘Liquidity and market efficiency’, *Journal of Financial Economics,* 87(2), pages 249–268.

Droke, C, 2002, ‘Stock Trading with Moving Averages’, Publishing Concepts.

Eisler, Z., J. Bouchaud & J. Kockelkoren, 2009, ‘The Price Impact of Order Book. Events: Market Orders, Limit Orders and Cancellations’, SSRN elibrary.

Evans, M. D.D. & Lyons, R. K, ‘Forecasting Exchange Rate Fundamentals with Order Flow’, viewed on 2 April 2014 from, http://faculty.haas.berkeley.edu/lyons/wp/Flows%20and%20fundamentals.pdf

Fama, E., 1970,‘ Efficient capital markets: a review of theory and empirical work‘, *The Journal of Finance‘*, 25 (2), pages 383–417.

Fang, J., Jacobsen, B. & Qin, Y, 2014, ‘Predictability of the simple technical trading rules: An out-of-sample test’, *Review of Financial Economics*, 23(1), pages 30–45.

Garfield, I. & D. & Epstein, M., D., 1992, The Psychology of Smart Investing, John Wiley & Sons.

Handa, P. & Schwartz, R.,1996, ‘Limit order trading’, *The Journal of Finance*, 51, pages 1835–1861.

Hanif, A., Smith, R., 2012, ‘Algorithmic, Electronic, and Automated Trading’, *The Journal of Trading*, 7(4), pages 78–86.

Holmberg, U., Lönnbark, C. & Lundström, C., 2012, ‘Assessing the profitability of intraday opening range breakout strategies’, "Umeå Economic Studies 845, Umeå University, viewed 13 March 2014, from http://www.usbe.umu.se/404?contentId=196616&languageId=3&assetKey=ues845

Kempf, A. & Korn. O., 1999, ‘Market depth and order size1’, *Journal of Financial Markets*, 2, pages 29-48.

Kendall, K., 2007, ‘Electronic and algorithmic trading technology: the complete guide’, Amsterdam, Academic Press.

Kendall, M. G. & Bradford H., A, 1953, ‘The Analysis of Economic Time-Series-Part I: Prices’, *Journal of the Royal Statistical Society*, 116(1), pages 11–34.

Kumar, K., Mamidi, V. & Marisetty, V., 2011, ‘Global markets exposure and price efficiency: An empirical analysis of order flow dynamics of NYSE-listed Indian firms’, 21(5), pages 686-706.

Lento, C., 2007, ‘The Profitability Of Technical Trading Rules: A Combined Signal Approach’, *Journal of Applied Business Research*, 23(1), pages 13–28.

Lin, X., Yang, Z. & Song, Y., 2011, ‘Intelligent stock trading system based on improved technical analysis and Echo State Network’, *Expert Systems with Application,* 38(9), pages 11347–11354.

Love, R. & Payne, R., 2008, ‘Macroeconomic News, Order Flows, and Exchange Rates’, *Journal of Financial and Quantitative Analysis*, 43(02), pages 467–488.

Lui., Y. H. & Mole, D., 1998, ‘The use of fundamental and technical analyses by foreign exchange dealers: Hong Kong evidence’, *Journal of International Money and Finance*, 17(3), pages 535–545.

Makwana, N., Kohli, S. S., 2012, ‘Algorithmic trading strategy, based on GARCH (1, 1) volatility and volume weighted average price of asset’, *OSR Journal of Business and Management*, 4(4), pages 30–35.

Marshall, B. R., Cahan, R. H. & Cahan.,J., 2007, ‘Can Commodity Futures be Profitably Traded with Quantitative Market Timing Strategies?’, *Journal of Banking & Finance*, 32(9), pages 1810–1819.

Martinez, V. H. and Rosu, I., 2013, ‘High Frequency Traders, News and Volatility’, *AFA 2013 San Diego Meeting*, viewed on 22 March 2014, from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1859265

Menkhoff, L. & Taylor, P.M., 2007, ‘The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis’, *Journal of Economic Literature*, 45(4), pages 936–972.

Menkhoff, L., 2010, ‘The use of technical analysis by fund managers: International evidence‘, *Journal of Banking & Finance*, 34 (11), pages 2573–2586.

Ming, L. & Siok-Hwa, L., ‘The profitability of the simple moving averages and trading range breakout in the Asian stock markets’, *Journal of Asian Economics*, 17(1), Pages 144–170.

Osler, C., 2003, ‘Currency Orders and Exchange Rate Dynamics: An Explanation for the Predictive Success of Technical Analysis’, *The Journal of Finance*, 58(5), pages 1791–1820.

Parisi, F., Vasquez, A., 2000, ‘Simple technical trading rules of stock returns: evidence from 1987 to 1998 in Chile’, *Emerging Markets Review*, 1, pages 152–164.

