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Trading Bot for Crypto Currency with MACD, RSI, TMA, TSI Algorithms

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Abstract

Crypto Currency is a virtual currency used by many internet marketers and has a lot of value in the market. Trading of crypto currency is the new trend and profitable. Since the crypto currencies are decentralized, no government has authorization on it and because no humans are involved in this it's easy to trade and predict the values of trading. Building a trading bot for crypto currency can be profitable and useful. By using different trading algorithms such as MACD, RSI, Golden Cross rule etc. those values can be predicted efficiently. This model elaborate how we can implement these algorithms into the bot and trade these into these crypto currencies.

Keywords: *Algorithms, Trading, Crypto, MACD, Market.*

1. Introduction

Recently there has been a rapid growth in the amount of automated trading in stock markets and other financial markets.[9]Automated trading is a general terminology used to characterize computerized trading. The computer technology has revolutionized money markets, and today these markets square measure extremely enthusiastic about AI. machine-controlled commercialism is additionally called recursive commercialism or automaton commercialism, wherever totally different securities square measure listed mechanically by computers, generating associate degree sign, supported a knowledge set. This signal may be generated by associate degree formula, typically spoken as a technical commercialism rule. [4]An investor trading in a financial market, cannot know for sure whether other participants operating in the same market, are computers or usual investors. Financial markets are said to have nonlinearity and chaotic dynamics. In Day and Huang they develop a deterministic model that generates stochastic fluctuating prices.

The extended model is tested based different numerical experiment, applying a subset of 10 dissimilar algorithmic rules. It is a common intuition saying that the more unsophisticated investors going into the financial market the more destabilization. In contrary, Suhadolnik et al. (2010) find that if one introduce more of these unsophisticated investors (robot traders) that are social integrated, then it causes more stabilized stock markets. The motive for using the seminal model by Day and Huang is a combination of its simplicity, and that it is able to provide several stylized facts about the stock market (more on the advantages of the model in section 5.8). Our main focus is to develop the extended model and to provide a functional environment for communication. The combination of the communication process and the 1 algorithmic trading is what differs this thesis from other papers.

2. Related Work

We use this model as a groundwork in our study. The objective of this thesis is to develop an extended version of the Day and Huang (1990) model, to see how heterogeneous and socially integrated investors affect the market. The investors use different algorithmic trading rules to operate in this stylized nonlinear model. The original model focus on a given population, but we are emphasizing on the individual investor in the extended model. β-investors are substituted by algo-traders in the extended model. While Day and Huang explain the stock volatility, we expand this view by looking beyond the "hidden surface" and focusing on the microstructure of the investors. A new dimension is given to the extended model, in the sense of a social integration process. We generate some sub-results of the original model, such as the bifurcation diagram of the flocking coefficient, and we made some

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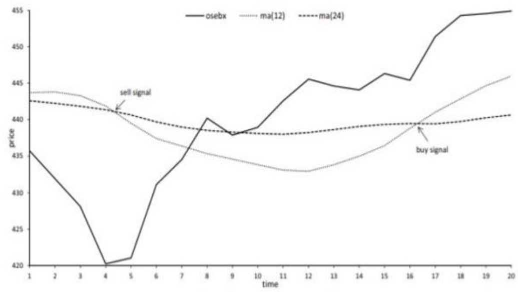
small corrections.

3. Methodologies Applied

A. Golden Cross

[2]This rule is predicated on 2 easy moving averages - one long-run and one short-run moving average. The long-run line captures the most trend, whereas the short-run line captures the shorter value movements(fig. 1.1). A obtain (sell) signal is generated if the short-run line breaks on top of (below) the long-run line. each intersection between the short-run line and also the long-run line generates a obtain or sell signal.

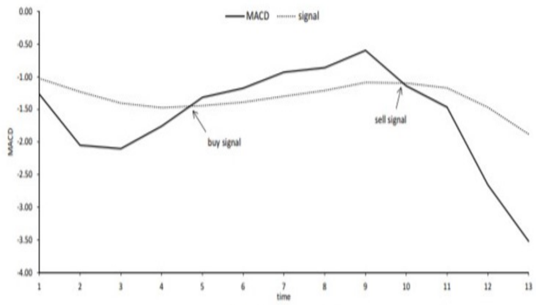


(a) Golden Cross rule

Figure 1.1: Golden Cross Rule

B. MCAD

[2]Moving Average Convergence/Divergence (MACD) could be a technical indicator. The MACD-rule, relies on a MACD line and an indication line(fig.1.2). If the MACD line breaks higher than the signal line, then chartists contemplate this as a purchase signal as a result of they expect the worth to extend. Similarly, it's a sell signal if the MACD line breaks below the signal line, as a result of the worth is predicted to decrease

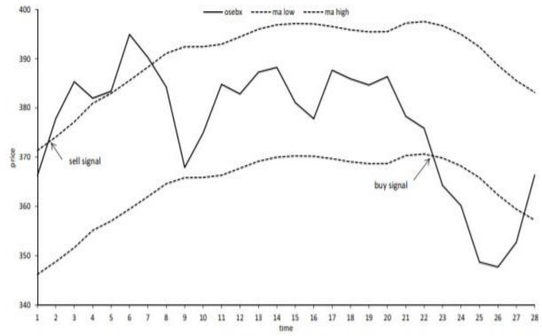


(b) MACD rule

Figure 1.2: MCAD Rule

C. Envelope

[2]The rule, Envelope, is defined by upper and lower price range levels, which are based one simple moving average (MA) of historical prices. A percentage is added to and subtracted from the MA to generate the upper and lower levels respectively. Envelope is used to identify conditions in which the stock is overbought or oversold in the market. If the price break above the upper level, the stock is considered as overbought which is a sell signal. Similarly, a buy signal is generated if the price breaks below the lower level, because the stock is oversold (see Figure 1.3). Analysts may apply and interpret the rule differently, but the overall strategy is to identify when the stock price breaks above the upper level and below the lower level.



