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Optimizing Algorithmic Strategies for Trading Bitcoin

Gil Cohen[1]

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Abstract
This research tries to establish to what extent three popular algorithmic systems for trading financial assets: the relative strength index, the moving average convergence diversion (MACD) and the pivot reversal (PR), are suitable for Bitcoin trading. Using data about daily Bitcoin prices from the beginning of April 2013 until the end of October 2018, we explored these strategies through particle swarm optimization. Our results demonstrate that the relative strength index produced poorer results than the buy and hold strategy. In contrast, the MACD and PR strategies dramatically outperformed the buy and hold strategy. However, our optimizing process produced even better results.

Keywords Algorithmic trading · Oscillators · Trading strategies · Optimizations

1 Introduction

First introduced to the world in January 2009, Bitcoin has dominated the new field called cryptocurrencies. The idea of issuing digital currency without a central bank or a single other administrator or intermediaries has fascinated investors around the globe. Since its introduction, Bitcoin's value has risen and fallen with a volatility that has made it difficult for investors to achieve positive gains on their investment. As a result, investors have sought algorithms to help them customize their investment systems for better results.

We investigated the usefulness of three well-established strategies for trading financial assets in achieving this goal: the relative strength index (RSI), the moving average convergence/divergence (MACD), and pivot reversal. Using data about daily Bitcoin prices from the beginning of April 2013 until the end of October 2018, we explored these strategies through particle swarm optimization. Our results demonstrate that the relative strength index produced poorer results than the buy and hold strategy. In contrast, the MACD and pivot reversal strategies dramatically

✉ Gil Cohen
gilc@wgalil.ac.il

1 Western Galilee Academic College, Acre, Israel

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outperformed the buy and hold strategy. However, our optimizing process produced even better results.

2 Literature Review

Investing in cryptocurrencies involves more risk than investing in traditional, well-regulated stock and bond exchanges. Such risk is due to the nature of the block-chain technology that undergirds Bitcoin and the lack of sufficient regulation and central monitoring. In addition to the high volatility involved in Bitcoin trading (for example: Baek and Elbeck 2014), investors must deal with fraud and structural risks. Moore and Christin (2013) have studied the risk involved in Bitcoin exchanges, which convert Bitcoin to hard currency and vice versa. They found that the exchange's transaction volume is a good proxy as to whether it is likely to close. Nevertheless, while less popular exchanges are more likely to be shut down, popular exchanges are more likely to suffer security breaches.

Trading strategies have been developed in the past by various researchers. A popular approach was to face trading as an optimal stopping problem (for example, Chow et al. 1971). Liu et al. (2020) modeled the "buy low, sell high" trading practice for currencies pairs, proving that this strategy is profitable while the only risk comes from a wrongly predicted positive drift when the market plunges.

Since cryptocurrencies are relatively new, there is little research on the factors or tools that can help people invest in them. The first group of studies linked the price of Bitcoin to social networks. For example, Kim et al. (2016) tried to predict fluctuations in the prices of cryptocurrencies by analyzing comments in online cryptocurrency communities. They found that positive user comments significantly affected the price fluctuations of Bitcoin, whereas the prices of two other cryptocurrencies—Ripple and Ethereum—were strongly influenced by negative user comments and replies. Garcia and Schweizer (2015) also demonstrated the existence of a relationship between returns and signals about the volume of trade, and Twitter valence and polarization. Matta et al. (2015) studied the existing relationship between Bitcoin's trading volumes and the number of queries on Google. They reported significant cross correlation values, demonstrating that the volume of searches could predict the trading volume of Bitcoin.

The second group of studies examined Bitcoin's market inefficiencies. Balcilar et al. (2017) discussed the predictability of Bitcoin returns and volatility based on transaction volume. They found that when extreme events are excluded, volume is an important predictor of price. Urquhart (2017) demonstrated that Bitcoin's price clusters at round numbers.[1] In studying Bitcoin's price dynamics and speculative trading, Blau (2017) concluded that speculative behavior could not be directly linked to the unusual volatility of the Bitcoin market. Brandvold et al. (2015) investigated the role of various Bitcoin exchanges in the price discovery process, noting that the information share is dynamic and evolves significantly over time.

[1] Round numbers such as $1000 and $6000 per 1 Bitcoin.

Feng et al. (2018) found evidence of informed trading in the Bitcoin market prior to major events. Moreover, when examining the timing of informed trades, they noticed that informed traders prefer to build their positions two days before large positive events and one day before large negative events. This result serves as proof of the market inefficiency that differentiates uninformed traders from informed traders of Bitcoin. Caporale and Plastun (2019) examined the day of the week effect in the cryptocurrency market. They determined that most cryptocurrencies such as Litecoin, Ripple and Dash do not exhibit this anomaly. The only exception is Bitcoin, for which returns on Mondays are significantly higher than those on the other days of the week.

