Algorithms for trading on online exchanges

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MOTIVATION

Automation has played a significant role in many domains and trading is no exception. A computer program that executes trades is known as **algorithmic trading**. Algorithmic trading is much better than manual trading in terms of speed and accuracy, which are very important aspects of profitable trading. The trading logic that decides when to buy and sell an asset is generally referred to as a **trading strategy**. Validating the performance of any predefined trading strategy on historical data plays a significant role in its live performance and is known as **backtesting**, which is a key feature of algorithmic trading.

The motivation for solving this problem is that **algorithmic trading offers many advantages** in addition to the ability to think the strategy ahead. A person as a trader is spared emotional involvement in the trade in real time, which is one of the main sources of burnout not only among beginning traders. Automated algorithms can perform **complex mathematics** in real time and make required decisions based on a defined strategy **without human intervention** and send trade orders for execution automatically from the computer to the exchange. A computer can trade **hundreds of problems simultaneously** using advanced algorithms with **layers of conditional rules**.

AIMS OF THE THESIS

Identify effective trading strategies based on selected technical indicators, namely Relative Strength Index (RSI), Commodity Channel Index (CCI), Money Flow Index (MFI), Bollinger Bands (BB), Simple Moving Average (SMA), Exponential Moving Average (EMA), Weighted Moving Average (WMA) and Hull Moving Average (HMA).

Design a trading robot which with using trading algorithms will be able to carry out trades on the exchange for the user.

Deal with samples of data obtained during backtesting of selected trading strategies.

Establishment of global null statistical hypotheses based on data exploration.

Hypothesis testing and **multiple comparisons.**

Report on the statistical and material results of the research.

METHODOLOGY

Data source

We decided to use **cryptocurrencies** as opposed to stocks or forex, as cryptocurrencies are a commodity that is traded non stop on various exchanges around the world and therefore, they do not have a regulator and are not subject to closing and opening markets.

Data collection

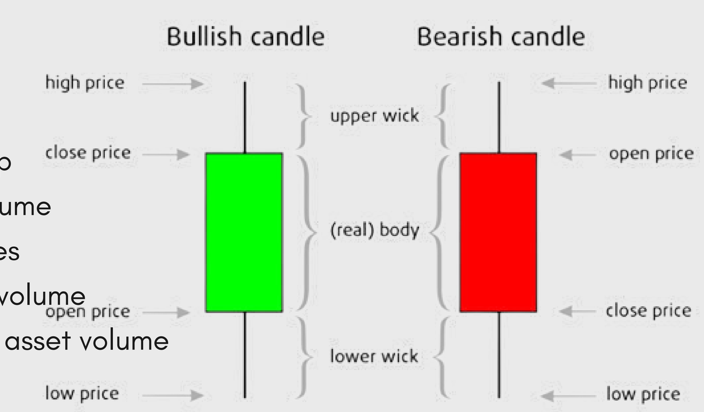
We obtained the data using an **API requests** for the selected exchange.

The logic of data collection, processing and analysis was programmed in scripts and can be seen in our trading robot model.

Data preview

Data after decoding into json format have the following form, which we can see on the left side and graphic visualization on the right side.

```
1607444700000,       // Open timestamp
"18879.99",          // Open
"18900.00",          // High
"18878.98",          // Low
"18896.13",          // Close
"492.363",           // Volume
1607444759999,       // Close timestamp
"9302145.66080",     // Quote asset volume
1874,                // Number of trades
"385.983",           // Taker buy asset volume
"7292402.33267",     // Taker buy quote asset volume
"0"                  // Ignore
```



Technical indicators and trading strategies

Subsequently, when we had obtained the necessary data, we could start calculating **the values of the indicators**, which will serve as **conditions for opening trades** and therefore looking for opportunities on the crypto market.

It is also worth mentioning that all indicators were calculated **using original formulas** and **no libraries or extensions** were used in the scripts, mainly due to **the experimental approach** and the possibility of adjusting indicators according to needs.

Each indicator had conditions for buying and selling the asset (as shown in the figure above), but all indicators had **the same parameters**.