Rockefeller, B., 2002, ‘The Global Trader– Strategies for Profiting in Foreign Exchange, Futures and Stocks’, John Wiley & Sons, New York.

Samuelson, P., 1972, ‘Proof That Properly Anticipated Prices Fluctuate Randomly.‘, *Industrial Management Review*, 6 (2), pages 41–49.

Schulmeister, S., 2009, ‘Profitability of technical stock trading: Has it moved from daily to intraday data?‘, *Review of Financial Economics*, 18(4), Pages 190–201.

SEC report, 2010, ‘Findings regarding the market events of May 6, 2010’, viewed on 5 April 2014 from, http://www.sec.gov/news/studies/2010/marketevents-report.pdf

Stothard, M., 2012, ‘Norway’s day traders take on the algos’, viewed on 5 April 2014 from, http://www.ft.com/intl/cms/s/0/ff2db7bc-9f40-11e1-a455-00144feabdc0.html#axzz2yToM04ZW

Treleaven, P., Galas, M. & Lalchand.V, 2013, ‘Algorithmic Trading Review‘, *Communications of the ACM*‘, 56 (11), pages 76–85.

Vasiliou, D., Eriotis, N. & Papathanasiou, S., 2008, ‘Technical Trading Profitability in Greek Stock Market’, *The Empirical Economics Letters*, 7(7), pages 749–756.

Yamamoto, R., 2012, ‘Intraday technical analysis of individual stocks on the Tokyo Stock Exchange’, *Journal of Banking & Finance*, 36(11), pages 3033–3047.

Yu, H., Nartea, G.V., Gan, C. & Yao, L.J., 2013, ‘Predictive ability and profitability of simple technical trading rules: Recent evidence from Southeast Asian stock markets’, *International Review of Economics and Finance*, 25, pages 356–371.

Zuckerman, G., 2005, ‘Renaissance's Man: James Simons Does the Math on Fund’, in The Wall Street Journal viewed on 22 March 2014, from http://online.wsj.com/news/articles/SB112018150042875023

Appendix

1. Example of code in R. Time adjustment and loading of *.csv files

```
#Automated returns calculator for one strategy - SMA
setwd("\\\\pohl.ut.ee/trepeka/VOD/")
temp = list.files(pattern="*.csv")

returns_matrix = matrix (NA, nrow = 100, ncol = length(temp))
buying_signals = rep (NA, length(temp))
selling_signals = rep (NA, length(temp))

#Defining function to transform HH:MM:SS into seconds totally
hhmmss_to_ss <- function  (x)
{
  hhmmss <- strsplit (x, ":", T)
  hh <- as.numeric (hhmmss[[1]][1])
  mm <- as.numeric (hhmmss[[1]][2])
  ss <- as.numeric (hhmmss[[1]][3])
  return ( hh * 3600 + mm * 60 + ss)
}

#Importing data file:
for (k in 1 : length(temp ){                    #This cycle makes analysis of all files in working
direction
  a1 = ("\\\\pohl.ut.ee/trepeka/VOD/")          # Code goes automatically over all files in folder
  a2 = temp[k]                                  # Selects *.csv file name for the day
  Take_a = paste(a1, a2, sep = "")              # Merges the file name and direction together, to pick
right file         data = read.csv(Take_a, header = TRUE, as.is=TRUE )
  # After importing data we need to adjust the time
  adjusting_time_1 = lapply (data$localtime ,hhmmss_to_ss)
  adjusting_time_vec_1 = array(unlist(adjusting_time_1), dim = c(dim(adjusting_time_1[[1]]),
length(adjusting_time_1)))
  # Binding back data together:
  data_tf = data.frame (adjusting_time_vec_1, data[34:35] )   # For SMA we need only time, price and
is_a_trade information
  data_tf = subset(data_tf, data_tf$is_a_trade == 1 )               # Filtering out trades from whole
information
  names(data_tf)[1] <- "localtime"                                # Fixing back data.frame column names
  #After procedure we have only time fixed data and original data - time correction finished
```

