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ALGORITHMIC TRADING STRATEGIES FOCUSSED ON CRYPTOCURRENCIES

Bakalářská práce

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Summary

This paper treats algorithmic trading and its application on the cryptocurrencies. Algorithmic trading is referring to the generation of buy and sell signals or orders by a computer algorithm and the management of these orders, without human intervention. Both cryptocurrencies and algorithmic trading are part of the recent advancement in financial markets. A few trading strategies based on technical indicators are backtested in this study. The process of backtesting consists of evaluating the performance of algorithms on historical data. It is also useful for improving these strategies. The strategies are then compared to a classic buy and hold strategy. The algorithmic strategies appear to be less risky than holding one position over a long time, but the potential gains are lower too. Some of the strategies are better performing than others.

Tato práce pojednává o algoritmickém obchodování a jeho aplikaci na krypto-měnách. Algoritmické obchodování představuje generování kupních a prodejních signálů nebo příkazů pomocí počítačových algoritmů a řízení těchto příkazů bez zásahu člověka. Jak krypto-měny, tak algoritmické obchodování jsou součástí nedávného vývoje na finančních trzích. V této studii je zpětně testováno několik obchodních strategií založených na technických ukazatelích. Proces zpětného testování neboli backtesting spočívá v hodnocení výkonnosti algoritmů na historických datech. Tento process je taky užitečný pro zlepšení těchto strategií. Algoritmické strategie jsou poté porovnány s klasickou strategií nákupu a držení. Strategie se zdají být méně riskantní než držet jednu pozici po dlouhou dobu, ale zároveň jejich potenciální profit je nižší. Některé strategie mají lepší výsledky než jiné.

CONTENT

Introduction

The purpose of this bachelor thesis is to demonstrate the possibility of backtesting various algorithmic strategies for trading BTC/USD and LTC/USD. We will automate the process of backtesting in simple and available software, Microsoft Excel. The algorithms are based on popular technical indicators.

In the first part, we will present some theoretical knowledge about financial markets, trading, cryptocurrencies, market analysis, algorithmic trading, and technical indicators. In the second part, we will propose some simple strategies, implement chosen indicators and strategies in Excel and provide results of the backtested strategies for historical data (01.08.2017 – 31.07.2019). The performance of the chosen algorithmic trading strategies computed in Excel (in terms of total revenues/losses, average buy and sell price, total of buy and sell orders) will be compared in the respective time-series and overall and the buy and hold strategy will be used as a universal benchmark.

I have chosen this topic because I was introduced to regular trading last year in South Korea during my Freemover student Exchange program. I appreciated this activity, but I wanted to extend my knowledge of trading in general and especially the domain of automated trading via different algorithmic computing techniques. This domain (I will use "Algorithmic trading" in the rest of the document) has been known now around for approximately three decades and it is a common tool employed by professionals and offered by brokers (a broker is a company offering trading services to customers). (Rao, 2015).

In the extremely competitive financial markets, many new algorithms are being developed in the pursuit of finding the best investment opportunities, generating the highest possible gains with the lowest possible risks. This task reveals itself quite difficult especially in the long term. Some algorithms can become obsolete because of the adaptation and evolution of markets, others might be effective only in particular conditions. Lately, cryptocurrencies emerged as a subject of high interest in the field of finance. This highly volatile market has attracted the attention of businesses and investors around all over the world.

THEORETICAL PART

1 Definitions

1.1 Financial market

A financial market is a market in which people and companies trade assets such as currencies, securities or commodities. Generally, financial markets decrease the transaction cost of inter-temporal exchanges (relocation of resources over time) by offering a centralised meeting point for economic agents, which are individuals, investors, companies, banks, and governments. (Bradfield, 2007).

Securities entitle their owners to get one or more future remittances. They include stocks bonds and derivatives. Derivatives include options, futures, forwards or warrants.

Commodities include crude oil, agricultural products, or precious metals. Precious metals can sometimes also be classified as currencies or securities according to different points of view.

Stock exchanges also called bourses are a typical form of financial markets where the transactions occur at a physical place. In stock exchanges, not only stocks are traded as the name suggests, but also for example derivatives or ETFs. The most known and largest are the New York Stock Exchange (NYSE), the Nasdaq (also in New York) or the Tokyo Stock Exchange**.** According to statista.com the market capitalization of NYSE is over 23 trillion dollars, 11 trillion dollars for the NASDAQ and 5.5 trillion dollars for the Tokyo Stock Exchange (statista.com, 2019). In the technology domain, the most important Stock Exchange is Nasdaq (National Association of Securities Dealers Automated Quotations), which gathers the largest companies like Google, Apple, Facebook, Amazon (a group also called GAFA). The Nasdaq also refers to a market index. This market index weight many stocks, as the one stated above according to their market capitalization.

Another example of an important financial market is the Foreign Exchange market (FOREX), where currencies are traded, primarily the majors (Dollar, Euro, Japanese Yen, and pound sterling).

In capital markets government or corporate bonds and stocks are traded. At the end of the 20th century, capital markets experienced large expansion (Obstfeld, Taylor,

2004). Many people started their trading activities in the Over the Counter Market (OTC). The OTC differs from the classical stock exchanges in the way assets are exchanged. There is no marketplace with centrally fixed prices, instead the trades are negotiated and executed online or via phones, by the market participants who are companies, individuals, corporations and market makers – brokers.

We will distinguish the buy and hold strategy from trading as two ways of achieving gains.

1.2 Trading

Two actions are naturally associated with trading – buy and sell. A trader will hope to make a profit by making the right decisions - buying a promising asset, whose price should rise in the near future, or selling one, because of an expected decrease in the asset value. There are two sides in the trading world, the buy side and the sell side. From one point of view, a trader is also performing the action of holding.

Apart from these actions, other ways of trading are made available thanks to financial derivatives. Strangely enough, generating profits with those financial derivatives does not depend on the price movements, the underlying security value can rise, decrease or even stay still. Depending on the chosen position, when the price of an asset does not move (or at least not too much) it is possible to make profits or losses aswell. It’s interesting to go a bit deeper into the mechanics of those financial derivatives, to illustrate the complexity of the trading world.

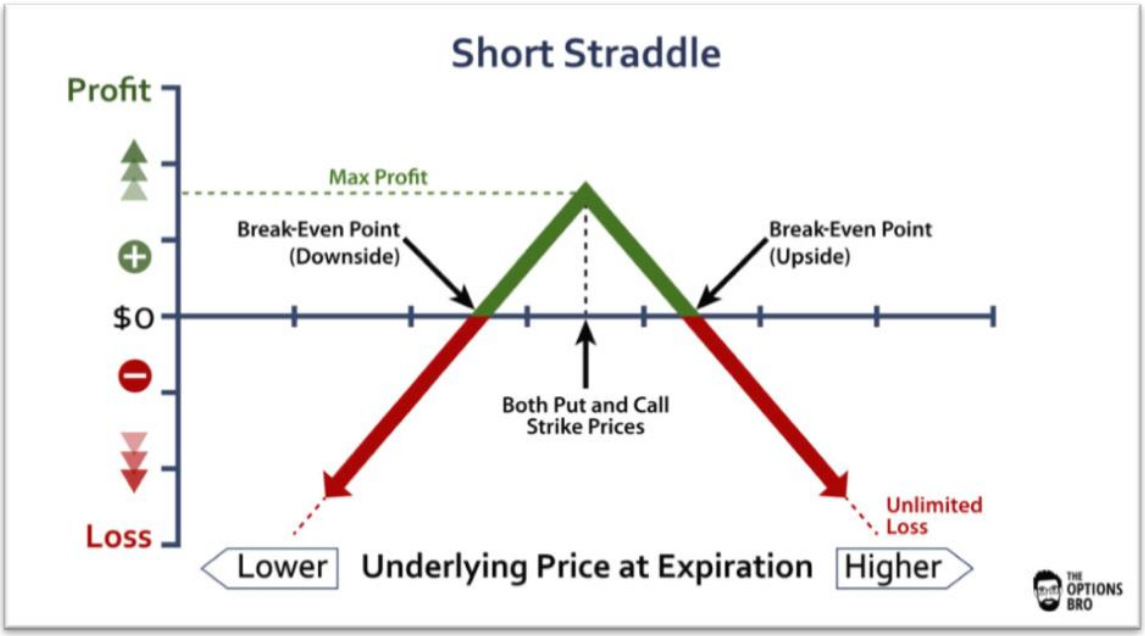


Figure 1: Short straddle

Let us take for example the options. An option is a financial derivative allowing one to bet on the future price of an asset.

The "Short Strangle" situation, showed on figure 1 (Ott, 2018) can be explained like this: the spot price (the current price) is used as the reference for the strike price (the price at which the investor can buy the asset until or at the date of expiration) and an investor decide to short a put option and short a call option of an underlying asset at the same time. In this case, when the underlying price of an asset at the time of maturity of the option is the same as the pre-agreed Strike price, the investor who has short both options will not lose any money and keep the amount they received for shorting these options. However, this position is extremely risky, especially for highly volatile markets. If there is a heavy increase or decrease in the underlying asset price, the investor may lose high amounts of money, therefore usually only trusted parties with large capital are allowed to short options (Hull, 2012). The position is shown in figure 1.0. Many other positions can be achieved with financial derivatives, they enlarge the range of possibilities of a trader/an investor. Derivatives are well described in many books like the one cited above.