Backtesting

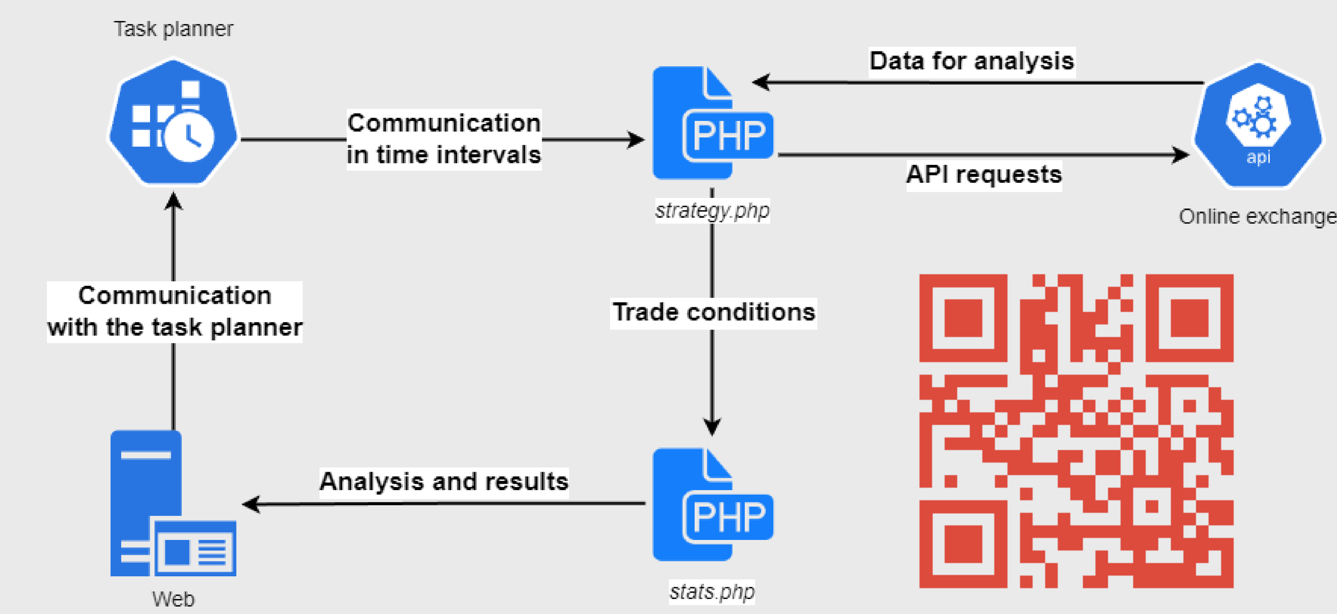
We have **one independent variable and six grouping variables** (risk to reward ratio, budget risk in %, timeframe, number of symbols, indicator length and buy and sell level), which represent our **input variables**.

All these variables are **nominal**, of which two are **polytomous** (strategy and buy/sell level) and the remaining five are **dichotomous**.

Technical indicator based strategy represented our independent variable, specifically we used the technical indicators mentioned in aims of the thesis.

Output variables are metrics for analysis backtesting performance, namely number of trades, number of winning trades, winratio, final capital, max and min achieved capital, return, drawdown, profit factor, RoMaD, average trade duration.

Trading bot model



ACHIEVED RESULTS

A total of 352 backtests evaluated 182,748 trades and stored the recorded data in the database, which we then used to test the results of our research. Our goal was to find **the best possible settings** for the indicator and the trade, and to confirm this by analyzing the results and evaluating the established hypotheses.

strategy	winratio Mean	1
SMA	24.79312	****
WMA	25.11469	****
MFI	25.76719	****
HMA	26.06812	****
BB	26.22188	****
EMA	26.36219	****
CCI	26.45891	****
RSI	27.05375	****

strategy	romad Mean	1	2
WMA	-0.993750	****	
EMA	-0.989688	****	
SMA	-0.985938	****	
HMA	-0.982500	****	
BB	-0.971875	****	
CCI	-0.912344	****	
MFI	-0.853906	****	
RSI	-0.712500		****

strategy	trades Mean	1	2	3
RSI	229.1562		****	
MFI	382.4063	****	****	
BB	521.6875	****	****	
CCI	534.3125	****	****	
EMA	609.4375	****		
SMA	630.9375	****		
WMA	713.7500	****		****
HMA	943.3125			****

Simple analysis of variance of sorting:
Results of hypothesis testing

Variable	Test statistic F	p-value
winratio	0.473	0.8537
pfactor	0.386	0.9102
romad	10.096***	0.0000
avghold	0.2258	0.9790
trades	6.9515***	0.0000
wins	4.9429***	0.0000
ebalance	15.48256***	0.0000
maxbalance	2.868**	0.0063
minbalance	14.65553***	0.0000
return	15.501***	0.0000
drawdown	14.667***	0.0000

strategy	avghold Mean	1
RSI	15.29625	****
HMA	16.71938	****
MFI	16.82750	****
SMA	16.88375	****
WMA	16.89062	****
EMA	17.01312	****
BB	17.13625	****
CCI	17.31437	****

strategy	drawdown Mean	1	2
RSI	70.83516		****
MFI	86.75547	****	
CCI	91.35766	****	
BB	94.64875	****	
EMA	96.35719	****	
SMA	96.73563	****	
WMA	97.49219	****	
HMA	98.09969	****	

strategy	return Mean	1	2	3
WMA	-96.9572	****		
HMA	-96.4916	****		
SMA	-95.6078	****		
EMA	-95.4619	****		
BB	-92.0950	****		
CCI	-85.0945	****	****	
MFI	-76.4848		****	
RSI	-60.3744			****