As described above, Bitcoin research concentrates mainly on two factors: the effect of social media on cryptocurrency prices and market anomalies. In contrast, we examine the trading strategies that might help uninformed traders in Bitcoin on a daily basis. Moreover, as far as we know, no previous research has investigated the extent to which well known trading strategies that are used for trading fiat[2] currencies and stocks can be beneficial to Bitcoin traders as well. We also optimized these strategies using particle swarm optimization to improve trading performance. Finally, we created utility functions that differentiate among investors based on their risk preferences and suggested the strategy that would fit their risk preferences best and optimize their results.

3 Research Design

We investigated the effectiveness of three well known trading strategies—the relative strength index (RSI), the moving average convergence diversion (MACD) and pivot reversal (PR)—using daily Bitcoin data from the beginning of April 2013 until the end of October 2018. We also modified these strategies using particle swarm optimization in a method we will discuss in detail later. The performance measurements we used are maximum drawdown (MDD), percentage of profitable trades (PP), profit factor (PF) and net profit (NP).

Maximum drawdown is a calculation that is used to assess the relative riskiness of one trading strategy versus another, as it focuses on capital preservation, which is a key concern for most risk-averse investors. It measures the largest decline in the value of a portfolio before a new peak is achieved. Maximum drawdown assesses only the size of the largest loss, without taking into consideration its frequency or how long it will take an investor to recover from that loss. A low maximum drawdown is preferable because it indicates that losses from the investment are small. The MDD is provided in both dollar terms and as the percentage of the amount invested.

The PP provides information about the percentage of profitable trades in relation to all trades. If it is above 50%, the trading system has generated more winning

[2] State-issued money that is neither convertible by law to any other thing, nor fixed in value in terms of any objective standard.

trades than losing trades. However, this does not mean that the net profit of all trades is positive and vice versa. A score less than 50% does not mean that the trading system is losing money.

The profit factor (PF) is defined as gross profits divided by gross losses. The result indicates the difference between the system's gains and losses. For example, if the profit factor is equal to 1.2, the system generated 20% more profits than losses.

The net profit (NP) calculation is the net profit for all trades generated by the trading system. Although one might assume that the three profit indicators (PP, PF and NP) move together, in fact they can vary dramatically, and therefore may confuse investors and algorithmic trading planners.

Due to the complexity of our optimization objectives, we used a multi-objective optimization formula. Such formulations are realistic models for many complex optimization problems. In many real-life problems, objectives under consideration conflict with each other, and optimizing a particular solution with respect to a single objective can result in unacceptable results with respect to the other objectives. A reasonable solution to a multi-objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution. Many of these processes were developed over the years and used to find solutions to various complex problems.

We selected particle swarm optimization that was developed by Kennedy and Eberhart (Kennedy and Eberhart 1995; Eberhart et al. 1996) as our primary optimization method. Eberhart and Shi (2001) demonstrated that it could be successfully applied to tracking and optimizing dynamic systems for most optimization problems. However, the most promising applications of this process are in robotics, decision making and simulations, all of which are related to our mission.

The particle swarm optimization involves using a stepwise process to change the velocity of each particle toward its best location. To utilize it in our research, we took several steps. First, given that we are applying predesigned technical oscillators to our Bitcoin price data, we used the values of the particles for each trading strategy suggested by the inventor of that strategy as our initial setup. Next, for each set of particles, we evaluated the desired optimization fitness function using our predefined goals: a small maximum drawdown and a maximum value for the percentage of profitable trades, the profit factor and the net profit.

We then compared the fitness of the setups with "*pbest*."[3] If the current value was better than "*pbest*," we set the "*pbest*" value to the current value. In addition, we compared the evaluations of the fitness of the setups with the population's overall previous best. If the current value was better than "*gbest*,"[4] we reset "*gbest*" to the current value and setups. Finally, we changed the trading setups according to Eqs. (1) and (2) and calculated the results:

[3] *"pbest"* = The setup that achieved the best results in reducing the maximum drawdown and maximizing the percentage of profitable trades, the profit factor and the net profit.

[4] "*gbest*" = global best identification.

$$V_{i+1,d} = V_{id} + C_1 Rand * \left(P_{id} - X_{id}\right) + C_2 Rand * \left(P_{gd} - X_{id}\right) \tag{1}$$

$$X_{i+1,d} = X_{id} + V_{id} \tag{2}$$

where V_{id} = the value of each particle of the setup, *Rand* = random number, P_{id} = the particle's initial identification and P_{gd} = the particle's global best identification.

We then looped to step 2 until the best results were achieved.