2. Example of code in R. Calculation of SMA

```
# SMA - period 10min
# Trading starts 08:00:00. We pospone start of trading by 30min in order to avoid trades in higher
volatility time periods and we need some data for our indicator.
#Trading ends at 16:10:00. We liquidate positions before 15min before markets close

start = 8 * 3600 + 30 * 60                              # Corresponds to starting at 08:30:00
end = 16 * 3600 + 15 * 60                               # Corresponds to finishing at 16:15:00
period = 10 * 60                                        # Corresponds to the period of SMA in seconds
start_in <- min ( which( (data_tf$localtime ) >= start ) )  # Index line to start trading
end_in <- max ( which ( (data_tf$localtime ) <= end ) )   # Index line to finish trading
data_tf["SMA_10 "] <- 0                                 # Creating column for indicator
SMA_in <- which( colnames(data_tf)=="SMA_10" )          # Getting index of column of indicator
localtime_in <- which( colnames(data_tf)=="localtime" ) # Getting index of time collumn
for (i in start_in : end_in ){                          # Cycle to compute average in selected period
    a <- subset(data_tf, localtime <= data_tf[i,localtime_in] & localtime > (data_tf[i,localtime_in]-period)
)
    delta_t = diff ( c (data_tf[i,localtime_in]-period,a$localtime) )  # Vector of time differences
    data_tf[i,SMA_in] = sum ( a [,3] * delta_t / period )              # Computation of moving average
}

... # Exactly the same procedure for different length average just that we change period parameter.

# To get the signal from simple moving averages strategy  we apply the following procedure:
# We take a difference between different time length moving averages
data_tf$difSMA = data_tf$SMA_Shorter - data_tf$SMA_Longer# We get a column of differences
data_tf["Signal"] <- 0                                          # Creating collumn for signal
Signal_in <- which( colnames(data_tf)=="Signal" )               # Getting index of column of indicator
difSMA_in <- which( colnames(data_tf)=="difSMA" )               #  Getting index of column of diff.
for (i in start_in:end_in){                                     # Cycle to compute signals
    if (data_tf[i,difSMA_in] > 0 & data_tf[i-1,difSMA_in] < 0){ # Buying signal condition
        data_tf[i,Signal_in] = 1    # 1 - corresponds to buying signal.
      }else if (data_tf[i,difSMA_in] > 0){
        data_tf[i,Signal_in] = 0    # 0 - corresponds to holding signal. No trading action
      }else if (data_tf[i,difSMA_in] < 0 & data_tf[i-1,difSMA_in] > 0){
        data_tf[i,Signal_in] = -1   # -1 - coresponds to selling signal.
      }
}
```

3. Example of code in R. Calculation of returns for given strategy

```
index_b = which (data_tf$Signal == 1)                     # Index of observations with buying signal
index_s = which (data_tf$Signal == -1)                    # Index of observations with selling signal
price_in <- which( colnames(data_tf)=="price" )           # Getting index of price column
returns = rep (NA, length.out = length (index_b))         # Creating empty vector of returns
end_trading <- max ( which ( (data_tf$localtime <= end ) ) ) # For observation to finish trading
Sold_at_in = 0                                            # This is needed for third condition inside cycle
    for (i in 1 : length (index_b)){
      if ( length(index_b) == 0 ){        # Condition to terminate counting of signals if there is no buying
signals
        #print("There was no buying signal")
        break
      }
    Bought_at_in = index_b[i]
    if ( Bought_at_in > max(index_s) ){  # Condition for the last trade to be done on market exiting time,
or if there is no selling signal
        Price_bought_at = data_tf[Bought_at_in,price_in]
        Price_sold_at = data_tf[end_trading,price_in]
        returns[i] = ( Price_sold_at - Price_bought_at ) / Price_bought_at
        #print("The cycle was broken")
        break
      }
    if (Bought_at_in < Sold_at_in){      # Condition to skip one loop if buying signal is generated after
another buying singal and no selling signal in between. This means we are still waiting for roposite trading
signal
        next()
      }
     Price_bought_at = data_tf[Bought_at_in,price_in]
     Sold_at_in = index_s[(min ( which (index_s > Bought_at_in)))]
     Price_sold_at = data_tf[Sold_at_in,price_in]
     returns[i] = ( Price_sold_at - Price_bought_at ) / Price_bought_at
     }
returns_fx <- returns[!is.na(returns)] # We fix returns in order to get only those that are real numbers and
not NA # Recording returns:
for (i in 1:length(returns_fx)){
    returns_matrix[i, k] = returns_fx[i]
    }
# Recording number of buy / sell signals
buying_signals[k] = length (index_b)
selling_signals[k] = length (index_s)
print(paste0("Calculated everything for day : ", k ) )
```

4. Testing of different RSI and MFI signal bands

Table 9. Results using different RSI signal bands with length of average 7 on AZN

Type of signal bounds	Average	Standard deviation	Profitable trades	Unprofitable trades	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
40 & 60	0,0002615	0,0023066	59,88%	27,91%	121	12246	10554	50,00%	50,00%
30 & 70	0,0003475	0,0032206	59,88%	27,91%	67	5381	4263	70,00%	30,00%
20 & 80	0,0003050	0,0033947	59,88%	27,91%	34	1933	1122	40,00%	60,00%
10 & 90	0,0009869	0,0045348	59,88%	27,91%	15	499	104	40,00%	60,00%

Table 10. Results using different RSI signal bounds with length of averege 7min on VOD