One of the most important factors to consider in trading is the time of opening and closing positions. It means choosing the side (position) of a buyer or seller. Contracts for

difference (CFD) are also sometimes classified as derivatives. A CFD is a contract where both parties agree to pay the difference (negative or positive) after a position is closed, it can simply be considered as a bet on the future price movement of an asset. They are occasionally used instead of the direct trading of assets such as cryptocurrencies, but are prohibited in the U.S.

1.3 Buy and hold

If trading is very dynamic and active by nature, there are other strategies used by market participants, more interested in long-term investment. The most known is named „buy and hold“ strategy, which consists of taking a buy decision on an asset (made on deep domain analysis or aligned with some business perspective of the company) and hold it a relatively longer amount of time (despite short-term price movement). This is clearly a more passive strategy. With this strategy, the investor can consider both a CFD or directly buying a cryptocurrency.

2 Cryptocurrencies

Today there are many types of currencies, as most states have their own currencies. Means of payment and money have developed over time, from the commodity currency, passing through the metal currency, to the first banknotes. Thanks to the technologies the currency can circulate and be stored virtually (not stored physically), the majority of the operations can be carried out on the internet, actually, around 85 % of the money supply is virtual. A new form of currency has appeared recently, the cryptocurrency. It has rapidly emerged in the past few years and has been the subject of much debate by the public and the media as well as speculation and criticism from investors and academics. First we will write about the history of cryptocurrencies then we will describe their functioning and also briefly the cryptography technology, afterwards we will try to discuss their advantages and disadvantages. I am also going to furnish some statistical data.

2.1 History and functioning

Cryptocurrencies are a form of digital currency (Chochan, 2017), that is based on cryptography technology. This technology ensures the security of payments and the issue of coins. The first cryptocurrency called Bitcoin was launched in January 2009. This cryptocurrency was created by an individual or a group called Satoshi Nakamoto, this name is just a pseudonym and the inventor or inventors are not known. Bitcoin remains today the number one of cryptocurrency in the world. The bitcoin can be divided by 100 million to get the smallest unit named Satoshi which is named after its creator. One of the first mentions about an anonymous distributed electronic cash system based on cryptography technology is described in b-money which was published by Wei Dai in 1998.

To perform a transaction between two bitcoin accounts, it is necessary to note the sender's and receiver's address and the amount traded. It is necessary to use a personal key that serves as a digital signature to confirm the possession of bitcoins. The receiver must check if there is not another transaction in progress (not validated) with the same shipping address in a register which contains all the previous transactions. This register

is called the blockchain (Herrera-Joancomartí, 2015). „The blockchain contains a certain and verifiable record of every single transaction ever made“. (Crosby et al., 2016, p.7).

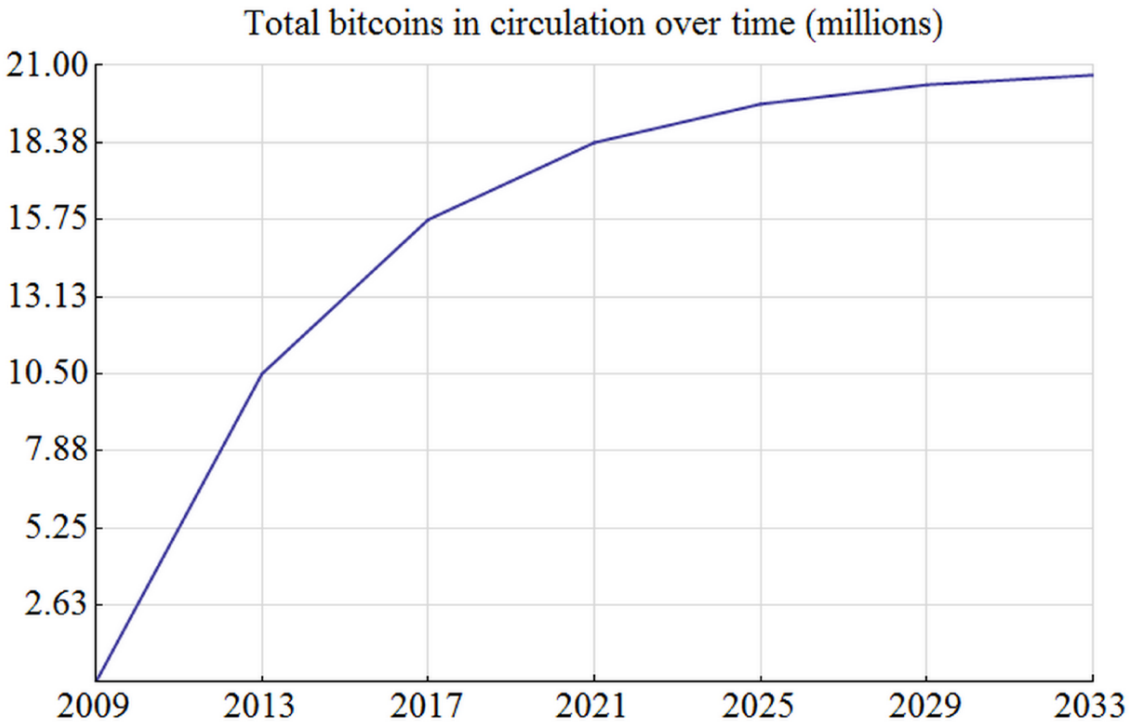


Figure 2: bitcoin supply

The creation of the money supply was exactly defined at the initiation of Bitcoin. It has a limit (not infinite) of units that is reached in a specific time in the future and the evolution of the rate of creation of money supply is given by an algorithm, we can see the speed of creation on the graph above (Benji1000.net, 2014). This limit is 21 million units, it will be reached in 2140. Bitcoin cash, another cryptocurrency will reach the same limit in the year 2050. This currency can be compared to the gold in terms of supply, which is also limited. We also use the same term: mining for the exploitation of new resources, here the new bitcoin units.

Mining is a process of calculations that solve and unblock access to new blocks (bitcoins), miners receive the units they find in exchange for calculations they perform with their machines. Each cryptocurrency is a little different from the others, that concerns their prices, their total units, as well as their technical properties and characteristics as the transaction speed, the encoding of addresses, the security, the degree of anonymity, etc. The factors that influence the prices of cryptocurrencies are among others: news and

trends, often also false news. The number of transactions and the speed of circulation are also decisive aspects. As an example we can name the official ban on cryptocurrencies in China (bitcoinist.com), currently, this country is trying to prevent access to foreign cryptocurrency trading platforms. For the false news, we can take the example of South Korea (www.forbes.com), where the Ministry of Justice announced a plan to prohibit the trade of these currencies. There is a lot of news on the internet about this subject, but we must be able to identify the valid ones and those that have a real impact on cryptocurrencies prices. To predict future prices and profitability, traders say: "Buy the rumor and sell the news". Cryptocurrencies are decentralized, they are not controlled by governments, they are only subject to the laws of the market, for example, the supply and demand, if demand increases the price also increases and vice versa. Technical analysis of price developments, including historical charts, also partly predict these prices.

In 2014 there a wave of new cryptocurrency has appeared, notably Etherum and Monnero. Many other cryptocurrencies have been created so far and new ones will very probably continue to be created in the future.

2.2 Advantages

This new form of money has many advantages over classical currencies. Among the main ones, we consider the following: First, it allows anyone to make transactions quickly and easily, the duration of the transaction is about 10 minutes, this is beneficial especially for international payments and for payments between different banks, where the transactions usually take few days to complete. The cryptocurrencies can accelerate international trade, flows of goods and services. The system is transparent and traceable.

Then, as I have already said, cryptocurrencies are not controlled by the government of a particular country. The governments have no opportunity to increase the money supply and therefore its users do not have to worry about the decisions on monetary policies of the state that can cause inflation of the currency. The "benevolence" of the state is not certain, one can take the example of the hyperinflation of the Zimbabwe dollar in 2008 where the central bank failed to calculate the rate of inflation, gave a false report on this rate. The government was using inflation as a tool to clear off political opponents (Jayson Coomer and Thomas Gstraunthaler). Money has always been regulated by the

state in history, but recently economic agents are free to make choices about the used currency. Cryptocurrencies may represent competition for the monopolies of classic currencies, which will have to try to hold their leadership position in a larger currency market. This feature of the cryptocurrencies was already highlighted at the time when they did not exist by the renowned economist Milton Freedman (6). He mentioned several times that the federal bank system should replace the governors with a computer. A network that would not be controlled or managed by any authority. This predefined system would have an order and would be more reliable and predictable.

Cryptocurrencies offer greater privacy of payments. The information is a priori anonymous, but with a little effort and some computer skills, it is often possible to trace users (Ben-Sasson, Chiesa, 2014). There are also cryptocurrencies as Zerocash trying to answer this problem by introducing the concept of a non-anonymous Basecoin, which exists alongside the Zerocash. It is possible to prove the ownership of some coins without revealing the amount and identity (a zero-knowledge proof). The Basecoin can be converted to Zerocash anytime. It is more secure and it is impossible to find private information on its users. However, we will see that this may have negative effects. Payments by cryptocurrency remain in principle less anonymous than in cash, but more anonymous than by transfer or card. Unfortunately, these currencies are not perfect, they also have some inconveniences. This applies also for the privacy of payments and it is mandatory to point out some negative attributes.