The use of a random variable in the above process is essential for keeping the optimization process unbiased and to ensure that all variables have an equal chance of entering the process.

Although we can look at each target's functions by itself, a general result that fits an individual investor can be reached by defining the following:

$$OMDD = 100 - MDD_p \tag{3}$$

$$NPF = (PF - 1) * 100 \tag{4}$$

where OMDD = opposite MDD is the percentage of dollar value invested, NPF = net profitability factor.

We now formulate our multi-objective optimization problem as follows:

$$\text{Maximize}U = \sum_{i=1}^{3} wi * lnF(Xi) \tag{5A}$$

where F (Xi) = [F1 (*OMDD*), F2 (*PP*), F3(*NPF*)], *wi* = the weight the individual investor assigns to each parameter and U = the individual's investment utility.

For example, suppose a specific investment setup resulted in the following: $MDD_p = 3\%$,[5] PP = 48%[6] and PF = 1.6.[7] A risk-averse investor might assign a weight of 40% importance to the first two parameters and only 20% to the last parameter. His/her utility function would be calculated as follows (6):

$$U = 0.4 * \ln 97 + 0.4 * \ln 48 + 0.2 * \ln 60 = 4.19 \tag{6}$$

A more aggressive investor might prefer weights of 0.1, 0.2 and 0.7 for OMDD, PP and NPF, respectively. In that case, the utility function would result in the following (7):

$$U = 0.1 * \ln 97 + 0.2 * \ln 48 + 0.7 * \ln 60 = 4.09 \tag{7}$$

Each individual investor should maximize his/her utility function across the spectrum of possible setups and investment strategies. If all of the weights are positive, then the maximization function provides a sufficient condition for pareto optimality (Zadeh 1963; Goicoechoa et al. 1982).

[5] Meaning that the maximum percentage drawdown of the investment equal 3%.

[6] Meaning that 48% of all trades are profitable.

[7] Meaning that the gross profits exceed the gross losses by 20%.

Table 1 Average daily percentage of returns of Bitcoin trading from April 1, 2013 to October 31, 2018

Year	Daily return	SD	Max	Min
2018	−0.16	4.28	13.95	−18.44
2017	0.86	5.09	26.77	−15.94
2016	−0.02	5.92	11.65	−16.40
2015	0.16	3.99	23.62	−29.20
2014	−0.15	3.92	17.37	−16.38
2013	1.08	7.70	36.15	−28.26
2013–2018	0.32	4.73	36.15	−29.20

The data for 2018 start on January 1, 2018 and end on October 31, 2018. The data for 2013 start on April 1, 2013 and end on December 31, 2013

In order to examine whether any changes in the investors' preferences would occur if the utility function were more sensitive to the gap between the different variables, we reformulated it as follows:

$$\text{Maximize } U = \sqrt{\sum_{i=1}^{3} wi * (\ln F(Xi))^2} \tag{5B}$$

Utilizing our sample data in this formula resulted in Eqs. 6A and 7A.

$$U = \sqrt{0.4 * (\ln 97)^2 + 0.4 * (\ln 48)^2 + 0.2 * (\ln 60)^2} = 4.2 \tag{6A}$$

$$U = \sqrt{0.1 * (\ln 97)^2 + 0.2 * (\ln 48)^2 + 0.7 * (\ln 60)^2} = 4.10 \tag{7A}$$

We also tested Eqs. 5A and 5B for differences in the investors' preferences.

4 Results

In presenting our results, we first list the descriptive statistics of our data. Second, we provide the results of simulating each trading system using the various setups generated by the particle stream optimization. Finally, we calculate the utility function for investors based on their level of risk aversion.

4.1 Descriptive Statistics

Table 1 summarizes the daily Bitcoin returns from April 1, 2013 to October 31, 2018.

Table 1 demonstrates that significant volatility in the daily Bitcoin returns. While the daily volatility is high, the average daily returns switch from positive to negative. These trading conditions may prove fruitful for algorithmic machine-based trading.

4.2 The Relative Strength Index

The relative strength index (RSI) is a momentum indicator developed by Wilder (1978), which compares the magnitude of recent gains and losses over a specified time period to measure the speed and change of price movements of a security. This index is used primarily to identify overbought or oversold conditions in the trading of a security. The formula for the RSI reads as follows.

$$RSI = 100 - \frac{100}{1 + RS} \tag{8}$$

where RS equals the average gain in up periods during the specified time frame divided by the average loss in down periods.

The RSI, whose values range from 0 to 100, provides a relative evaluation of the strength of a security's recent price performance, thus making it a momentum indicator. In his book, Wilder suggested using 14 trading days as the default time frame for comparing up periods to down periods. He also stated that when the RSI is 70 or above, it indicates that the security is becoming overbought, and therefore may be primed for a trend reversal. On the other hand, if the RSI value is 30 or below, the security is oversold and might be ready to move upwards.