Type of signal bounds	Average	Standard deviation	Profitable trades	Unprofitable	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
40 & 60	0,0013965	0,0020996	63,87%	10,08%	119	9841	7446	90,00%	10,00%
30 & 70	0,0014535	0,0026993	58,82%	11,76%	68	3870	3210	90,00%	10,00%
20 & 80	0,0007058	0,0040783	46,88%	25,00%	32	1228	771	70,00%	30,00%
10 & 90	0,0000521	0,0039987	35,29%	11,76%	17	315	154	50,00%	50,00%

Explanation of terms in tables:
Average – average return per trade. Standard deviation here is standard deviation for all of trades of representing strategy, not standard deviation of daily strategy returns.
Trade – we consider trades as a set of actions: execution of buying after buying signal and selling after selling signal as a trade.
Profitable trade - a trade with positive returns, unprofitable trade – a trade with negative return.
B&H outperformed – strategy generates higher return in this % of tested days compared to buy&hold strategy.
B&H underperformed – strategy generates lower return in this % of tested days compared to buy&hold strategy.

Table 11. Results using different MFI signal bounds with length of 7min on AZN

Type of signal bounds	Average	Standard deviation	Profitable trades	Profitable trades	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
40 & 60	0,0000351	0,0013935	54%	31%	252	12796	16782	50%	50%
30 & 70	0,0001182	0,0015123	58%	33%	180	8915	11046	50%	50%
20 & 80	0,0001339	0,0017648	57%	34%	125	5302	6465	50%	50%
10 & 90	0,0001296	0,0023146	60%	35%	78	2449	2862	60%	40%

Table 12. Results using different MFI signal bounds with length of 7min on VOD

Type of signal bounds	Average	Standard deviation	Profitable trades	Profitable trades	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
40 & 60	0,00066072	0,00155413	50,79%	14,29%	252	13471	16901	90,00%	10,00%
30 & 70	0,00065240	0,00169477	50,00%	17,16%	204	9500	12384	70,00%	30,00%
20 & 80	0,00053576	0,00200557	47,22%	18,75%	144	5982	7937	50,00%	50,00%
10 & 90	0,00081048	0,00245198	59,14%	18,28%	93	2700	4530	50,00%	50,00%

5. Single indicator based strategies results

Table 13. Results for single indicator price approach strategies

Share	Indicator (setting)	Average	Standard deviation	Profitable trades	Unprofitable trades	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
AZN	RSI (7)	0,0001943	0,0050534	36,36%	26,36%	110	1951	1799	56,67%	43,33%
	RSI (10)	0,0006624	0,0046928	36,00%	16,00%	100	1574	1303	66,67%	33,33%
	RSI (20)	0,0008088	0,0053659	37,23%	15,96%	94	1752	1508	68,33%	31,67%
	RSI (30)	0,0008962	0,0052838	37,23%	14,89%	94	2131	2210	68,33%	31,67%
VOD	RSI(7)	0,0010626	0,0028792	58,27%	16,80%	369	21093	20784	85,00%	15,00%
	RSI(10)	0,0011187	0,0037135	55,04%	18,91%	238	15714	14279	88,33%	11,67%
	RSI(20)	0,0003714	0,0048319	37,80%	22,83%	127	12181	8984	68,33%	31,67%
	RSI(30)	0,0001816	0,0058669	36,89%	22,33%	103	11650	8977	66,67%	33,33%
AZN	SMA (3&10)	-0,000097	0,0013606	26,01%	59,15%	1711	1712	1714	26,67%	73,33%
	SMA (5&10)	-0,000061	0,0014101	27,51%	55,72%	1581	1582	1596	35,00%	65,00%
	SMA (5&15)	-0,000044	0,0016570	26,73%	59,37%	1115	1116	1119	35,00%	65,00%
	SMA (5&20)	-0,000026	0,0018299	25,68%	62,84%	923	923	934	35,00%	65,00%
	SMA (10&20)	0,0000601	0,0020278	31,11%	55,83%	781	781	789	45,00%	55,00%
	SMA (10&30)	0,0000737	0,0024690	33,16%	58,25%	570	570	573	56,67%	43,33%
	SMA (20&60)	0,0001125	0,0029571	33,86%	57,77%	251	251	265	46,67%	53,33%
VOD	SMA (3&10)	-0,001062	0,0013656	6,83%	68,54%	2371	2386	2398	1,67%	98,33%
	SMA (5&10)	-0,000772	0,0015308	10,01%	53,99%	2078	2092	2103	8,33%	91,67%
	SMA (5&15)	-0,000993	0,0016203	8,97%	66,05%	1617	1617	1616	6,67%	93,33%
	SMA (5&20)	-0,001036	0,0017595	9,46%	69,87%	1311	1311	1314	5,00%	95,00%
	SMA (10&20)	-0,000662	0,0018977	13,99%	52,96%	1065	1065	1067	13,33%	86,67%
	SMA (10&30)	-0,000801	0,0021666	13,60%	62,80%	750	750	746	15,00%	85,00%
	SMA (20&60)	-0,000585	0,0026800	19,50%	59,75%	323	311	23430	35,00%	65,00%