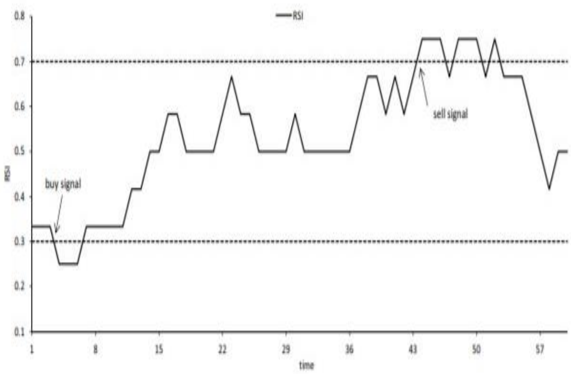
(c) Envelope rule

Figure 3.1: Technical trading rules; golden gross, MACD and Envelope

Figure 1.3: Envelope

D. Relative Strength Index

[1]Relative strength index (RSI) is a momentum indicator and is based on recent gains and losses. The idea is to compare average losses and gains during the last 14 days9 to determine conditions in which the stock is overbought or oversold. The index ranges from 0 to 100. An increase in the RSI indicates a "strength", while a decrease is a sign of "weakness". If the RSI breaks below (above) a predetermined support (resistance) level, then the stock is oversold (overbought). The support and resistance level are normally set equal to 30 and 70 respectively(fig 1.4). It is considered as a sell signal if the stock is overbought, and similarly it is a buy signal if the stock is oversold.



(b) RSI rule.

Figure 1.4: RSI

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4. Existing System

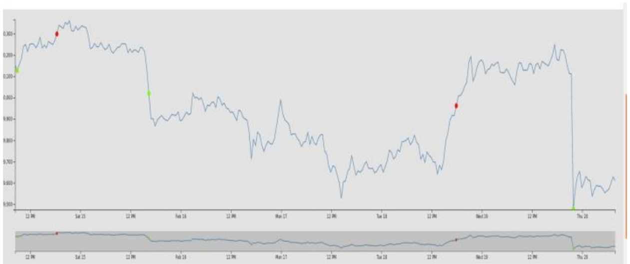
Financial markets or security exchanges are established to meet the needs of different traders, and organizing markets of trading. Back in time, direct negotiations was needed to trade securities, but in modern finance the market has emerged from meeting places to more efficient electronic market platforms. [7]Broadly speaking on might distinguish between three trading systems (applied in the United States): over-the-counter (OTC), electronic communication network (ECN) and formal exchanges, according to Bodie et al. (2011, p. 62). NASDAQ is an over-the-counter quotation system for securities not listed on regular stock exchanges. The system was develop to link brokers and dealers in computer networks (electronic trading) to median quotes. Today NASDAQ is a trading system, handling the majority of trades with sophisticated electronic trading platforms, and typically the standard for exchange markets worldwide. It is a computer-based market, with a system of market makers. NASDAQ was one of the major developers of ECN, which is a computer operated trading network offering financial products on the outside of stock exchanges. Formal exchanges are manages through a specialist, and New York Stock Exchange (NYSE) is an example of such an exchange. Specialists may act either as a broker or a dealer, and each security is assigned to one specialist.

Algorithm	Advantages	Disadvantages	Efficiency
MACD	Fast	Frequently Trading	50-70%
RSI	High accuracy	Time Taking	70-80%
TMA	High number of trades	Less accuracy	40-60%
TSI	Can be used for complex trades	Time taking	50-60%

5. Output & Conclusion

Backtest result

START TIME	2020-02-14 08:51:00	AMOUNT OF TRADES	5
END TIME	2020-02-20 08:23:00	SHARPE RATIO	48.07
TIMESPAN	6 days	START BALANCE	10228.00000
START PRICE	10128.00000	FINAL BALANCE	10348.77253
END PRICE	9582.00000	SIMULATED PROFIT	
MARKET	-5.39100%		1.18080%



The objective of this work was to develop an extended version of the Day and Huang model with heterogeneous and socially integrated investors. The investors use different algorithmic trading rules to operate in this stylized nonlinear model. In the first part we investigated carefully the original Day and Huang model and its dynamics. Our main concern was the β-investors, and their relative importance in the market, which is denoted by the flocking coefficient b. A bifurcation diagram was made to see how different it can be.

Different algorithms are used in this model and the outputs for those different algorithms can be analyzed and can be chosen the best algorithms for different uses.
Some results are show below.

Roundtrips

Entry at (UTC)	Exit at (UTC)	Exposure	Entry balance	Exit balance	P&L	Profit
2020-02-14 08:52	2020-02-14 18:22	10 hours	10227.750	10374.433	146.68	1.43%
2020-02-15 16:22	2020-02-18 17:52	3 days	10348.497	10263.080	85.42	-0.83%

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