The notion of overbought and oversold levels is common to many other technical oscillators, meaning that the momentum is approaching its peak and a price turnaround is about to occur in the near future. If we apply this strategy to Bitcoin in its original format, we would buy Bitcoin when the RSI indicator falls to 30 and sell it when the indicator rises to 70. The results of the optimized simulations using different RSI setups are presented in Table 2.

Table 2 indicates that the initial RSI setup (number 9) that is used to trade stocks and fiat currencies is not suitable for Bitcoin trading. While setup 17 achieved the best profit, setup 16 has the lowest MDD. Note that setup 12, which has the highest percentage of profitable trades (PP), is a losing setup, because there are more losses on losing trades than there are profits on winning trades. The highest net profit (NP) is that for setup 17, which is dramatically inferior to the buy and hold profit of $6135 for the entire period.

Using Eqs. 5A and 5B, we tried to tweak the weights of the algorithms to reflect the level of risk aversion of the investors. For those who had relatively high levels of risk aversion (U1), we assigned the OMDD, PP and NPF the weights of 0.4, 0.4 and 0.2, respectively. For the risk neutral investor (U2), we gave each parameter the same weight of 0.33. Finally, for risk-seeking investors (U3), the weights that were chosen were 0.2, 0.2 and 0.6, respectively.[8]

Table 3 summarizes the results of these different strategies.

Table 3 indicates that setup 16 is optimal for all of the investors, regardless of their level of risk aversion,[9] and for the two utility functions (Eqs. 5A and 5B). It also gives them the greatest utility, as opposed to the maximum profit in setup 17

[8] The weights that were chosen for each type of investor are only an example of the possible weights.

[9] Risk-averse investors, risk-neutral investors and risk seekers.

Table 2 MDD, PF, PP and NP for different RSI setups

Setup	N	OS	OB	Number of trades	MDD	PF	PP	NP
1	16	30	68	13	7895 (7.89)	−0.06	53.85	−7600
2	16	30	70	13	7762 (7.76)	−0.10	53.85	−7230
3	16	32	70	17	7820 (7.52)	−0.10	47.06	−7295
4	16	30	72	11	7872 (7.87)	−0.10	54.55	−7338
5	15	30	68	19	7746 (7.74)	−0.632	57.89	−2971
6	15	30	70	17	7834 (7.80)	−0.07	52.94	−7546
7	14	30	68	21	7683 (7.63)	−0.63	61.90	−2910
8	14	28	70	17	7747 (7.70)	−0.07	52.94	−7458
9	**14**	**30**	**70**	**17**	**7954 (7.95)**	**−0.07**	**47.06**	**−7668**
10	14	32	70	22	2596 (2.60)	−0.92	50.00	−393
11	14	30	72	17	7953 (7.95)	−0.09	47.06	−7431
12	13	28	70	21	7607 (7.60)	−0.647	61.90**	−2833
13	13	29	70	23	3982 (3.98)	1.13	60.87	791
14	13	29	71	21	3960 (3.96)	1.28	57.14	793
15	13	30	69	26	2263 (2.26)	1.27	57.69	1434
16	13	30	70	26	2185** (2.18)	1.53	61.54	2725
17	13	30	71	24	2279 (2.28)	1.53**	58.33	2727**
18	13	30	72	22	2530 (2.53)	1.25	54.55	1229
19	13	31	69	26	2309 (2.31)	1.26	57.69	1388
20	13	31	70	26	2230 (2.23)	1.51	61.54	2678
21	13	31	71	22	2325 (2.33)	1.52	58.33	2681
22	13	31	72	22	2577 (2.58)	1.23	54.55	1183
23	13	32	70	26	4070 (4.06)	−0.977	57.69	−163

Table 2 (continued)

Setup	N	OS	OB	Number of trades	MDD	PF	PP	NP
24	12	30	70	26	2309 (2.31)	1.26	57.69	1389
Average	13.83	30.17	70.13	20.63	5062 (5.04)	0.43	55.78	−2075
SD	1.20	1.05	1.19	4.55	2633	0.90	4.62	4196
Max	16	32	72	26	7954	1.53	61.90	2727
Min	12.00	28	68	11	2185	−0.98	47.06	−7668

N = number of days, OS = oversold, OB = overbought, MDD = maximum drawdown in absolute value (the numbers in the brackets are in terms of the percentage of the investment), PF = profit factor, PP = percentage of profitable trades, NP = net profit. Setup 9 is Wilder's (1978) original setup for the RSI. Minimum MDD and maximum PF, PP and NP are marked with **