Table 14. Results for single indicator price approach strategies

Share	Indicator (setting)	Average	Standard deviation	Profitable trades	Unprofitable trades	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
AZN	MACD Sig. 1	0,0000551	0,0031650	28,17%	67,96%	284	1044071	935231	41,67%	58,33%
	MACD Sig. 2	-0,0000999	0,0022748	27,98%	67,33%	554	578	583	35,00%	65,00%
VOD	MACD Sig. 1	-0,0011699	0,0028014	14,17%	80,84%	381	482944	533241	20,00%	80,00%
	MACD Sig. 2	-0,0014102	0,0018352	8,37%	85,00%	920	948	946	6,67%	93,33%
AZN	SO Sig. 1	0,0004112	0,0030267	69,23%	25,79%	221	358489	386936	56,67%	43,33%
	SO Sig. 2	-0,0000485	0,0016804	33,47%	50,68%	959	1868	1847	36,67%	63,33%
VOD	SO Sig. 1	0,0016208	0,0024968	86,49%	8,52%	481	189066	168249	88,33%	11,67%
	SO Sig. 2	-0,0011058	0,0014629	8,41%	66,17%	1070	2007	2167	10,00%	90,00%
AZN	CCI	0,00025987	0,00340183	65,61%	30,16%	189	205649	185176	55,00%	45,00%
VOD	CCI	0,0010944	0,0036232	67,83%	19,57%	230	372950	395433	76,67%	23,33%
AZN	TRB 10	-0,0002540	0,0019665	26,52%	64,28%	739	14279	13338	26,67%	73,33%
	TRB 30	0,0000677	0,0034680	12,58%	19,62%	244	8501	7218	43,33%	56,67%
	TRB 60	-0,0002720	0,0025808	26,79%	64,95%	136	6035	5214	25,00%	75,00%
	TRB 120	0,0002319	0,0055073	3,79%	6,09%	74	4459	3477	41,67%	58,33%
VOD	TRB 10	-0,0018202	0,0029343	15,60%	74,68%	391	9239	7633	13,33%	86,67%
	TRB 30	-0,0015782	0,0038084	24,16%	66,85%	178	6565	5083	31,67%	68,33%
	TRB 60	-0,0015976	0,0044646	25,71%	65,71%	105	3140	3233	36,67%	56,67%
	TRB 120	-0,0013050	0,0051505	30,77%	64,62%	65	1666	1935	48,33%	51,67%

Table 15. Results for single indicator volume approach strategies

Share	Indicator (setting)	Average	Standard deviation	Profitable trades	Unprofitable trades	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
AZN	VMA (03&10)	-0,0000409	0,0012219	26,49%	54,01%	2057	2059	2065	38,33%	61,67%
	VMA (05&10)	0,0000028	0,0012898	29,48%	48,01%	1937	1941	1956	45,00%	55,00%
	VMA (05&15)	-0,0000095	0,0015359	28,63%	52,79%	1362	1363	1369	41,67%	58,33%
	VMA (05&20)	0,00001416	0,0017167	28,80%	56,57%	1073	1073	1078	45,00%	55,00%
	VMA (10&20)	0,00005960	0,0016855	32,11%	50,72%	978	978	982	55,00%	45,00%
	VMA (10&30)	0,00008499	0,0020254	32,72%	53,46%	709	709	711	51,67%	48,33%
	VMA (20&60)	0,00009529	0,0026033	34,06%	56,66%	323	323	332	46,67%	53,33%
VOD	VMA (03&10)	-0,0006720	0,0014137	10,90%	53,23%	2816	2829	2842	6,67%	93,33%
	VMA (05&10)	-0,0004423	0,0015170	15,30%	44,00%	2432	2447	2455	10,00%	90,00%
	VMA (05&15)	-0,0005082	0,0016071	13,88%	48,27%	1794	1794	1790	16,67%	83,33%
	VMA (05&20)	-0,0005571	0,0017263	12,36%	50,97%	1497	1497	1497	20,00%	80,00%
	VMA (10&20)	-0,0002790	0,0018811	18,51%	40,70%	1221	1221	1219	33,33%	66,67%
	VMA (10&30)	-0,0003406	0,0020613	18,64%	45,87%	896	891	1219	36,67%	63,33%
	VMA (20&60)	-0,0001606	0,0025246	21,69%	44,97%	378	378	366	50,00%	50,00%
AZN	VWAP	-0,0002424	0,00148945	6,15%	88,38%	1739	1099835	879779	15,00%	85,00%
VOD	VWAP	-0,0015206	0,00098554	1,455%	95,78%	3436	482729	533598	0,00%	100,00%
AZN	OBV SMA 03 10	-0,0000095	0,0014500	33,45%	49,83%	1471	1472	1475	40,00%	60,00%
	OBV SMA 05 10	0,0000242	0,0015322	35,26%	47,25%	1401	1402	1403	46,67%	53,33%
	OBV SMA 05 20	0,0000341	0,0019091	34,92%	53,35%	776	779	781	46,67%	53,33%
	OBV SMA 10 20	-0,0000097	0,0024009	36,46%	54,38%	491	491	488	40,00%	60,00%
VOD	OBV SMA 03 10	-0,0003266	0,0018888	21,94%	42,85%	1349	1362	1362	30,00%	70,00%
	OBV SMA 05 10	-0,0002095	0,0019189	24,06%	38,32%	1297	1312	1310	43,33%	56,67%
	OBV SMA 05 20	-0,0002826	0,0023110	24,73%	40,99%	744	744	740	46,67%	53,33%
	OBV SMA 10 20	-0,0001743	0,0028313	29,92%	40,16%	488	488	489	46,67%	53,33%