2.3 Disadvantages

Firstly the price of cryptocurrencies is unstable, investments in these currencies are accompanied by very high risks because of the prices changes from one second to another, this effect applies for most currencies, but the fluctuations are usually much smaller. Bitcoin has a volatility ten times higher than the dollar (Barker, 2019) Cryptocurrencies have a great weakness which is the difficulty of making thrifts, they do not perform well in one of the three main functions of money, the storage of wealth. While many people who have invested in cryptocurrencies made a profit, many others have lost money. This is especially valid for people who have no decent knowledge of the economy and factors that influence the prices of cryptocurrencies.

Bitcoin has begun to play a growing role in illegal activities, mainly on the dark web. The dark web is a part of the World Wide Web, just like the deep web that forms most of the internet (90 %), darkweb is just 6%. Bitcoin is actively used in the buying and selling of illegal goods and services on the dark web. This includes money laundering, cybercrime, illegal drugs and trade, the financing of terrorism (Gabriel Weimann), trafficking in human beings, child pornography, illegal software and documents such as passports, cards, identities, university degrees, etc. About half of all bitcoin transactions involve illegal transactions either directly or indirectly on the dark web. In conclusion, the cryptocurrencies facilitate and make accessible crimes and obscure desires.

Secondly, cryptocurrencies are also not totally secure against theft. There have been some incidents in the history of Bitcoin caused by problematic or malicious transactions. In the worst of these incidents and the only one of its kind, someone created an illusion of an infinite possession of Bitcoin for almost 9 hours (10). It is mostly the public keys that can be vulnerable to computer attacks. Today‘s cryptocurrencies may stand in front of developement challenges. With the quick technological developement of recent years, the cryptocurrencies will also have to follow this direction and progress, otherwise there is a potential danger from other new technologies they will have instruments to attack and even destroy the current cryptography technology. In addition to software threats, there are also criminals who extort money (Bitcoins, Litecoins, etc.) by stealing laptops or other hardware from unsuspecting victims. In addition there are victims of cybercriminals on gaming sites and also victims of prestigious companies and the financial and entertainment sectors (11). Other currencies like Dash, Monnero, Litecoin are starting to be popular on the dark web, Zcoin and Zcash may be ideal candidates for these activities.

Mining is accompanied by massive electricity consumption. The consumed electricity represents additional costs and therefore they depreciate the value of cryptocurrencies. Even though renewable energy resources (solar, hydro, wind, etc.) start to form a large part of electricity production, there are still nuclear power plants that reduce uranium reserves and pollute the earth. We see that cryptocurrencies have an impact on many aspects of life.

2.4 Statistics

If we look at the extent of the cryptocurrency market we can see that at this moment (15.11.2019) the value of this market is worth over 233 billion dollars which is more or less equivalent to the GDP of Czech Republic. The Bitcoin counts for 65.9 % and Litecoin for 1.58 % of the total market capitalization. The market capital peaked over 800 billion USD on January 8th, 2018. There are around 2400 cryptocurrencies and many more are in development. We can see the evolution of the total market value on the following graph: (coinmarketcap.com, 2019)

Figure 3: Market capitalization of cryptocurrencies (01.08.2017-15.11.2019)

Here are some statistics for the 5 largest cryptocurrencies (15.11.2019):

	Total Value	Value of one coin	Number of coins	Volume traded in the last 24hours
Bitcoin	153 277 483 626$	8 491.99$	18 052 508	21 796 856 471$
Ethereum	19 598 770 324$	180.52$	108 587 446	8 815 678 477$
Ripple	11 329 241 896$	0.261654$	43 298 481 685	1 548 251 349$
Bitcoin Cash	4 795 268 314$	264.71$	18 117 731	1 918 658 721$
Tether	4 113 666 666$	1.00$	4 108 044 429	25 291 395 573$
Litecoin	3 681 894 624$	57.81$	63 698 257	3 195 878 562$

By the end of 2017 and the first month of 2018, bitcoin transaction fees have dramatically increased. It was a stimulus for Bitcoins owners to sell their assets. With rising fees at the end of 2017, companies have begun to withdraw from the network. Bitpay, which offers the transaction management service between users, has set up a minimum transaction amount of $100 for a moment. The reaction from consumers was very negative and the firm decided to lower the minimum amount to $ 5. Because of these problems, the companies decided to stop to support the payments via cryptocurrencies. For example, a video game maker Valve stopped accepting payments from Bitcoin for its Steam platform in December 2017. „Then, Stripe, a major credit card processor, also stopped accepting Bitcoin payments for its customers in January 2018, arguing that because of the very high fees there were fewer and fewer users in the payment network“ (Lee, 2018). As Bitcoin's transaction fees were on the rise, many companies started using other cryptocurrencies like Ethereum, Monero or Bitcoin Cash which resulted in the increase of these cryptocurrencies values.

The transaction costs are not considered in the further described strategies and results, as they may vary greatly depending on the type of brokers, dealers (which charges include bid/ask spread, commissions) and occasionally on the time of the transaction occurrence. Extra costs may be constituted of unexpected risks such as power outage or network issues on both sides.

3 Financial market analysis

This chapter will present different ways – strategies – to analyse the financial markets, in order to predict (or at least try) the future of assets value evolution. In the practical part of the paper we will only concentrate on the technical analysis strategy, but it is important to beware that it is not the only possibility.

3.1 Technical analysis strategy

The technical analysis is entirely based on historical prices fluctuations of a time series. Those fluctuations are studied to develop special values, called „indicators“. It is a very old strategy whose first real usages can be found in the 17th-century Dutch financial markets. A great contributor to the diffusion of the many aspects of this strategy is Richard W. Schabacker, who has published several books on the subject.

Time series are datasets ordered sequentially by time, e.g. the total sales of a company at the end of each day. Time series analysis and forecasting are two different tasks. The time series analysis consists of describing an ordered historical data sample. The forecasting implies the formulation of strategies and models which aim is to predict the future development of the time series. The forecasting is based on the on the evolution of past time series (Pole, West, Harrison, 1994).

The techniccal analysis is now a popular trade method used by many traders sometimes referenced as „chartists“. The calculus of indicators is usually based on volume, open prices, closed prices, high prices, low prices. More types of indicators exist, like trend indicators, momentum indicators (also named oscillators), or volume indicators. The formula defining those calculi will be presented in chapter 5. The indicators are used for creating strategies (in chapter 7), which generate buy/sell signals.

3.2 Fundamental analysis strategy

Fundamental analysis of any asset is very different from technical analysis. It stands on analyzing economic factors that might affect the price of an asset. These factors are various macroeconomic factors as interest rates, GDP, inflation, microeconomic factors as businesses revenues, price to earnings ratios (P/E ratio), to name a few examples (Fama, 1965)

It can also be anything else, for instance, political situation, media statements, intense lobbying by the industry or judicial challenges. (Yildiz, Yezegel, 2010).

3.3 Pairs trading strategy

Pairs trading is defined as a statistical arbitrage, where the prices of several financial instruments are moving together in the same direction. Habitually these instruments are related to each other or one is influencing another, as an example, we can state the value of Canadian Dollar (CAD) which partially depends on the value of crude oil, as Canada is a large oil exporter. The same is true for the swiss franc which is correlated with Gold. When the price of such instruments diverges or creates a spread, pairs trading implies selling the instrument which is currently increasing its price compared to the other instrument. On the contrary, the currently "undervalued" instrument is bought. Assuming history is repeating itself, the prices should move toward each other again, and thus the investor will obtain profit(Gatev, Goetzmann, and Rouwenhorst 2006).

3.4 Order anticipation strategy

Order anticipation is a kind of strategy that aims to predict large orders creation. In doing so, traders can take advantage of other traders by trading ahead of them. Since large orders attract investors, the strategy consists of buying before these orders are realized and selling for a higher price afterwards. This is a basic way of how the order anticipation strategies are designed to make profits.

4 Algorithmic trading

This chapter will provide a brief explication of algorithmic trading. This new financial feature intensively uses mathematical models, computers and telecommunications networks to automate the buying, selling or holding decisions. Algorithmic trading created new challenges and also opportunities for the financial industry and its regulators.

The computer-based automation has improved trading by reducing human error, lowering costs and increasing its productivity. Algorithmic trading has become a permanent and important part of the financial environment because it can save costs and permit bigger operating efficiency. As written in the journal of Economic Perspectives: "Thanks to the twin forces of competition and innovation, the drive toward "faster, cheaper, and better" is as inexorable as it is profitable, and the financial industry is no stranger to such pressures." (Kirilenko, Lo 2013, p. 52).

The common usage of computer algorithms for handling trading orders began 25 years ago (Chaboud, Chiquoine, Hjalmarsson, Vega, 2014). Algorithmic trading (AT), also called automated trading, is referring to the generation of buy and sell signals or orders by a computer algorithm and the management of these orders, without human intervention. One precise definiton of AT is: „Algorithmic trading can be defined as placing a buy or sell order of a defined quantity into a quantitative model that automatically generates the timing of orders and the size of orders based on goals specified by the parameters and constraints of the algorithm." (Rao, 2015).