Table 3 Investors' utility for different RSI setups

Setup	U_1		U_2		U_3	
	5A	5B	5A	5B	5A	5B
13	3.98	4.05	3.71	3.82	3.27	3.89
14	4.11	4.13	3.94	3.99	3.72	3.75
15	4.11	4.14	3.94	3.99	3.70	3.74
16	4.28**	4.28**	4.18**	4.21**	4.12**	4.13**
17	4.25	4.26	4.16	4.19	4.11	4.12
18	4.08	4.10	3.89	3.95	3.65	3.68
19	4.11	4.13	3.93	3.98	3.68	3.72
20	4.27	4.27	4.17	4.19	4.10	4.10
21	4.25	4.25	4.16	4.18	4.10	4.10
22	4.06	4.09	3.87	3.93	3.60	3.64
24	4.11	4.13	3.93	3.98	3.68	3.72
Average	4.13	4.15	3.97	4.02	3.76	3.84
SD	0.09	0.08	0.15	0.12	0.27	019
Max	4.28	4.28	4.18	4.21	4.12	4.13
Min	3.98	4.05	3.71	3.82	3.27	3.64

Setups 1 to 12 produced negative net profits. U1 = Utility 1 with weights of 0.4, 0.4 and 0.2 for OMDD, PP and NPF, respectively. U2 = Utility 2 with weights of 0.33 for all three target functions. U3 = Utility 3 with weights of 0.2, 0.2 and 0.6 for OMDD, PP and NPF, respectively. 5A = Equation 5A, 5B = Equation 5B. The maximum value of each utility function is marked with **

(see Table 2). Furthermore, setup 16 has the lowest MDD in both dollar value and percentage of investment. In summary, the RSI trading strategy in its original format falls far short of the buy and hold strategy. However, our optimization of the

RSI using 13 days of trading and the values of 30 and 70 for recognizing when Bitcoin is oversold and overbought proved an excellent strategy.[10]

4.3 MACD

Developed by Gerald Appel (1979), the moving average convergence divergence oscillator (MACD) is one of the simplest and most effective momentum indicators available. The MACD turns two moving averages into a momentum oscillator by subtracting the longer moving average from the shorter moving average. The MACD fluctuates above and below the zero line as the moving averages converge, cross and diverge. Traders can look for signal line crossovers, centerline crossovers and divergences to generate signals. Because the MACD is unbounded, it is not particularly useful for identifying when investment vehicles are overbought and oversold. The equation for calculating the MACD is:

$$MACD = EMA(X) - EMA(Y)$$

$$signal = EMA(Z)$$

where $EMA(X)$ = the exponential moving average of the price for X days (fast length), $EMA(Y)$ = the exponential moving average of the price for Y days (slow length), $EMA(Z)$ = the exponential moving average of the MACD for Z days.

The typical value for the fast length (X) is 12 days, for the slow length (Y) 26 days, and for the MACD length (Z) it is 9 days. When a new trend occurs, the fast line will react and eventually cross the slower line. When this crossover occurs, and the fast line starts to "diverge" to the upside from the slower line, it signals a positive trend. At this point, the trader should hold a "long"[11] position. In contrast, when the fast line falls below the slow line, it usually indicates a downward trend that should lead to a "short"[12] trading position. The results of the optimized simulations using different MACD setups are presented in Table 4.

Table 4 demonstrates that Gerald Appel's setup 8 used by traders worldwide for trading stocks and fiat currencies produced $14,428 net profit, whereas buying and holding Bitcoin resulted in a gain of just $6135. Moreover, setup 8 is inferior to setup 18 in terms of profit (PF and NP) and MDD ($2994 compared to $3476). This setup, which utilizes 13, 26 and 10 days for X, Y and Z, respectively, results in a profit of $20,207. Setup 19 produced the highest percentage of profitable trades, with a net profit of $18,762. The results of the utility functions for the MACD strategies are summarized in Table 5.

Table 5 indicates that MACD strategy setup 18 is best for all investors, regardless of their level of risk aversion. Again, this setup is different from Gerald Appel's original setup for MACD.

[10] As opposed to Wilder (1978), who suggested 14, 30, and 70 setups.

[11] A long position means buying rather than selling a financial asset.

[12] A short position means selling rather than buying a financial asset.