Table 16. Results for single indicator volume approach strategies

Share	Indicator (setting)	Average	Standard deviation	Profitable trades	Unprofitable trades	Trade s	Buying signals	Selling signals	B&H outperfor med	B&H underperf ormed
AZN	MFI (7)	0,0000311	0,0018156	51,72%	37,41%	727	33733	37950	48,33%	51,67%
	MFI (10)	0,0000228	0,0024305	54,50%	36,72%	433	27452	30243	46,67%	53,33%
	MFI (20)	0,0001748	0,0044413	56,16%	43,15%	146	13979	17384	55,00%	45,00%
	MFI (30)	0,0003498	0,0058776	52,63%	43,42%	76	7118	10279	50,00%	50,00%
VOD	MFI (7)	0,0006823	0,0021935	52,97%	18,81%	606	19821	23430	80,00%	20,00%
	MFI (10)	0,0004071	0,0028782	45,94%	25,21%	357	14872	17731	73,33%	26,67%
	MFI (20)	0,0000658	0,0055369	38,78%	30,61%	98	6235	9713	61,67%	38,33%
	MFI (30)	-0,0002035	0,0063889	46,00%	42,00%	50	2627	5845	63,33%	36,67%

Table 17. Results for single indicator order flow approach strategies

Share	Indicator (setting)	Average	Standard deviation	Profitable trades	Unprofitable trades	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
AZN	OFIB# 0.6	0,0000607	0,0025143	36,89%	53,55%	366	7701	12718	45,00%	55,00%
	OFIB# 0.7	0,0000420	0,0028179	40,08%	53,70%	257	4685	6866	43,33%	56,67%
	OFIB# 0.8	-0,0000301	0,0037961	43,14%	49,67%	153	2452	3300	45,00%	55,00%
	OFIB# 0.9	0,0000100	0,0040480	47,26%	46,58%	146	1317	1491	43,33%	56,67%
VOD	OFIB# 0.6	-0,0001832	0,0024690	20,59%	44,67%	544	20760	37711	48,33%	51,67%
	OFIB# 0.7	-0,0000836	0,0026563	23,37%	43,48%	368	12878	26632	53,33%	46,67%
	OFIB# 0.8	0,0000758	0,0031872	28,57%	42,86%	224	6578	15528	61,67%	38,33%
	OFIB# 0.9	-0,0001244	0,0036892	29,91%	45,79%	214	2392	6127	55,00%	45,00%
AZN	OFIB£ 0.6	0,0000918	0,0021462	38,07%	49,65%	570	14203	18817	55,00%	45,00%
	OFIB£ 0.7	0,0000869	0,0023473	40,39%	50,25%	406	8677	10838	48,33%	51,67%
	OFIB£ 0.8	-0,0000632	0,0028226	42,70%	49,64%	274	4951	5713	45,00%	55,00%
	OFIB£ 0.9	0,0000226	0,0035692	43,02%	49,42%	172	2560	2949	48,33%	51,67%
VOD	OFIB£ 0.6	-0,0002345	0,0018548	20,34%	41,47%	1008	42592	53313	38,33%	61,67%
	OFIB£ 0.7	-0,0002136	0,0020736	20,98%	41,10%	820	32322	42129	46,67%	53,33%
	OFIB£ 0.8	-0,0000804	0,0023163	26,37%	39,71%	622	21488	30466	56,67%	43,33%
	OFIB£ 0.9	-0,0001610	0,0027221	25,19%	43,70%	389	11527	18337	55,00%	45,00%
AZN	OBIB 0.4	0,0002621	0,0014397	51,51%	30,54%	1827	211058	146188	83,33%	16,67%
	OBIB 0.5	0,0003264	0,0019050	52,71%	33,46%	1013	115315	73234	73,33%	26,67%
	OBIB 0.6	0,0004620	0,0028501	56,65%	36,03%	519	53135	31435	70,00%	30,00%
	OBIB 0.7	0,0004427	0,0040399	56,64%	37,61%	226	18768	10457	51,67%	48,33%
	OBIB 0.8	0,0012195	0,0061996	59,34%	36,26%	91	4309	2394	58,33%	41,67%