In 2004 AT became the dominant kind of trading in the United States (Moldovana, Moca, Nitchi, 2011). AT accounted for 5–17 % of all trading volume in 2005 (Kunz, Martin, 2013). According to the Journal of finance (Hendershott, Jones, Menkveld 2011), more than 73 % of the traded volume is assigned to AT in the United States in 2009. Over the last twenty years, algorithmic trading has been facilitated by three major trends in the financial sector.

The first is that the financial system has become more complex because of economic growth and globalization in the world. As a result, the number of market participants as well as the variety of financial transactions, the amounts involved increased.

The second trend is the development of "financial technology", quantitative models of financial markets that have been developed by the great scholar actors of the financial economy, such as Black, Cox, Fama, Lintner, Markowitz, Merton, Miller, Modigliani, Ross, Samuelson, Scholes, Sharpe and others. Based on them, modern quantitative financial analysis and algorithmic trading were developed and improved.

The third is a huge improvement in computer technology, hardware, software, data availability and their interconnections as like as their electronic accessibility.

AT has advantages compared to regular trading. It can execute trades and process information much faster than humans are able to do. AT strategies are based on traditional market analysis strategies (presented in the previous chapter) and computing facilities. Combining different analysis and approaches results in a huge variety of AT strategies. The figure below gives an example of the integration of AT strategies (Moldovan, Moca ,Nitchi 2011).

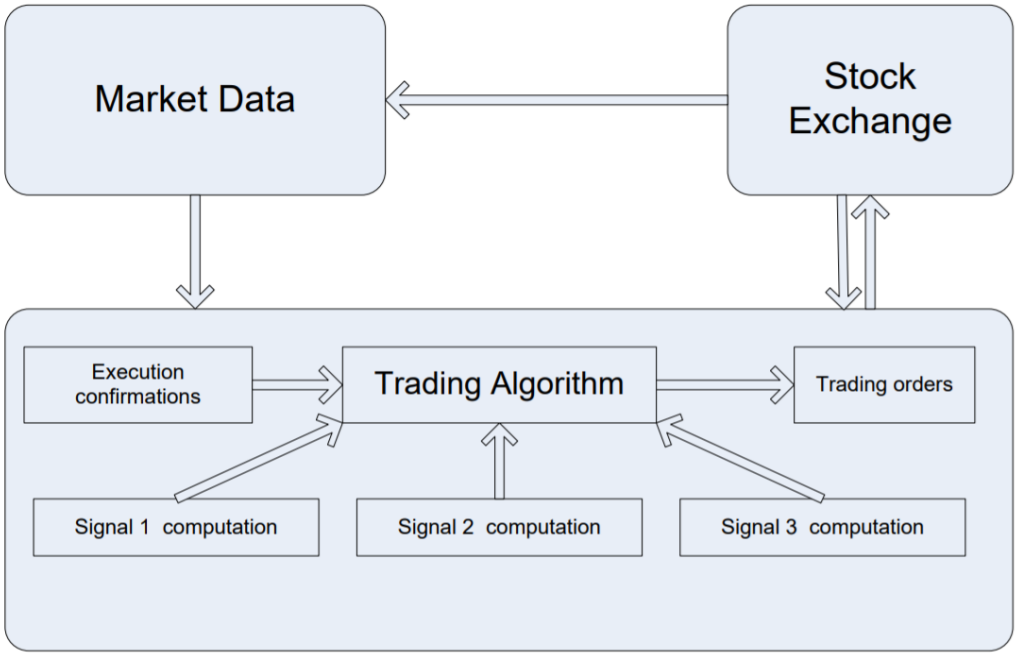


Figure 4: Integration of AT strategy

The advantage of technical relaibility lies in eliminating human emotions and mistakes in trading. For example unexpected price movements on the market can cause that some traders will become distressed. Emotions such as fear or greed can produce losses. An algorithm is not affected by emotions and so does not produce some erors humans do.

However, the speed of AT might prove itself a double edged-sword. In 2002 the Dow Jones Industrial Average dropped by 100 points (dollars), because of an accidentally produced sell order of $4 billion. Before the error was found, $600 million dollars changed ownership (Clark, 2010). There are also additional costs for the maintenance of equipment and infrastructure related to AT (hardware, software).

One type of strategies is based entirely on technical analysis and traditional trading indicators as relative strength index, moving average, or the Fibonacci sequence. (Huang et al., 2019). I am going to discuss trading indicators in chapter 5 and strategies using them in chapter 7.

4.1.1 Order anticipation

In the case where a large order is not publicly displayed, algorithmic traders have ways to search for them. Pinging is one of them, in which traders send small orders to detect if they match another order, if they do, the algorithm knows about it and is designed to react and adapt its trading strategies.

Another way to find hidden orders is to predict them before they exist. This type of order anticipation is highly dependent on algorithms and analysis of data and statistics, it's similar to the basic algorithmic trade strategy but designed to target large orders.

4.1.2 Arbitrage trading

Many new brokers and other market players are present in markets such as the forex, or the stock exchanges and theoretically not all exchange rates are exactly equal at some point in time. Trading robots can scan the market for the purpose of finding arbitrage opportunities. In general arbitrage trading is one of the three main types of trading, the other ones being speculation and hedging. Arbitrage consist of Such opportunities that could take place for example when two brokers fix distinct prices on the same instrument at the same time, in this case, it is enough to sell the instrument to one market maker and simultaneously buy it from the other.

4.1.3 Trigger trading

The Trigger trades is an algorithmic trading strategy that allows to quickly send orders from a computer to trade, buy or sell assets. This strategy is called the „trigger

trades “because the algorithms observe the market and once the condition set by the user occurs it triggers a series of orders (for example an order to purchase shares as soon as their value reaches 20 $) (Yesha Yadav, 2015).

4.2 High-frequency trading

High-Frequency Trading (HFT) principles lie in the massive execution of trades over a short period of time. „HFT firms typically trade hundreds or thousands of times per day, with a typical holding period measured in seconds or minutes“ (Jones, 2013), the positions are for example not hold overnight. Gains or losses generally represent only a few pips. A pip is an acronym for "percentage in point" For example for the major currency pairs, like the USD/GBP, one pip is 0.0001 USD (or GBP). For the BTC/USD it often represents 0,1 USD but it can be more or less depending on the broker. Recently the term ultra-high-frequency trading appeared, which is even faster than HFT and can execute trades in milliseconds. The HFT and UHFT are used by market-makers to adapt their ask and bid prices as quickly as possible according to the newest market information. (Jones,2013) This prevents some losses, caused by slow reactions to price movements. The majority of research until today shows that HFT is lowering trading costs and increasing liquidity. But there are also some disadvantages, for example, the market participants who do not have the capital to afford trading technology could be at a disadvantage (Chlistalla, 2011).

As the most used type of trading, high-frequency trading can be hard to differentiate from others since its main characteristics, necessary use of algorithms and securities changing hands in milliseconds, are also present in slightly slower (still in milliseconds) tradings.

Since real-time management of trades is not possible for high-frequency trading, traders have to rely entirely on their algorithms, whence their vital importance. To operate such rapid trades, equipment is also important to be able to analyse large volumes of data. Moreover, algorithms also have to process and analyse news rapidly by focusing on keywords, this can sometimes be risky as the faster the analysis is, the better the results. But faster algorithms analyse news, faster they are prone to errors. (Yesha Yadav 2015)

Some European countries desire to regulate HFT as it may have negative consequences on markets. HFT is responsible for around 70 % of Flash Crashes. A flash

crash is a fast drop in price, followed by a rebound to the original price level, on average the flash crashes last for over 12 minutes (Bellia et al., 2018). This new subject is subject to further research.

The job of a high-frequency trader is not the same as the usual one, as he has to anticipate and predict future changes in the next few seconds of the market and not over relatively long periods.

5 Chart indicators:

In this chapter, I will describe a few technical chart indicators that are used in the strategies and which are built on the technical analysis. The indicator computation in excel will be described in the practical part, chapter 8.

5.1 The Stochastic Oscillator

The stochastic oscillator is an indicator that measures the momentum, as its name indicates, the indicator oscillates around a central point or channel. Typically the channel ranges from the values of 20 to 80. This indicator is calculated for each selected period of time (for each candlestick bar), for example, it can be a minute, an hour, 4 hours or a day. (Moldovana et al., 2011). The limitation of this indicator is its inability to identify market trends. For this purpose other indicators as various types of moving averages are employed. This oscillator is used to identify overbought or oversold conditions. (P. Fernández et al, 2008). The formula for calculating this indicator is:

$$K = 100\frac{C - L_n}{H_n - L_n}$$

Where K is a value of the stochastic indicator, which is ranging from 0-100, because the value of Hn ≥ C and both of these values are positive:

$$0 > (C - L_n) / (H_n - L_n) > 1$$

C is the closing price at the current candlestick/period.
H_n is the highest price of the last n candlesticks/period.
L_n is the Lowest price of the last n candlesticks/period.
n is the number of all previous periods plus the current period.

I will use this indicator for generating buy and sell signals. There are several interpretations of this indicator. One of the interpretations is to set values for which the market is overbought and for which the market is oversold. It is possible to adjust these values depending on various factors like the desired level of risk (E.g. a risk-averse trader may set these values at 10/90) or the targeted market (Öztürk, 2015).
D = 3day moving average of K

Which is the sum of values for the last 3 periods of K divided by 3.