Table 4 MDD, PF, PP and NP for different MACD setups

Setup	X	Y	Z	Number of trades	MDD	PF	PP	NP
1	10	26	9	137	2970** (2.66)	2.15	47.45	15,887
2	11	26	9	127	2970** (2.65)	2.23	48.82	16,262
3	11	25	9	133	2970** (2.65)	2.16	48.87	15,801
4	11	27	9	127	2970** (2.66)	2.15	49.61	15,386
5	11	26	8	137	2970** (2.66)	2.20	48.18	16,804
6	11	26	10	121	3476 (3.11)	1.95	50.41	13,916
7	12	25	9	125	2970** (2.66)	2.19	50.40	15,665
8	**12**	**26**	**9**	**123**	**3476 (3.11)**	**2.03**	**50.41**	**14,428**
9	12	27	9	127	3476 (3.11)	2.06	47.24	14,907
10	12	26	8	131	2970 (2.66)	2.14	48.85	15,611
11	12	26	10	125	3476 (3.11)	2.16	47.20	16,138
12	13	26	9	127	3476 (3.11)	2.14	46.46	16,020
13	13	25	9	121	3476 (3.11)	2.09	50.41	15,190
14	13	27	9	121	3476 (3.09)	2.48	47.93	18,748
15	13	28	9	121	3476 (3.10)	2.54	47.11	18,947
16	13	29	9	121	2994 (2.67)	2.55	47.11	18,288
17	13	26	8	125	2970** (2.66)	2.16	49.60	15,430
18	13	26	10	117	2994 (2.67)	2.74**	49.57	20,207**
19	13	27	10	113	2994 (2.67)	2.59	50.44**	18,762
20	14	26	9	119	3479 (3.10)	2.59	49.58	19,243
21	14	26	10	113	3774 (3.41)	2.30	48.67	16,634
Average	12.22	26.26	9.09	124.91	3081.83 (2.86)	2.27	48.66	16,612
SD	1.38	0.92	0.60	8.15	740.56	0.22	1.32	1733
Max	15	29	10	147	3774	2.74	50.44	20,207
Min	9	25	8	113	2970	1.95	46.46	13,916

Table 4 (continued)

X = number of days for the fast length, Y = number of days for the slow length, Z = number of days for the MACD length. MDD = maximum drawdown in absolute value (the numbers in the brackets indicate the percentage of the investment), PF = profit factor, PP = percentage of profitable trades, NP = net profit. Setup 8 is Appel's (1979) original setup for the MACD. Minimum MDD and maximum PF, PP and NP are marked with **

Table 5 Investors' utility for different MACD setups

Setup	U_1		U_2		U_3	
	5A	5B	5A	5B	5A	5B
1	4.32	4.34	4.35	4.39	4.53	4.54
2	4.35	4.36	4.38	4.42	4.58	4.59
3	4.34	4.35	4.36	4.40	4.55	4.55
4	4.34	4.35	4.37	4.40	4.54	4.55
5	4.34	4.35	4.37	4.41	4.56	4.57
6	4.31	4.32	4.31	4.33	4.43	4.44
7	4.36	4.37	4.38	4.42	4.57	4.58
8	4.32	4.33	4.33	4.36	4.48	4.48
9	4.30	4.32	4.32	4.35	4.48	4.49
10	4.33	4.35	4.36	4.39	4.54	4.54
11	4.32	4.34	4.35	4.38	4.54	4.55
12	4.31	4.33	4.34	4.38	4.52	4.54
13	4.34	4.35	4.35	4.38	4.51	4.52
14	4.38	4.40	4.44	4.48	4.69	4.70
15	4.38	4.40	4.44	4.49	4.71	4.73
16	4.38	4.44	4.45	4.49	4.71	4.73
17	4.34	4.36	4.37	4.40	4.55	4.56
18	4.42**	4.45**	4.50**	4.55**	4.79**	4.82**
19	4.41	4.43	4.48	4.52	4.74	4.76
20	4.40	4.42	4.47	4.52	4.74	4.76
21	4.36	4.37	4.40	4.44	4.61	4.63
Average	4.34	4.36	4.38	4.41	4.58	4.59
SD	0.03	0.04	0.05	0.06	0.09	0.10
Max	4.42	4.45	4.50	4.55	4.79	4.82
Min	4.30	4.32	4.31	4.33	4.43	4.44

U1 = Utility 1 with weights of 0.4, 0.4 and 0.2 for OMDD, PP and NPF, respectively. U2 = Utility 2 with weights of 0.33 for all three target functions, U3 = Utility 3 with weights of 0.2, 0.2 and 0.6 for OMDD, PP and NPF, respectively. 5A = Equation 5A, 5B = Equation 5B. The maximum value of each utility function is marked with **