Table 18. Results for single indicator order flow approach strategies

Share	Indicator (setting)	Average	Standard deviation	Profitable trades	Unprofitable trades	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
VOD	OBIB 0.2	0,0004707	0,0042817	42,53%	32,18%	174	77248	63175	66,67%	33,33%
	OBIB 0.25	0,0004098	0,0044325	43,24%	33,33%	111	46706	34072	61,67%	38,33%
	OBIB 0.3	0,0007983	0,0055127	53,52%	35,21%	71	28100	18383	63,33%	36,67%
AZN	AOS (3&10)	0,0000779	0,0010615	40,81%	32,59%	2857	2857	2855	61,67%	38,33%
	AOS (5&15)	0,0001013	0,0011950	42,89%	32,74%	1961	1961	1963	56,67%	43,33%
VOD	AOS (3&10)	0,0000651	0,0015117	27,17%	25,01%	2127	2127	2131	68,33%	31,67%
	AOS (5&15)	0,0001270	0,0017353	30,98%	26,77%	1401	1402	1398	66,67%	33,33%

6. Combined strategies results

Table 19. Results for combined strategies - VOD stock

Share	Indicator (setting)	Average	Standard deviation	Profitable trades	Unprofitable trades	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
VOD	MACD MFI (10)	-0,000006	0,006695	52,78%	44,44%	36	599	621	58,33%	41,67%
VOD	MACD MFI (15)	-0,003808	0,007064	27,27%	63,64%	11	116	176	51,67%	48,33%
VOD	MACD MFI (5)	0,001228	0,003904	52,63%	20,30%	133	2566	3057	71,67%	28,33%
VOD	MFI RSI (10)	0,000710	0,004650	53,60%	27,20%	125	5516	4909	68,33%	31,67%
VOD	MFI RSI (20)	0,000737	0,007149	42,86%	38,10%	42	3014	2455	70,00%	30,00%
VOD	MFI RSI (5)	0,001278	0,002624	65,40%	14,44%	367	12468	13069	88,33%	11,67%
VOD	OBV(0305) RSI (10)	0,000231	0,005285	48,61%	37,50%	72	182	170	58,33%	41,67%
VOD	OBV(0310) RSI (10)	0,001018	0,006088	59,26%	35,19%	54	110	88	63,33%	36,67%
VOD	OBV(0510) RSI (10)	0,001325	0,005966	59,02%	36,07%	61	114	92	68,33%	31,67%
VOD	OBV(0515) RSI (15)	0,000766	0,007760	51,28%	35,90%	39	66	57	58,33%	41,67%
VOD	OFIB (0.6) RSI (10)	0,001546	0,006168	58,82%	31,37%	51	771	1508	66,67%	33,33%
VOD	OFIB (0.6) RSI (20)	0,001553	0,007769	46,88%	37,50%	32	694	1039	60,00%	40,00%
VOD	OFIB (0.6) RSI (30)	0,000962	0,009458	38,46%	42,31%	26	790	1262	60,00%	40,00%
VOD	SMA VWAP SO (0310)	-0,000198	0,007175	37,14%	48,57%	35	94	65	60,00%	40,00%
VOD	SMA VWAP SO (0510)	-0,000622	0,006673	33,33%	51,52%	33	67	61	63,33%	36,67%
VOD	SMA VWAP SO (0515)	-0,000263	0,006232	32,14%	53,57%	28	42	41	60,00%	40,00%
VOD	SMA VWAP SO (0520)	-0,000470	0,007533	37,04%	48,15%	27	41	30	58,33%	41,67%

Table 20. Results for combined strategies - VOD stock

Share	Indicator (setting)	Average	Standard deviation	Profitable trades	Unprofitable trades	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
VOD	SMA (0310) RSI10	-0,000252	0,005975	48,21%	37,50%	56	114	118	60,00%	40,00%
VOD	SMA (0515) RSI(15)	-0,000382	0,007108	49,09%	41,82%	55	138	113	61,67%	38,33%
VOD	VMA (0305) CCI	0,000265	0,004857	51,56%	31,25%	128	643	609	70,00%	30,00%
VOD	VMA(0310) CCI	-0,000088	0,005027	52,68%	32,14%	112	390	353	65,00%	35,00%
VOD	VMA (0510) CCI	0,000186	0,004877	57,55%	29,25%	106	316	295	66,67%	33,33%
VOD	VMA (0515) CCI	-0,000181	0,005335	48,15%	35,80%	81	192	166	63,33%	36,67%
VOD	VWAP SO	-0,000769	0,006383	23,53%	55,88%	68	3557	4238	56,67%	43,33%