5.2 On-Balance Volume

On-Balance Volume, or OBV, is a momentum indicator that continuously measures the flow of the total number of shares or contracts of a security or a whole market. If this flow tends to go up, the price is probably about to increase.

5.3 MACD

The Moving Average Convergence Divergence (MACD) is a popular indicator created by Gerald Appel in the 1970s. To calculate the MACD indicator it is required beforehand to compute two Exponential moving averages (EMA). The simple moving average (SMA), also sometimes referred to as arithmetic moving average is the average price of the n previous periods (which is the sum of the current and previous period prices divided by the number of periods). The general formula for a moving average is as follow (Ramazan, Stengos, 1998):

$$SMA = \left(\frac{1}{n}\right) \times \sum_{i=0}^{n-1} (C_{t-i})$$

Where SMA represents moving average and Ct is the close price for each n periods. In contrast with the SMA, the EMA contribute more importance to recent prices. The closer the period is to the current price, the greater is it‘s weight in the EMA indicator. The EMA takes into account previous EMA values: Since I have limited access to historical data, I cannot compute this indicator unless I compute the first value of EMA with the value of SMA.
Here is the formula for EMA and MACD:

$$EMA_t = (Close - EMA_{t-1}) \times (\frac{2}{n+1}) + EMA_{t-1}$$

$$MACD = EMA_{\mathbf{12}} - EMA_{\mathbf{26}}$$

The MACD is calculated by subtracting the longer EMA (close price, 26 periods) from the shorter EMA (close price, 12periods). Unlike the stochastic oscillator, MACD takes into consideration more aspects as the momentum, the trend strength and direction

as well as the inversion of trends. As the indicator emphasizes the most current movements in prices it should follow closely the underlying security. Therefore the indications will not be false too long. (Yazdi, Lashkari, 2013). This, however, might not always be true for high volatility markets as cryptocurrencies are. The indicator is also suitable for hourly, daily, weekly or monthly tick data. Its parameters can be adjusted to better fit in these different timeframes, or markets/assets. The indicator may be interpreted in many ways, we will propose two of them in chapter 7.

5.4 VWAP

Volume Weighted Average Price (VWAP) is an indicator, that can be used as a guideline to help us get some information about the price graph evolution. It can be described as a line going through the graph similarly as a moving average and its value is derived from the price and volume of traded assets. It can be easily mistaken for moving average but in moving average the calculation of volume is not counted in. It tells us about the trend and the value of an asset.

Rising volume weighted average price and its value being above the real price of the instrument means the price is plausible to go up. Declining volume weighted average price and its value being under the real price of the asset means the price is plausible to go down. Many investors use this guide as an accessing tool to tell if they bought at the right time of the day. If the price they paid during the day is higher than the volume weighted average price, the investor had likely paid more than he could. If the price they paid during the day is lower than the volume weighted average price, the investor had made the right call and bought at the right time. Volume weighted average price can be calculated by the formula:

$$VWAP = \sum Price \times Volume \,/\, \sum Volume.$$

The calculation is done by summing up the amount of money traded over a day and dividing it by the total volume of trades. To calculate it yourself, you must take a period and add up high, low and close values and divide them by three. This value is the average price of the asset at the chosen period. If you divide the average price multiplied by volume by the total volume of the asset traded over a day you get the volume weighted average price.

Small investors and retail traders use volume weighted average price as a tool of confirmation for their trades. If the volume weighted average price is below the price they only look for long positions. If the price is below the volume weighted average price they only look for short positions.

It may seem that the volume weighted average price is a great benchmark, but it is a one-day indicator that restarts at the beginning of each new day. Trying to count in more days would get us further from the true value of the volume weighted average price. Also considering strong uptrends, the price will rise for a few days without sinking below the volume weighted average price so to conclude, this indicator should not be used as the only assessment of the market. I am not going to use this indicator in my strategies since typically it is used when trading on shorter periods, or over a whole day, but I wanted to provide an example of a volume based indicator.

5.5 RSI

The Relative Strength Index (RSI) is a momentum indicator, which is convenient for the validation of entering a position. It can also be used effectively (Yazdi, Lashkari, 2013) for recognizing divergences of the price movements relative to the indicator movements. The formula for computing this index which value is ranging between 0 and 100 is:

$$RSI = 100 - \frac{100}{1 + Average\ Loss/Average\ gain}$$

The average gain (AG) is the previous value of AG times the number of periods minus one (n-1) plus the gain if any (can be equal to zero). This result is then divided by the number of periods (n). The average loss (AL) is the previous value of AL times n-1 plus the loss, all divided by n, as illustrated in the formulas:

$$AL = \frac{AL(prev) \times n - 1 + Loss}{n}$$

$$AG = \frac{AG(prev) \times n - 1 + Gain}{n}$$

In the equation above, Loss is the negative difference between current and previous period's close price if any (otherwise equal to 0). Gain is the positive difference, if any. (Öztürk, 2015)

Since this calculation requires previous values of AG and AL we cannot compute the first value with the above formulas. Therefore the first values of AG and AL are calculated differently than the rest. The first AG is the sum of positive changes in the close prices between two periods, for the last n periods, including the current one divided by n, in other words, it is the average of all positive increases between two periods over n periods. In our backtest 14 periods are taken into account for the calculation, it is not necessary the best setting for the parameter. In general choosing the right parameters of indicators may be a long process of testing. There are obviously better-suited values for the parameters, but the ideal parameter might change when applying on different assets and times series. The value 14 is picked because it is the original value suggested by the developer of the indicator (Wilder, 1978) The average loss (AL) is the sum of negative movements in price over each period, divided by 14.

$$AG = \left(\frac{1}{n}\right) \times \sum_{i=0}^{n-1}(C_{n-i} - C_{n-i-1})$$
$$\forall C_{n-i} > C_{n-i-1}$$

and

$$AL = \left(\frac{1}{n}\right) \times \left|\sum_{i=0}^{n-1}(C_{n-i} - C_{n-i-1})\right|$$
$$\forall C_{n-i} < C_{n-i-1}$$

The employed period is n=14, note that another value can be used for this variable. C_n is the current Close price at the period n (C_{14}).

5.6 Rate of Change

Rate of Change, or ROC, is an indicator that compares the current close price and the close price n periods ago and in doing so as its name indicates, shows how fast the price changes in a specified period. The calculation of the indicator is as follows:

$$ROC = (Close - Close(prev, n))/ Close(prev, n) * 100$$

where n is the period, ROC is the rate of change value, Close is the current close price and Close (prev, N) is the close price N periods ago. This indicator is not going to be used in our strategies and backtesting, but still serve as an additional example.

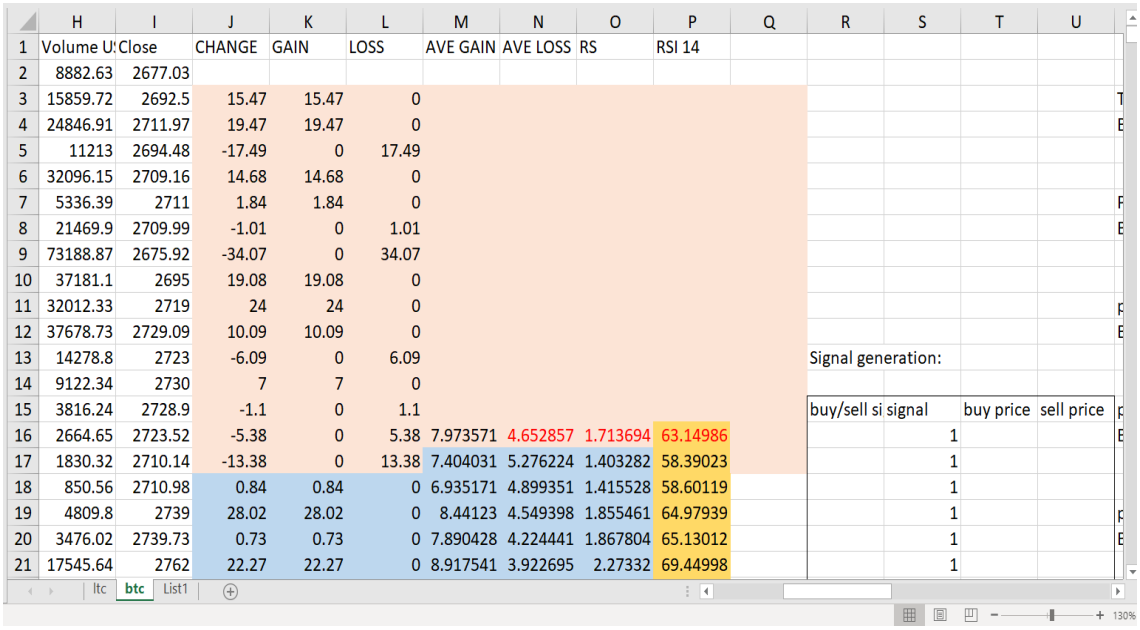
PRACTICAL PART

6 Methodology

The historical data is taken from cryptodatadownload.com which provides data from different exchanges. I chose to use the data from Exmo Exchange, because some data taken from other exchanges were missing/uncomplete/repeating the same data, thus the calculations led to errors. Different brokers/exchanges may have different prices as well as historical data. The data is free of charge but unfortunately does not include ask and bid prices, therefore the amount of historical spreads is unavailable. The downloaded data are in CSV format. The Excel worksheets can be found in the CD which is provided along with the paper. There are 4 worksheets with the computed indicators and strategies.

