Approaches to algorithmic trading techniques: First sell and moving average crossover

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Abstract

Knowing how to interpret the signals in markets as critical as the synthetic indices and keeping the appropriate stop operations are, without denying it, two important variables when operating in trading. In this research, two manual trading sell techniques are proposed, one based on the first sell after the BOOM 500 trigger and the other based on moving average crossovers. The results showed an efficiency close to 70% for the first proposal, and the second regularly obtains an efficiency close to 100%.

Keywords:
Trading, Synthetic Index, BOOM 500

1 Introduction

Almost every area of human life has changed dramatically over time, and the pace of change is now much quicker. This also applies to financial techniques. Until the end of the twentieth century, actively managed funds had been at the heart of investment policy all over the world. The development of passive investing techniques has considerably reduced the expense of active fund managers and the risk associated with policies. market circumstances are more favorable than for conventional ones. Index funds are one of the biggest innovations the financial community has ever seen. Moreover, as it is, it is undeniable that it is beneficial to everyone who saves. Much cheaper than an actively managed fund. But a handful of companies Those who have passively managed funds should also be afraid. They are It may also affect future elections (Tahmaz & Medin, 2019).Trading platforms are influencing price discovery and volatility in the forex market. Humans trade every minute and empirical analysis provides some important insights beginning. There is evidence that algorithmic trading tends to correlate, and algorithmic strategies. The ones used on the market are not as diverse as those used by non-algorithm traders. Second, it despite the clear correlation of algorithmic trading, there is no clear causal relationship between them increased volatility in algorithmic trading and exchange rates. If anything, a more algorithmic existence of the transactions is associated with lower volatility. Third, some algorithm traders Algorithm traders seem to be shrinking activity minutes after the release of macroeconomic data increase the liquidity supply over the first hour after each release (Chaboud, Chiquoine, Hjalmarsson, & Vega, 2014). This paper introduces a technique that may be appropriate for working with the Boom 500 synthetic index based on experience and mobile media. The final objective consists of working with accounts of less than 100 dollars, and in the measure of the cases, trying to obtain 8 dollars a day, with absolute restriction to the generation of any greater amount. It is also attempted to propose a ROC curve that essentially process in the methodology. To clarify the research proposal, the necessary description is described in this regard. Market depends on the structure and psychology, scalping the Boom and Crash market is the norm. As a result, many traders concentrate on the lower time periods, specifically M1 to M15. This makes it difficult to persuade traders to turn away from the spikes (which are so evident and influential in smaller time frames) and focus on the market's overall broad Fig. 1 (the market trend)1.

[1] https://www.motivation.africa/how-to-trade-boom-and-crash-indices-successfully.html

Fig. 1. Boom 500

A favorable risk-to-reward ratio necessitates excellent risk management. The first step to a successful transaction is to understand risk management (Fig 1). This is because excellent risk management is the one method that never fails. To do so, one must have a strong understanding of their risk-to-reward ratio. Normally, expert recommend a risk-to-reward ratio of 1:3 for Boom 500, which means risking 5 pips for a 15 pips reward. Although it may not appear appealing, it is the most effective strategy to increase tiny accounts[2]. Likewise, in this proposal, it is necessary to be attentive to the trains. At the time of operating a capital hunt, a set of large candlesticks is known as a train. It is true that they can work, but they can affect the proposal of this research because the large number of candlesticks radically decrease the capital at risk during operations (see candles Fig 1).

Fig. 2. Moving Average

Fig 2 (red line) shows the moving average a financial instrument's average price has changed over time. Mobile media, on the other hand, comes in a variety of forms. They usually differ in how various data points are weighted or awarded importance. An unweighted moving average is known as a simple moving average (SMA). This implies that each time in the data collection is equally important and weighted. As time passes, the oldest data point is deleted and a new one is inserted at the start of the next period. The price of the SMA lags the most out of all the moving averages. The question is when to operate. What is the best time? What are the appropriate settings and at what times? How to reduce the risk? In this research, certain strategies are proposed for the manual moment to operate on the Boom 500 and maintain an adequate profit balance. Boom-Crash-spike-detector[3](BCSD) is used as an aid for the inference of the Boom 500 explosion and moving average crossover (MAC)[4]. The result of the application of these indicators has resulted in an efficiency close to 70% and 100%. For more details, this paper start with a state of the art that talks about algorithmic trading. To explain the methodological steps used by the authors for the execution of profits on Boom 500, show the execution on a real account in the experimentation, and finally describe the conclusions and recommendations.

2 Art State

Mutual funds and exchange-traded funds that use hedge fund indexes as their benchmarks as synthetic hedge funds. From distributional features to risk-adjusted performance, replication success is assessed from several angles. When compared to an adequate benchmark index, synthetic hedge funds perform significantly worse.