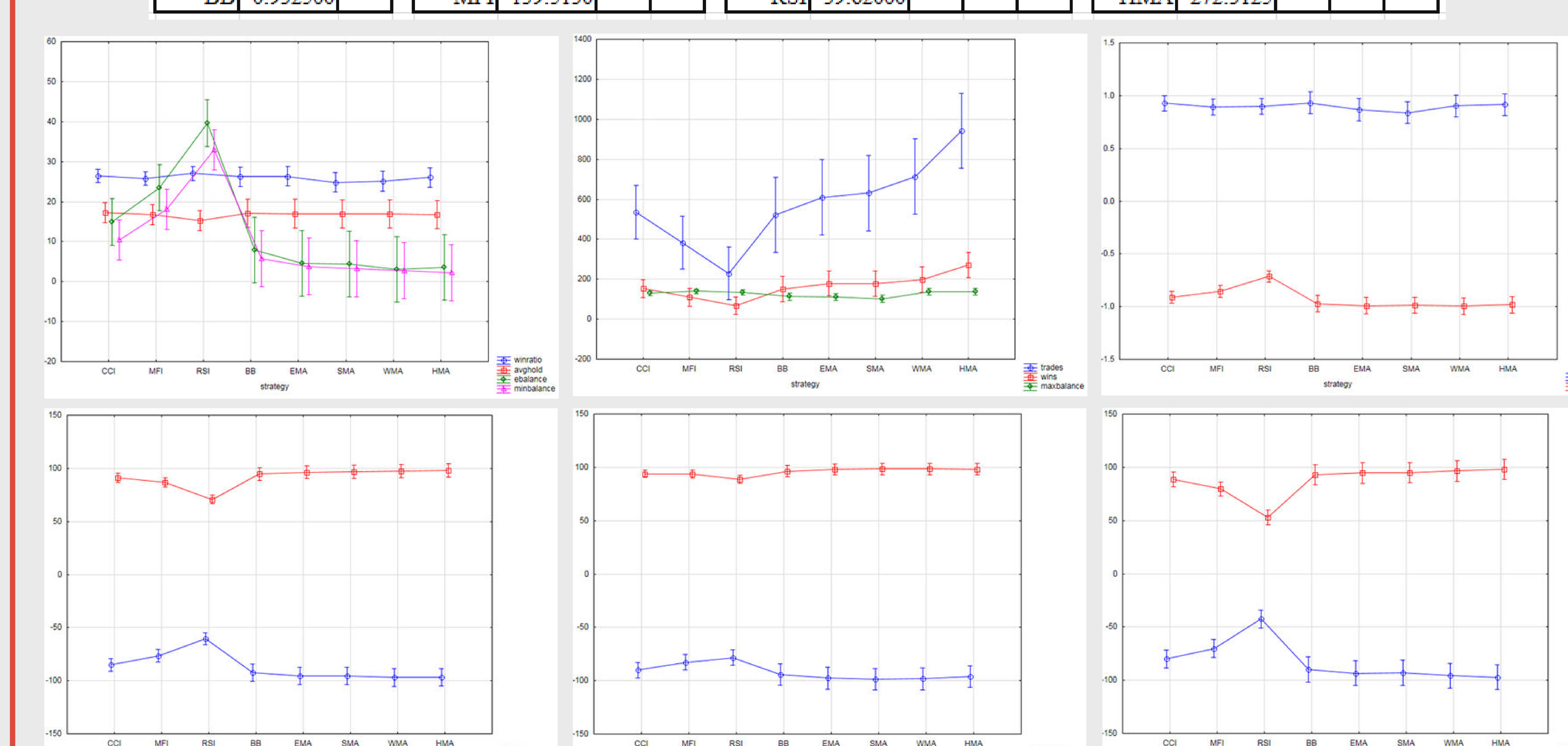
strategy	minbalance Mean	1	2	3
HMA	2.22906	****		
WMA	2.70469	****		
SMA	3.23563	****		
EMA	3.79781	****		
BB	5.70437	****		
CCI	10.38469	****	****	
MFI	18.08406		****	
RSI	32.97531			****

strategy	pfactor Mean	1
SMA	0.839687	****
EMA	0.868125	****
MFI	0.891250	****
RSI	0.899531	****
WMA	0.903437	****
HMA	0.915312	****
CCI	0.927969	****
BB	0.932500	****

strategy	maxbalance Mean	1	2
SMA	102.5834		****
EMA	110.6666	****	****
BB	113.0812	****	****
CCI	129.7555	****	****
RSI	133.4519	****	****
HMA	137.4491	****	
WMA	137.9387	****	
MFI	139.5130	****	

strategy	ebalance Mean	1	2	3
WMA	3.06250	****		
HMA	3.50844	****		
SMA	4.39500	****		
EMA	4.57187	****		
BB	7.93875	****		
CCI	14.91672	****	****	
MFI	23.51516		****	
RSI	39.62000			****

strategy	wins Mean	1	2	3
RSI	67.7813	****		
MFI	109.4063	****	****	
BB	152.0625	****	****	
CCI	153.6875	****	****	
SMA	176.5625	****	****	****
EMA	179.3125	****	****	****
WMA	198.1250		****	****
HMA	272.3125			****



CONCLUSION

The analysis of the results, their objective interpretation and the evaluation of the hypotheses showed us how much **the individual settings** of the indicators and **the conditions** of the trading itself **matter**. **The number of parameters** on which the trade depends and **the experimental approach** is something that we consider as **the biggest contribution** of this work and **a recommendation for future practice**.