The analysed time period is one hour long, and for every scheduled time period there are 5 inputs. Open, low, high and Close price and volume are all available. Where open price refers to the earliest data in one hour range and close price refers to the latest data in this one hour period. Low represents the lowest and high the highest price throughout the period. These data are manipulated to obtain the value of indicators which then serve as signals for buying and selling. A total of 17535 records from 31.07.2017 to 31.07.2019 are available for both LTC/USD and BTC/USD pairs. This interval is also divided into four time series, of 6 months. The algorithms are possibly created by traders, who are developing them by testing their performance on historical data. This process is called the backtesting. (Chan, 2017).

In this paper we will implement some of the indicators and the chosen strategies in Microsoft Excel. I will backtest created algorithms on Cryptocurrencies, first on BTC/USD, then LTC/USD. For the illustration of excel computation check the figure below:



	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	Volume U	Close	CHANGE	GAIN	LOSS	AVE GAIN	AVE LOSS	RS	RSI 14					
2	8882.63	2677.03												
3	15859.72	2692.5	15.47	15.47	0									
4	24846.91	2711.97	19.47	19.47	0									
5	11213	2694.48	-17.49	0	17.49									
6	32096.15	2709.16	14.68	14.68	0									
7	5336.39	2711	1.84	1.84	0									
8	21469.9	2709.99	-1.01	0	1.01									
9	73188.87	2675.92	-34.07	0	34.07									
10	37181.1	2695	19.08	19.08	0									
11	32012.33	2719	24	24	0									
12	37678.73	2729.09	10.09	10.09	0									
13	14278.8	2723	-6.09	0	6.09						Signal generation:			
14	9122.34	2730	7	7	0									
15	3816.24	2728.9	-1.1	0	1.1						buy/sell si	signal	buy price	sell price
16	2664.65	2723.52	-5.38	0	5.38	7.973571	4.652857	1.713694	63.14986			1		
17	1830.32	2710.14	-13.38	0	13.38	7.404031	5.276224	1.403282	58.39023			1		
18	850.56	2710.98	0.84	0.84	0	6.935171	4.899351	1.415528	58.60119			1		
19	4809.8	2739	28.02	28.02	0	8.44123	4.549398	1.855461	64.97939			1		
20	3476.02	2739.73	0.73	0.73	0	7.890428	4.224441	1.867804	65.13012			1		
21	17545.64	2762	22.27	22.27	0	8.917541	3.922695	2.27332	69.44998			1		

Figure 5: Computation illustration of indicators and strategies in Microsoft Excel

These simulations are done not only to evaluate the potential of the strategies but mostly to correct and improve them (Treleaven, Galas, Lalchand, 2013). We have to note that positive results of backtesting these strategies do not guarantee any profits in the present market real conditions. This is true, especially when applying these strategies only to one time series and one asset pair because all the data from this interval and pair could have been processed to form a perfect AT strategy.

Moreover, transaction costs and spreads are overlooked/unavailable. In real market time and conditions, the market makers want their part of the cake. The spread of ask and bid prices may vary but generally is not bigger than a few pips, but there are also other potential risks and fees. To recall a pip is an acronym for „percentage in point“. The quantities traded in the backtest are always equal to 0.01 BTC and 1 LTC, this is subject to change, some algorithms might even imply different trading volumes for each trades.

Here are the BTC/USD (graph1.0) and LTC/USD (graph 1.1) exchange rates over the backtested time series:

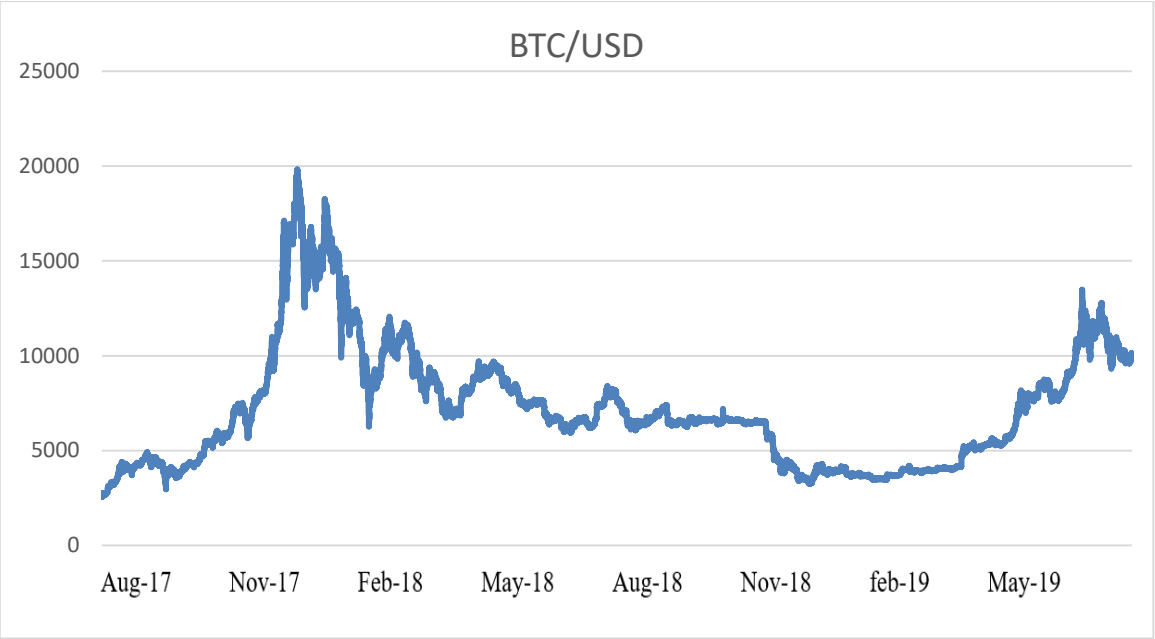


Figure 6: BTC Close prices in USD – 01.08.2017-31.07-2019

Figure 7: LTC Close prices in USD – 01.08.2017-31.07-2019

7 Chosen strategies

In this part, I will present the algorithmic trading strategies I used for backtesting. They stand on trading rules, which as already mentioned can produce only 2 outcomes, a buy or sell order. These strategies are rather simple, they trigger a signal when an indicator crosses a value.

7.1 Strategy based on Stochastic indicator

7.1.1 K value cross

This strategy is backtested on historical data with the knowledge of the last fourteen highest and lowest prices of each fourteen past days(periods). Therefore, if someone wanted to apply this strategy in real-time he would need access to continually updated data of the past days highest and lowest prices, as well as the closing prices for these days.

Firstly I've elaborated a strategy consisting of the following rule: when the stochastic oscillator indicator returns a value which is smaller than 20 ($Kt<20$), the excel function will generate a buy signal and at the same time when the value is bigger then 80 ($Kt>80$), a sell signal will be generated.

This algorithm resulted in a different number of buy and sell orders. This may be an undesired outcome of trading for investors who wish to close all their positions and retire their investments. At the stop of the algorithm, the trader would have to close these positions or hold them with the consciousness of uncertain future price movements. Therefore, to achieve the same amount of buy and sell signals a new rule was added. This rule is assuring the alternation of buy and sell signals by returning a blank if the preceding signal was identical (it can be a signal from the last 3 periods). The signals are occurring only when the K value crosses above or below the respective thresholds.

7.1.2 D value cross

The next strategy is further altering the first one by taking into account the D value of the stochastic oscillator alongside with the K values. I had the same outcome as in the

strategy one at first (inequality of buy and sell signals), but the rule was again adjusted. The exact trigger of the signal occurs when K is above 80(sell) or below 20(buy) and when D crosses these values. The cross can more precisely be described by forming conditions which are expressed:

Sell signal:

$$D_{n-1} < 80$$

$$D_n > 80$$

Buy signal:

$$D_{n-1} > 20$$

$$D_n < 20$$

7.2 Strategy based on RSI

The second strategy is similar to the previous ones because the trading rules are nearly the same but we use a different indicator. The Relative Strenght Index is used as a signal value for evaluating whether to buy, sell or do nothing. When the value of this indicator crosses above the value of 70 a sell signal is generated and when RSI crosses below 30 a buy signal occurs. I used 14 periods to compute the first value of RSI. These values/parameters were suggested by Mr Wilder.

7.3 Strategy based on MACD

7.3.1 Trigger line cross

This strategy is based on the MACD indicator. When a 9period EMA of MACD (the trigger line) crosses below the MACD indicator a sell signal is generated, and when this 9period EMA crosses above MACD, a buy signal is generated.

7.3.2 MACD cross

Another simple rule for trading with the MACD lies in taking short positions when the value of MACD crosses below zero and taking long positions when MACD crosses above zero.

8 Excel computation

As past data is needed to evaluate the values of indicators, the generation of buy and sell signals will only start in the first period for which the value of an indicator is calculated.

8.1.1 Stochastic oscillator – K

The function: "MIN" was used in column I, and the function: "MAX" in column J to find the minimum and maximum values at each period. These functions return the lowest or highest value of the fourteen previous lows or highs respectively.