[2] https://www.motivation.africa/how-to-trade-boom-500-successfully.html
[3] https://economicgrapevine.com/boom-crash-spike-detector/
[4] https://www.earnforex.com/es/indicadores-metatrader/cruce-de-medias-m%C3%B3viles-con-alerta/

Furthermore, mutual funds with active portfolio management can yield return characteristics that are more like hedge fund benchmarks than exchange-traded funds with passive management. From the standpoint of a single approach, we see a picture of heterogeneity. In terms of market circumstances, we see bigger return variations for exceptional market situations than for normal market conditions (Fischer, Hanauer, & Heigermoser, 2016). Generating dependable buying and selling indicators is a difficult project for economic marketplace professionals. Studies designs a singular decision-guide machine (DSS) for algorithmic buying and selling and applies it empirically on predominant crude oil markets. The novel DSS allows buyers to interactively construct algorithmic buying and selling techniques through fine-tuning numerous predefined critical elements. The predominant novelty of this have a look at is the forecasting process encompassed into the DSS, and the ability of the machine that lets in customers to adjust the parameters of the predictive version embedded and the duration of the recursive window, primarily based totally on individual alternatives and the trade-off among prediction accuracy (multiplied computing intensity) and computing efficiency (Tudor & Sova, 2022). Algorithmic trading approach to Bitcoin Markets that take advantage of daily price volatility by classifying direction. Based on previous work, this paper takes advantage of both internal features of Bitcoin. Network and external capabilities to notify predictions of various machine learning models. As Empirical testing of the model uses real trading strategies to fully evaluate the model (Crone, Brophy, & Ward, 2021). The implementation of ideas from research into high reliability organizations offers a way for trading firms to curb some of the technological risk associated with algorithmic trading. Paradoxically, however, certain systemic conditions in markets can allow individual firms` high reliability practices to exacerbate market instability, rather than reduce it. We therefore conclude that in order to make automated markets more stable (and curb the impact of failures), it is important to both widely implement reliability enhancing practices in trading firms and address the systemic risks that follow from the tight coupling and complex interactions of markets (Min & Borch, 2021). Investigations provides an overview of high frequency trading and the use of machine learning in the market. Machine learning is a vibrant subfield of computer science take advantage of models and methods in statistics, algorithms, computational complexity, artificial intelligence, control theory, and many other disciplines (Kearns & Nevmyvaka, 2013). Analyses of the Machine learning based uncertainty absorption in financial markets applying machine learning techniques to investment management, trading, or risk management problems. Critical model uncertainty refers to the inability to explain how and why the machine learning models. Absorption and multiplication of uncertainty in machine learning models requires further research on finance(Hansen & Borch, 2021). This research promotes observation techniques that can be implemented with the identification of patterns towards machine learning. As explained in the methodology, it is based on the increase in profit when there is a sell after the BOOM 500 trigger and approaching that trigger by crossing moving averages.

3 Methodology

The process is manual with ROC curve emphasis. This research suggests that the high points of the Boom 500 suggest more gains than losses when certain conditions related to moving averages are met:

Input:
Moving average 200
Moving average 100
Moving average 50
Moving average 25
Conditions:

1. When any moving average crosses the 200 moving average, no matter up or down, always expect a Boom 500 boom.
2. When the Bom 500 appears open a single sell trade, especially towards 0.20. In this case you should keep the multiplier at 1.
3. You can use a sell of 1 and a multiplier of 1, and a take profit of 3. Execute this process in the case that it is required to obtain resource speed.
4. If the daily amount obtained is 8 dollars, all operations must be suspended.
5. Trade steps 1 to 5 if you see the Boom 500 with candles down.

Never trade steps 1 through 4 when the Boom 500 is above the moving averages.

4 Experimentation

Fig. 3. Boom 500: Blue Moving Media 200, Yellow Moving Media 50, Green Moving Media 100

Figure 3 shows that the Boom 500 candles are above the moving averages. There are several falling candlesticks which are then offset by the explosion of the Boom 500.

Fig. 4. Boom 500 optimal operate conditions

Fig. 4 shows falling candles and a train falling enough to raise capital. After it, a large explosion of the Boom 500 would be expected.

Fig. 5. Boom 500 indicators

After the decline and the intersection of the Boom 500 with the moving averages, it is necessary to wait for the eminent explosion of the Boom 500. The blue and red arrows of BCSD indicate the appearance of the boom, which in decline, if the methodological steps are followed, will have little effect on the profit, waiting for immediate recovery (Fig. 5).

Fig. 6. Boom 500 moving average

Figure 5 shows the crossing of the 200 and 100 moving averages, with the eminent appearance of the BOOM 500.