Table 6 MDD, PF, PP and NP for different pivot reversal setups

Setup	X	Y	Number of trades	MDD	PF	PP	NP
1	3	1	91	4515 (4.13)	2.47	51.65	15,095
2	3	2	81	5631 (5.14)	2.18	54.32	12,361
3	3	3	75	7618 (6.91)	1.91	53.33	10,558
4	3	4	60	4618 (6.78)	2.19	55.00	12,228
5	4	1	73	1523** (1.22)	7.39**	50.68	23,575**
6	**4**	**2**	**63**	**3188 (2.63)**	**5.03**	**52.38**	**18,133**
7	4	3	61	3053 (2.55)	4.46	50.82	16,720
8	4	4	52	3053 (2.55)	4.80	51.92	16,726
9	4	5	47	3321 (2.82)	4.25	55.32**	14,616
10	5	1	70	1646 (1.34)	6.40	47.14	20,959
11	5	2	60	3285 (2.8)	3.71	50.00	13,833
12	5	3	58	3322 (2.85)	3.34	48.28	13,032
Average	3.92	2.58	65.92	3731 (3.48)	4.01	51.74	15,653
SD	0.79	1.31	12.52	1681	1.73	2.54	3807
Max	5	5	91	7618	7.39	55.32	23,575
Min	3	1	47	1523	1.91	47.14	10,558

X = number of days for the first bar, Y = number of days for the second bar. MDD = maximum drawdown in absolute value (the numbers in the brackets are the percentage of the investment), PF = profit factor, PP = percentage of profitable trades, NP = net profit. Swing traders often use X = 4 and Y = 2 (setup 6). Minimum MDD and maximum PF, PP and NP are marked with **

4.4 Pivot Reversal

Pivot points can be used to determine directional movement and potential levels of support or resistance.[13] They use the prior period's high, low, and closing prices to estimate future support and resistance levels. Trading above the pivot point on the subsequent day indicates bullish[14] sentiment, while trading below the pivot point indicates bearish[15] sentiment. Pivot points were originally used by floor traders to

[13] Support and resistance levels are the lowest and highest prices a financial asset has reached in a specific period of time.

[14] Bull markets refer to upward trends.

[15] Bear markets refer to downward trends.

Table 7 Investors' utility for different pivot reversal setups

Setup	U_1		U_2		U_3	
	5A	5B	5A	5B	5A	5B
1	4.40	4.42	4.45	4.49	4.70	4.71
2	4.37	4.38	4.39	4.43	4.57	4.58
3	4.31	4.31	4.30	4.32	4.41	4.41
4	4.37	4.38	4.40	4.43	4.58	4.58
5	4.70**	4.79**	4.94**	5.08**	5.58**	5.68**
6	4.61	4.67	4.80	4.89	5.31	5.38
7	4.57	4.62	4.74	4.82	5.21	5.27
8	4.60	4.65	4.77	4.87	5.27	5.33
9	4.59	4.63	4.74	4.82	5.19	5.24
10	4.64	4.72	4.86	4.99	5.46	5.56
11	4.52	4.58	4.65	4.72	5.06	5.10
12	4.47	4.51	4.59	4.65	4.96	5.00
Average	4.49	4.53	4.60	4.67	4.97	5.01
SD	0.11	0.14	0.19	0.22	0.35	0.38
Max	4.70	4.79	4.94	5.08	5.58	5.68
Min	4.31	4.31	4.30	4.32	4.41	4.41

U1 = Utility 1 with weights of 0.4, 0.4 and 0.2 for OMDD, PP and NPF, respectively. U2 = Utility 2 with weights of 0.33 for all three target functions. U3 = Utility 3 with weights of 0.2, 0.2 and 0.6 for OMDD, PP and NPF, respectively. 5A = Equation 5A, 5B = Equation 5B. The maximum value of each utility function is marked with **

set key levels. At the beginning of the trading day, floor traders would look at the previous day's high, low and closing prices to calculate a pivot point for the current trading day. The setup usually used by swing traders[16] is 2- and 4-day trading bars.

The results of the optimized simulations using different pivot reversal setups are summarized in Table 6.

Table 6 indicates that the standard trader's setup 6 makes a net profit of $18,133, far surpassing that of the buy and hold strategy. However, setup 6 is not the best setup in terms of MDD, PF and NP. The best setup in those terms is number 5, producing $1523, 7.39 and $23,575 for MDD, PF and NP respectively. The best setup in terms of percentage of profitable trades is setup 9. The results of the utility functions for the pivot reversal strategies are summarized in Table 7.

Table 7 demonstrates that setup 5 is the best setup for all three types of investors, regardless of their risk preferences.

[16] Swing traders' investment horizons vary from a few days to a few months.

5 Summary and Conclusions

This research tries to establish the extent to which three popular algorithmic trading systems are suitable for Bitcoin trading. We tested three well-known strategies: RSI, MACD and pivot reversal, using daily data about Bitcoin returns from the beginning of April 2013 till the end of October 18, 2018. We also optimized the original setups for each strategy using particle swarm optimization, which is a well-known multi-objective optimization formula. We assessed the performance of each strategy using four parameters: maximum drawdown (MDD), percentage of profitable trades (PP), the profit factor (PF) and net profit (NP). Moreover, we considered the investors' level of risk aversion in identifying the setup that would provide them with the greatest utility.