For the Stochastic oscillator the function „maximum" was used in the column: K to identify the biggest value for the high price (H) over the 14 last periods (for each period starting from the 14th). The function „minimum" was utilized in the column: J to find the smallest low price (L) of the last 14 periods (for each period starting form the 14th). The variable K is calculated for each in the column: R by substituting the values in the formula used in chapter 5.1: 100× (C – L) / (H – L) with the close price data (C) and the maximum(H) and minimum(L) prices we found. The values of K will serve us for generating buy and sell signals.

Firstly I've elaborated a strategy consisting of the following rule: when the stochastic oscillator indicator returns a value which is smaller than 20 (Kt<20), the excel function will generate a buy signal and at the same time when the value is bigger then 80 (Kt>80), a sell signal will be generated. This showed to be inefficient. This algorithm resulted in a different number of buy and sell orders. This may be an undesired outcome of trading for investors who wish to close all their positions and retire their investments. At the end of the period, the trader would have to close these positions or hold them with the consciousness of uncertain future price movements. Therefore, to achieve the same amount of buy and sell signals a new rule was added. This rule is assuring the alternation of buy and sell signals by returning a blank if the preceding signal was identical (it can be a signal from more than one period). The signals are occurring only when the K value crosses above or below the respective thresholds.

The next step is the signal generation. To assure the signal alternation we first use the column: V. In the first row(15th) of this column we set the value as 1. In the next row, we build a rule referring to the column: U which stands for the signal generation. The rule

is designed as follows: if U is equal to „buy" set the value of V as 0, inversely, if U is equal to „sell" set the value of V as 1, otherwise copy the previous value of the column V. The buy signal is generated in column U when it meets 3 conditions: The value of the indicator is smaller than 20, the previous value of RSI is bigger than 20 and the previous value in column V is not equal to 0. The sell signal is generated when the indicator value is bigger than 80, the previous RSI is smaller than 80 and the previous value in column V is not equal to 1. (The signal cannot be generated for the first 14 values, as the stochastic indicator first calculated value is in the 14th period).

8.1.2 Stochastic oscillator - D

We can further extend this indicator by averaging the last 3 periods of K, we note this new indicator D. The K value is computed in column M, the D value is computed in the column N. A buy signal is generated. The trading rules are the same as for the stochastic K except, there is an additional condition. The value of D has to be smaller than 20 for the buy signal, or bigger than 80 for the sell signal.

8.1.3 RSI

The first value step to compute the RSI in excel is to take the difference of the current and previous period close prices (in column J). Gain is filled in column K when the column J is positive, otherwise, the value is set as zero. Loss is filled in column L when column J is negative, otherwise, the value is set as zero. The first AG value is computed in M16 as the average of the 14 last periods gains (including the current one). The next periods (rows) are calculated as the previous period value of AG multiplied by 13, then added to the gain of the current period, and finally divided by 14. The first AL value is computed in N16 as the average of the 14 last periods losses. The next periods are calculated as the previous period value of AL multiplied by 13, then added to the loss of the current period, and finally divided by 14. RS (Relative Strenght) in column O is equal to AG/AL. RSI computed in column P is equal to 100-(100/(1+RS).

For the signal generation, we once again use a column (S) as a tool assuring the signal alternation, the first value set in this column is equal to 1. The next values in the column are equal to 0 or 1. When a buy signal is generated the value is set to 0, when a

sell signal is generated the value is set to 1, otherwise the previous value is replicated. The signals occur in column R, the algorithm produces a buy when 3 conditions are met, the current RSI < 30, the previous RSI > 30 and the previous value in column S ≠ 0. The sell signal is produced when the current RSI > 70, the previous RSI < 70 and the previous value in column S ≠ 1. The column T and V are used to see the buy and sell prices at the respective periods and are also needed for the analysis of results.

8.1.4 MACD

The MACD computation stands on the EMA's. For calculating the MACD there are as already mentioned several steps. The SMAs is evaluated by averaging the last 12 periods (in the column K) and 26 periods (in the column O). We will use SMA as the first value for the EMA, the next values are computed (in column M and Q) by multiplying the difference between close price minus the previous period EMA by respectively 2/13 or 2/27 and then adding this result to the previous EMA value again. The longer EMA's is subtracted from the shorter EMA's (in column S) to form the MACD indicator. The MACD indicator is calculated from the 26th period. Then we set the 9 periods EMA of the MACD indicator, the trigger line (in the column V). First, the 9 periods SMA of MACD is calculated (in column T) as the first value of the trigger line, again by averaging the 9 last periods of MACD. The next values of the trigger line are calculated taking the difference between the MACD at the present period and the previous period EMA, and multiplying them by 2/10, and finally adding the previous EMA again. Now both the MACD indicator and the trigger line are set, buy and sell signals can be created.

The strategy 7.3.2 generates a buy signal when the value of the trigger line crosses above zero, inversely when it crosses below zero a sell signal is produced. In excel there is one column (Y) that verifies that the current value of the trigger line (in column V) is bigger than 0 and the previous value is smaller than 0. The column Z verifies that the current value of the trigger line is smaller than 0 and the previous value is bigger than 0.

The strategy 7.3.1 generates a buy signal when the 9 hours EMA of MACD is bigger than MACD. At the same time, the previous value of 9 hours EMA of MACD has to be smaller than the previous value of MACD. The sell signal is produced when the opposite is true.

9 Results

In the tables, **sum buy** refers to the sum of all buy signals, **sum sell** is the sum of all sell signals, **total buy** refers to the total number of all buy signals, **total sell** is the number of sell signals, **sell/ buy%** is equal to 100 times the sum sell divided by sum buy, **%return** is the percentage increase or decrease of sum sell compared to sum buy (also the profit/loss divided by sum buy). Note that the results of sum buy, sum sell, average buy, average sell, profit/loss are all displayed in dollars. Some of the algorithms generated one more buy signal than a sell signal. The investor could decide to hold his last buy position or to close it. For the consistency of results, a manual sell signal had to be added at the last period of the dataset. It is the only case of a manual intervention in the algorithms. If we took transaction costs into consideration, the results of all strategies would be inferior to the ones presented.

9.1 Buy and hold

The buy and hold strategy result in high profits in the first and last time series (01.08.2017 – 31.01.2018 and 01.02.2019 – 31.07.2019) for both cryptocurrencies pairs. Buying 0.01 BTC would earn 79.36 USD (+294.1 %) for the first time series and 66.34 USD (+189.5 %) for the last time series. The buy of one LTC would earn 129.22 USD (+316.9 %) for the first time series and 67.35 USD (+210.3 %) for the last time series. However, this strategy is not always profitable, because the second and third time series (01.02.2018 – 31.07.2018 and 01.08.2018 – 31.01.2019) are producing a large loss. A buy investment in 0.01 BTC would result in a loss of 29 USD, or -27.2 % for the second period and a loss of 42.58 USD, or -54.9 % for the third period. A buy invevestment of one LTC would result in a loss of 90.86 USD (-53.4 %) and a loss of 47.1 (-59.5 %) respectively. If we look at the overall outcome of the buy and hold over the 2 years it would still be highly profitable, but that is not necessarily true for a future buy and hold investment, the prices could move down again. With this strategy it is important to choose the right time, e.g. if we examined a period from January 2018 to Ooctober 2019 the results for this strategy would be opposite. We can conclude that without any crucial information on cryptocurrency (from fundamental analysis), it is not a consistent investment and a way to make profits, but can still be useful, e.g. for the diversification

of an investor portfolio. The table below shows prices of BTC and LTC at the end of each time series as well as the initial price (01.08.2017):

Price	Initial price	End of times series 1	End of times series 2	End of times series 3	End of times series 4
BTC	2723.52	10660.00	7759.68	3500.76	10135.00
LTC	40.78	170.00	79.14	32.03	99.38

9.2 Algorithmic strategies:

9.2.1 Total results

The total returns (profit/loss) over the 2 years period were mostly around zero. The 7.3.2 (based on MACD) was the only strategy with positive returns for both BTC and LTC pairs. The rest of the strategies returns were very slightly negative. In terms of percentage returns, only the strategy 7.2 (based on RSI) and the strategy 7.3.2 had significant loss and profits respectively. We can see that the strategies have a different occurrence of signals, ranging from 110 to 1402 signals, therefore the probability to produce a signal varies for each strategy. Compared to the buy and hold strategy the %returns are very small, for both negative and positive returns.