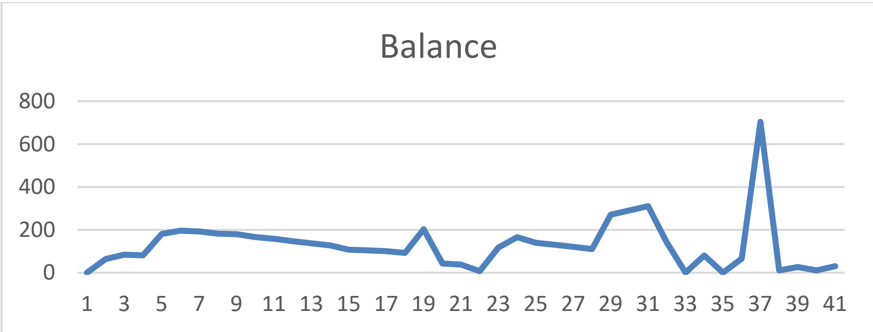

Fig. 7. Methodology cash results

Cash results show that the methodology works even when there are test lows due to the appearance of rising candlesticks. There is an economic recovery at each point of the methodological execution (Fig 7).

5 Conclusions

To trade Boom 500 with amounts less than 100 dollars, it is not recommended to enter trades when it is above the averages (Fig. 3). This is since at that time many high candles are expected, and even though the lot is at 0.2 and the multiplier at 1, there will not be enough capital to support the number of candles to be produced during its appearance. of a train When two candles appear simultaneously, it is necessary to immediately stop the operations. All this is even though it seems that the Boom 500 is at the bottom due to the large number of falling candles that you have, but it is necessary to observe the big shot of the Boom 500 after them. In those conditions, it is not recommended to operate. The optimal operating conditions are those in which the candles are in decline, and especially when the Boom 500 is under the curves, it is there where it is effectively recommended to operate constantly (Fig. 4). Perhaps it is also possible to propose not to operate with recovery with more than five downward candles, to avoid surprises during operations. Likewise, it is recommended for small capitals-profit not to have more than 2 open sales operations at the same time. It can be said that if perhaps more sales operations are required, it is necessary to have at least 1 purchase to prevent the possible appearance of the Boom 500. Figure 5 shows the signals it produces for the Boom 500. The ROC curve efficiency shows the following results:

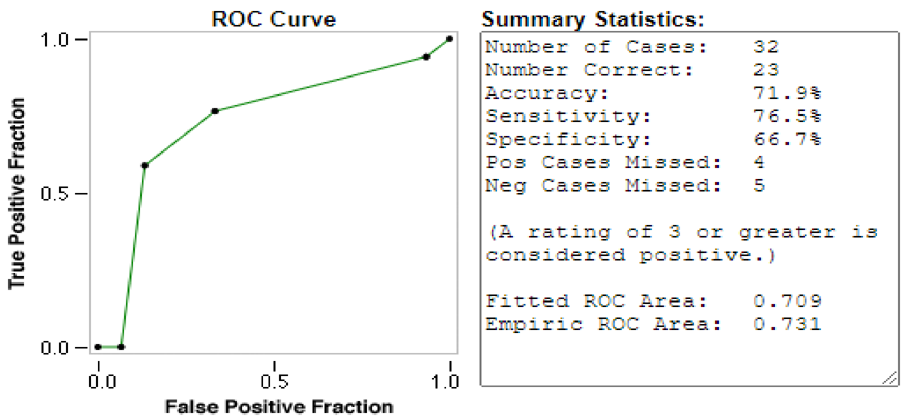

Fig. 8. ROC to BCSD indicator

The results (Fig. 8) on 60 observations show results close to 70%. It is necessary to clarify that there are occasions of error in which the arrows appear and then disappear, or the jumps typical of Boom 500 that prevent the prediction. The crossing of moving averages, especially with the moving average of 200, we can ensure that in all cases it produces the outbreak of the BOOM 500 and therefore, and especially if it is under all the moving averages, it is time to open the sales operations (Fig 6). The methodology works for the recovery of capital. The experimentation was carried out even with five open operations, three of which were in sell. It is recommended to close the operations when it has reached $8. Once the 8 dollars per day has been obtained, do not operate anymore, although ambition may dictate something else (Fig 7). The following work will result from continuing to observe the behavior pattern of the BOOM 500 before proceeding to the use of computer algorithms such as neural networks that can establish certain classification parameters (Asgari & Khasteh, 2022; Śmieja, 1993). The combination of experience and algorithmic apparatus is extremely necessary in this type of context since the imprecision of a synthetic market does not evolve easily to algorithmic concentration.

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