Table 21. Results for combined strategies - AZN stock

Share	Indicator (setting)	Average	Standard deviation	Profitable trades	Unprofitable trades	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
AZN	MACD MFI (10)	0,0002037	0,0050434	45,95%	45,95%	74	2543	1527	35,00%	65,00%
AZN	MACD MFI (15)	0,0009463	0,0068163	58,33%	38,89%	36	800	346	36,67%	63,33%
AZN	MACD MFI (5)	0,0002603	0,0039306	46,07%	48,31%	178	8706	4554	43,33%	56,67%
AZN	MFI RSI (10)	0,0007254	0,0045164	60,00%	35,20%	125	6044	8342	58,33%	41,67%
AZN	MFI RSI (20)	-0,0001577	0,0073088	40,91%	47,73%	44	1811	3195	51,67%	48,33%
AZN	MFI RSI (5)	0,0001074	0,0025612	53,01%	37,98%	366	14344	17647	53,33%	46,67%
AZN	OBV(0305) RSI (10)	0,0008081	0,0050068	60,71%	35,71%	84	199	259	56,67%	43,33%
AZN	OBV(0310) RSI (10)	0,0010999	0,0067723	54,84%	38,71%	62	117	144	51,67%	48,33%
AZN	OBV(0510) RSI (10)	0,0005193	0,0059537	51,67%	48,33%	60	110	145	48,33%	51,67%
AZN	OBV(0515) RSI (15)	0,0009545	0,0070908	50,00%	44,74%	38	62	61	53,33%	46,67%
AZN	OFIB (0.6) RSI (10)	0,0004724	0,0060553	51,52%	45,45%	33	532	899	46,67%	53,33%
AZN	OFIB (0.6) RSI (20)	-0,0011551	0,0079107	25,00%	75,00%	16	270	834	36,67%	63,33%
AZN	OFIB (0.6) RSI (30)	0,0010985	0,0089114	38,46%	61,54%	13	233	871	43,33%	56,67%
AZN	SMA VWAP SO (0310)	0,00235169	0,00586957	57,89%	42,11%	19	36	30	51,67%	48,33%
AZN	SMA VWAP SO (0510)	0,00275085	0,00495245	70,00%	30,00%	20	33	21	51,67%	48,33%
AZN	SMA VWAP SO (0515)	0,00316369	0,00545464	69,23%	30,77%	13	17	12	45,00%	55,00%
AZN	SMA VWAP SO (0520)	0,00399278	0,00544180	70,59%	29,41%	17	19	9	46,67%	53,33%

Table 22. . Results for combined strategies - AZN stock

Share	Indicator (setting)	Average	Standard deviation	Profitable trades	Unprofitable trades	Trades	Buying signals	Selling signals	B&H outperformed	B&H underperformed
AZN	SMA (0310) RSI10	-0,0003429	0,0060329	45,45%	50,91%	55	107	120	48,33%	51,67%
AZN	SMA (0515) RSI(15)	0,0002750	0,0059111	50,88%	43,86%	57	101	118	48,33%	51,67%
AZN	VMA (0305) CCI	0,0000177	0,0040329	62,77%	32,85%	137	601	664	53,33%	46,67%
AZN	VMA(0310) CCI	0,0000597	0,0046917	59,65%	30,70%	114	330	375	51,67%	48,33%
AZN	VMA (0510) CCI	0,0000830	0,0044816	65,05%	30,10%	103	284	317	50,00%	50,00%
AZN	VMA (0515) CCI	0,0002703	0,0057367	62,69%	34,33%	67	148	169	51,67%	48,33%
AZN	VWAP SO	0,0017578	0,0063090	50,00%	47,92%	48	5701	3457	58,33%	41,67%

License

Non-exclusive licence to reproduce thesis and make thesis public

I, **Martynas Trepeka** (date of birth: 1989.10.08),
(*author's name*)

1. herewith grant the University of Tartu a free permit (non-exclusive licence) to:

   1.1. reproduce, for the purpose of preservation and making available to the public, including for addition to the DSpace digital archives until expiry of the term of validity of the copyright, and

   1.2. make available to the public via the web environment of the University of Tartu, including via the DSpace digital archives until expiry of the term of validity of the copyright,of my thesis

Development of an algorithmic trading model for intraday trading on stock markets based on technical analysis methods,
(title of thesis)
supervised by Raul Kangro,
(supervisor's name)

2. I am aware of the fact that the author retains these rights.

3. I certify that granting the non-exclusive licence does not infringe the intellectual property rights or rights arising from the Personal Data Protection Act.

Tartu, **19.05.2014**