Strategy 7.1.1 (K value cross)

Total	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
BTC	26989.6	26945.2	385	385	70.1	70.0	-44.45	99.835 %	-0.165 %
LTC	38143.1	38158.8	403	403	94.7	94.7	15.70	100.041 %	0.041 %

Strategy 7.1.2 (D value cross)

Total	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
BTC	14927.6	14884.3	196	196	76.2	75.9	-43.24	99.710 %	-0.290 %
LTC	21243.53	21228.69	233	233	91.2	91.11	-14.84	99.930 %	-0.070 %

Strategy 7.2 (Strategy based on RSI)

Total	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
BTC	4069.7	3961.0	55	55	74.0	72.0	-108.72	97.329 %	-2.671 %
LTC	5133.8	5106.5	55	55	93.3	92.8	-27.26	99.469 %	-0.531 %

Strategy 7.3.1 (trigger line cross)

Total	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
BTC	48967.1	48874.3	701	701	69.85	69.72	-92.81	99.810 %	-0.190 %
LTC	65147.5	65023.4	688	688	94.69	94.51	-124.12	99.810 %	-0.190 %

Strategy 7.3.2 (MACD cross)

Total	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
BTC	14090.5	14306.0	200	200	70.45	71.53	215.44	101.529 %	1.529 %
LTC	18653.2	18991.1	207	207	90.11	91.74	337.91	101.812 %	1.812 %

9.2.2 Six month time series

In our two years data set the average return for any 6 month time series (which correspond approximately to 4400 periods), is shown in the table below. Once again one signal was counted at the end of each 4400 periods if the number of sell and buy signal was not equal.

Average Returns	Strategy 7.1.1	Strategy 7.1.2	Strategy 7.2	Strategy 7.3.1	Strategy 7.3.2
BTC	-17.72	-16.00	-39.80	-34.48	46.06
LTC	-6.78	1.78	-5.69	-42.57	77.17

Next tables display results obtained for each strategy for BTC and LTC cryptocurrency pair and for each of the four time series.

Strategy 7.1.1 (K value cross)

This strategy was profitable except the first and last time series for the BTC/USD pair.

BTC	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
Time series1	7296.39	7270.70	91	91	80.18	79.90	-25.69	99.648 %	-0.352 %
Time series 2	8432.84	8455.79	103	103	81.87	82.10	22.95	100.272 %	0.272 %
Time series 3	5541.69	5565.19	102	102	54.33	54.56	23.50	100.424 %	0.424 %
Time series 4	5820.12	5759.73	90	90	64.67	64.00	-60.39	98.962 %	-1.038 %

LTC	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
Time series1	10553.41	10578.6	88	88	119.93	120.21	25.19	100.239 %	0.239 %
Time series 2	13731.59	13801.37	101	101	135.96	136.64	69.78	100.508 %	0.508 %
Time series 3	5152.85	5167.72	109	109	47.27	47.41	14.87	100.289 %	0.289 %
Time series 4	8737.26	8781.50	106	106	82.43	82.84	44.24	100.506 %	0.506 %

Strategy 7.1.2 (D value cross)

This strategy was more efficient in the second and third time series. In the first and last time series it was underperforming.

BTC	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
Time series1	4095.43	4092.07	43	43	95.24	95.16	-335.74	99.918 %	-0.082 %
Time series 2	4767.77	4769.13	57	57	83.65	83.67	135.80	100.028 %	0.028 %
Time series 3	2797.33	2821.36	51	51	54.85	55.32	24.03	100.859 %	0.859 %
Time series 4	3368.44	3308.00	46	46	73.23	71.91	-60.44	98.206 %	-1.794 %

LTC	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
Time series1	4723.58	4647.49	40	40	118.09	116.19	-76.09	98.389 %	-1.611 %
Time series 2	8902.54	9045.95	67	67	132.87	135.01	143.41	101.611 %	1.611 %
Time series 3	3313.17	3331.81	71	71	46.66	46.93	18.64	100.563 %	0.563 %
Time series 4	4403.62	4373.85	56	56	78.64	78.10	-29.77	99.324 %	-0.676 %

Strategy 7.2 (Strategy based on RSI)

For the BTC the strategy proved to be highly inefficient in half of the total time series. For the LTC the strategy was efficient in the first 3 time series, but made high losses in the last period.

BTC	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
Time series1	1234.54	1235.16	15	15	82.30	82.34	0.62	100.050 %	0.050 %
Time series 2	1008.70	963.51	12	12	84.06	80.29	-45.19	95.520 %	-4.480 %
Time series 3	839.00	836.03	15	15	55.93	55.74	-2.97	99.646 %	-0.354 %
Time series 4	1088.89	1032.55	14	14	77.78	73.75	-56.34	94.826 %	-5.174 %

LTC	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
Time series1	1584.82	1616.25	13	13	121.91	124.33	31.43	101.983 %	1.983 %
Time series 2	1735.3	1777.45	12	12	144.61	148.12	42.15	102.429 %	2.429 %
Time series 3	685.67	697.15	15	15	45.71	46.48	11.48	101.674 %	1.674 %
Time series 4	1227.36	1186.07	16	16	76.71	74.13	-41.29	96.636 %	-3.364 %

Strategy 7.3.1 (trigger line cross)

This strategy made losses for each LTC time series, for the BTC there were some positive results of backtesting in the third and last time series.

BTC	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
Time series1	12519.53	12445.68	159	159	78.74	78.28	-73.86	99.410 %	-0.590 %
Time series 2	13358.64	13333.81	162	162	82.46	82.30	-24.83	99.814 %	-0.186 %
Time series 3	10690.79	10711.32	189	189	56.57	56.67	20.53	100.192 %	0.192 %
Time series 4	12433.18	12461.12	192	192	64.76	64.90	27.93	100.225 %	0.225 %

LTC	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
Time series1	19715.28	19660.24	185	185	106.57	106.27	-55.04	99.721 %	-0.279 %
Time series 2	23390.45	23331.96	171	171	136.79	136.44	-58.49	99.750 %	-0.250 %
Time series 3	7442.64	7391.69	157	157	47.40	47.08	-50.95	99.315 %	-0.685 %
Time series 4	14599.15	14639.51	175	175	83.42	83.65	40.36	100.276 %	0.276 %

Strategy 7.3.2 (MACD cross)

Only the third time series resulted in losses for this strategy for both BTC and LTC.

BTC	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
Time series1	3653.71	3808.35	43	43	84.97	88.57	154.64	104.232 %	4.232 %
Time series 2	4136.79	4164.81	51	51	81.11	81.66	28.02	100.677 %	0.677 %
Time series 3	3121.10	3105.68	57	57	54.76	54.494	-15.42	99.506 %	-0.494 %
Time series 4	3178.93	3227.14	49	49	64.88	65.86	48.21	101.517 %	1.517 %

LTC	sum buy $	sum sell $	total buy	total sell	average buy $	average sell $	Profit/ loss	sell/ buy%	%return
Time series1	4326.19	4602.96	42	42	103.00	109.59	276.77	106.398 %	6.398 %
Time series 2	7079.54	7115.39	54	54	131.10	131.77	35.85	100.506 %	0.506 %
Time series 3	2745.58	2723.45	57	57	48.17	47.78	-22.13	99.194 %	-0.806 %
Time series 4	4501.88	4549.3	54	54	83.37	84.25	47.42	101.053 %	1.053 %

The strategy 7.1.1 and 7.1.2 were both performing well for the second and third time series where the price was declining (a downwards trend). This may be of good use for diversifying an investor porfolio only consisting of a buy and hold strategy, because this strategy is obviously not performening in donwnwards trends. Those strategies can be complementary.

9.3 Possible improvement of strategies

The trading strategies backtested in excel are rather simple. It is possible to create more complex strategies as bearish and bullish divergences, or possibly improve the tested strategies. One way is to combine the rules and indicators. New rules/strategies can be added as stop loss/take profit rules, e.g. when the current close price is 1% smaller than the previous buy signal, produce a sell signal, or when the current close price is 3%bigger also produce a sell signal, etc. Only a few technical indicators were backtested, other technical or possibly fundamental indicators might be more or less suitable for cryptocurrencies. The thresholds and periods used are also subject to change. To implement more complex rules and strategies, more advanced software as Metaeditor, Python, Tradestation would serve as a better tool. If someone wanted to analyse a much longer period of time with shorter time frames it would also be less appropriate to use excel or even impossible. Obviously techniques used by HFT involve much more tooling with specific computer programming and networking optimizations. Those techniques are developed by high profile computing companies, which are keeping in secret of the domain. This is far beyond the scope of my work. Furthermore, excel only serves as a signal generator and it does not itself submit trade orders to a server.

10 Conclusion

In this bachelor thesis we implemented and backtested algorithmic strategies in a publicly common software, Microsoft Excel. The strategies are found on technical analysis indicators: Stochastic indicator, RSI and MACD. We compared these algorithmic strategies in available time series for the BTC/USD and LTC/USD respectively and overall with the buy and hold strategy. The data has a frequency of one hour. The rules of the strategies are built in a way assuring the alternation of buy and sell signals.

The profitable strategies for the total backtested period were the buy and hold, as well as the strategy based on MACD cross (7.3.2). In comparison with the passive investment buy and hold strategy, the algorithmic strategies are not making drastic losses or profits over the different time series. The strategy 7.1.1 and 7.1.2 were overall unprofitable but, for the the moments of bearish (downwards) trends it show consistent profits, contrarily to the buy and hold strategy.

Algorithmic trading or automated trading is a computerized trading process used by traders for the execution of trades utilizing pre-set trading instructions. Algorithms in automated trading systems are determined by a computer programming language. Algorithmic trading has become a major concern in trading and financial environment.

As with the enormous number of existing currencies for a trader to comprehend a new means of payment and money have been developed over time. Cryptocurrencies are a new form of digital currency that is based on cryptography technology. This technology ensures the security of payments and the issue of coins. Both cryptocurrencies and AT are modern fields that offer new possibilities of investment and trading and which still have much room for improvement.

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