Our results demonstrate that the RSI strategy yielded poorer results than the buy and hold strategy over the same period of time. Wilder's (the inventor of the RSI strategy) original setup led to a net loss of $7668 compared to our best performing setup that yielded a profit of $2727. In contrast to the RSI's poor performance, Gerald Appel's original MACD setup and the pivot reversal strategy of most traders dramatically outperformed the buy and hold strategy. However, our optimization process produced even better results. Utilizing our utility functions, we showed that, for all investors, regardless of their level of risk aversion, the best results for trading Bitcoin occur using MACD setup 18, which utilizes 13, 26 and 10 days for X, Y and Z, respectively, and results in a profit of $20,207, and pivot reversal setup 5, producing $1523, 7.39 and $23,575 for the maximum drawdown, profit factor and net profit, respectively. This research has studied Bitcoin trading strategies based on direct transaction prices. Future studies should focus on possible economic factors such as interest rates and precious metal prices, that may affect the Bitcoin price. Because of the large number of such possible factors, future research should first use well known variable selection methods (for example: Yang et al. 2018).

References

Appel, G. (1979). *The moving average convergence divergence method*. Great Neck, NY: Signalert.

Baek, C., & Elbeck, M. (2014). Bitcoin as an investment or speculative vehicle? A first look. *Applied Economics Letters, 22*, 30–34.

Balcilar, M., Bouri, E., Gupta, R., et al. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling, 64*, 74–81.

Blau, B. M. (2017). Price dynamics and speculative trading in Bitcoin. *Research in Business Finance, 41*, 493–499.

Brandvold, M., Molnár, P., Vagstad, K., et al. (2015). Price discovery on Bitcoin exchanges. *Journal of international Finance Markets Institutions and Money, 36*, 18–35.

Caporale, M. G., & Plastun, A. (2019). The day of the week effect in the cryptocurrency market. *Finance Research Letters*, *31*, 258–269.

Chow, Y. S., Robbins, H., & Siegmund, D. (1971). *Great expectations: The theory of optimal stopping*. Boston, MA: Houghton Mifflin.

Eberhart, R. C., & Shi, Y. (2001). *Tracking and optimizing dynamic systems with particle swarms*. Seoul: Congress on Evolutionary Computation.

Eberhart, R. C., Simpson, P. K., & Dobbins, R. W. (1996). *Computational intelligence PC tools*. Boston: Academic Press Professional.

Feng, W., Wang, Y., & Zang, Z. (2018). Informed trading in the Bitcoin market. *Finance Research Letters, 26*, 63–70.

Garcia, D., & Schweizer, F. (2015). Social signals and algorithmic trading of Bitcoin. *R Soc Open Sci, 2*, 9.

Goicoechoa, A., Hansen, D. R., & Duckstein, L. (1982). *Multiobjective decision analysis with engineering and business applications*. New York: Wiley.

Kennedy, J., & Eberhart, R. C. (1995). Practical Swarm Optimization. In *International conference on neural networks, IV* (pp. 1942–1948).

Kim, Y. B., Kim, J. G., Kim, W., Im, J. H., Kim, T. H., Kang, S. J., et al. (2016). Predicting fluctuations in cryptocurrency transactions based on user comments and replies. *PLoS ONE, 11*(8), e0161197.

Liu, Y., Yang, A., Zhang, J., & Jingjing, Y. (2020). An optimal stopping problem of detecting entry points for trading modeled by geometric Brownian motion. *Computational Economics*, *55*, 827–843.

Matta, M., Lunesu, L., & Marchesi, M. (2015). The predictor impact of Web search media on Bitcoin trading volumes. In *7th international joint conference on knowledge discovery, knowledge engineering and knowledge management*.

Moore, T., & Christin, N. (2013). Beware the middleman: Empirical analysis of Bitcoin-exchange risk. In A. R. Sadeghi (Ed.), *Financial cryptography and data security. FC 2013. Lecture Notes in Computer Science* (Vol. 7859). Berlin: Springer.

Urquhart, A. (2017). Price clustering in Bitcoin. *Economics Letters, 159*, 145–148.

Wilder, J. W. (1978). *New concepts in technical trading systems*. Greensboro, NC: Trend Research.

Yang, A., Xiang, J., Yang, H., & Jinguan, L. (2018). Sparse bayesian variable selection in probit model for forecasting U.S. recessions using a large set of predictors. *Computational Economics, 51*(4), 1123–1138.

Zadeh, L. A. (1963). Optimality and non-scalar-valued performance criteria. *IEEE Transaction on Automatic Control, 8*, 59–60.