Trading Algorithm Model Based on Technical Indicators

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ABSTRACT

Today the rapid proliferation of the internet provides an environment where efficient e-commerce solutions can be developed. The electronic market is gaining more attention in the global economy, it gives buyers and sellers more liberty to trade cost-effectively and allows access to an adequate amount of data for analysis. New trading agents have been developed for the best utilization of such data. These agents design strategies using financial analysis techniques such as technical indicators. Two very well-known technical indicators used to develop strategies are Convergence-Divergence (MACD) and Stochastic Oscillator (SO). This paper aims to devise a trading algorithm that combines MACD and SO in a single strategy and check the reliability of the combined signals it generates. JTAP simulation system has been used to test the proposed strategy. In this paper, we evaluated the performance of our proposed strategy when implemented on shares of Karachi Stock Exchange, Pakistan which proves improvement of strategy.

KEYWORDS: Trading strategies, technical indicators, moving average convergence-divergence, Stochastic Oscillator, genetic algorithm

1. INTRODUCTION

Initially, trading was executed in an open floor environment by the experts using the method of open outcry. The rapid growth of technology and developments in communication makes it possible to replace the open outcry system with electronic trading systems. It has transformed the nature of stock trading all over the world. Traders can purchase and sell stocks remotely using an internet-based order submission protocol. Such markets that are fully capable of electronic execution started working in the 1980s [1]. With the facilitation of remote trading in the stock market, different autonomous agents started to develop which can place buy or sell orders on their owner's behalf. Trading agents use the electronic trading markets more efficiently and act autonomously on behalf of their owners. These agents process all the related information around the clock and can decide on when and how much to buy or sell any stock. They are intelligent enough to take cognizant decisions autonomously and are equipped with sophisticated strategies for maximizing utility and profit. Such strategies are based on technical analysis which has been used in financial markets for decades. Many financial technical indicators have

been used for market analysis and designing strategies. The most widely used trend indicator is MACD which shows the relationship between price and moving averages. It was introduced by Gerald Appel, in the 1970s that works by taking the difference of faster-moving average from slower moving average [2]. It indicates the traders to take benefits while they are holding the stocks for the long term or short term. Another popular technical indicator is the stochastic oscillator which was developed in the late 1950s by George C. Lane. It shows the location of the close relative to the high-low range over a set number of periods. Stochastic Oscillator neither follows the price nor follows volume but it follows the speed or the momentum of price.

In this paper, we evaluated the profitability of a trading strategy that combines MACD and SO. During experimentation, it's seen that technical indicators affect the trading strategy and can be used to improve the performance. Combining SO and MACD results in better signals because stochastic measures the relationship between a stock's closing price and its price range over a certain period, while MACD analyzes the difference between moving

averages diverging from and conversing with each other. JTAP simulation system has been used to test the proposed strategy. This system was developed by the Artificial Research Group [3].

In section 2., related work is reviewed. Section 3. presents our proposed architecture and its implementation. Section 4. presents evaluation criteria and our obtained results and in section 5., the conclusion and future work is discussed.

2. RELATED WORK

As the stock market is a complex dynamic system, so the stock prices are not only dependent on fundamentals but are highly motivated by short trading behavior. Trading agents can then design the strategies keeping such behaviors in consideration. Bloembergen, Daan, et al [4] analyze the dynamics of three different trading strategies which are based on trading behavior on the current market price only. Their result shows that it is hard to predict in advance which trading strategy will perform better. If the information is freely available, then fundamentals can work at best. After then Jose Alberto et. al. [5] defines a methodology that creates a process of modeling, developing, and evaluating trading systems. In this process, they create a multi agent system that integrates artificial intelligence techniques, allows the addition of new agents, guides the testing of different techniques, and enables the distribution of agents when computational resources are limited. However, these tools, due to the simplicity of their structure, perform poorly with adverse market conditions. Some sophisticated approaches are then designed to combine trading rules which helps in overcoming the problem [6]. These approaches were designed using genetic algorithms and genetic programs. Wooldridge [7] made a substantial contribution in establishing the generic framework of agent theory. M A H Dempster and C M Jones [8] also developed a trading system that consists of rules based on combinations of different indicators. A starting arrangement of such guidelines is selected by a genetic algorithm applied to several indicators.

Further, development focused on designing strategies for trading agents using financial analysis techniques. Technical indicators are then widely used in the financial market to predict future stock prices and market momentum which enhance trading profitability [6], [9], [10], [11]. Recent research focuses on a combination of technical indicators for precision. Genetic algorithms and genetic programs were used to combine different trading rules to overcome the poor behavior in adverse market conditions when implemented separately. This helped autonomous agents to achieve profitability in dynamic market conditions. Allen and Karjalainen [6] also used genetic programming to develop optimal trading rules which they found useful on a

risk-adjusted basis. In further investigation, it is observed that genetic algorithm approaches are better when the transaction costs are zero. Besides, the indicator for technical analysis, which is based on fuzzy logic is also proposed [12]. In the article by Escobar et. al., it was concluded that agents using proposed indicators earn more profit, but the number of transactions is very high which is a disadvantage as each transaction has an associated cost.

Shah, Nabeel M [13] designed trading strategies using different financial indicators that were able to trade in multiple financial markets. Many other research studies have verified the importance of technical indicators focusing on trading strategy design and analyzing the statistical characteristics of these technical indicators [14], [15]. Technical analysis assumed that the future performance of stock markets relies on the historical performance of the market, so one can develop profitable trading rules using historical data. There has been continuous effort to investigate the performance of the technical trading analysis. Many researchers believed that technical analysis cannot generate abnormal profit [16], [17], [18]. In an article, Biondo et. al. [19] concluded that standard trading strategies and their algorithms can be successful occasionally, but it is better to use a random trading strategy for consistent profitable results. However, on the other hand, Traynor and Ferguson [20] concluded that technical analysis can produce a sizeable profit when non-public information is considered. Gunasekarage and Power [21], Chong and Ng [22] also concluded that a significant return is possible through technical trading rules. Lui and Chong [23] reported that traders who work through technical analysis significantly outperform those who do not use technical analysis. Brock, Lakonishok, and LeBaron [24] researched whether Moving Average and Trading Range Break are valid tools for trading. They tested these methods on 90 years of data from the Dow Jones Industrial Average. They found consistent results across the sub-periods in their dataset and found predictable patterns. By generalizing these two indicators they suggested that technical analysis can be a great help in predicting stock price changes.

In research at B.V. Patel Institute of BMC and IT [25], it was examined whether the technical indicators assumed any helpful part in the timing of investment at the stock market.

Test statistics are then developed to check any positive return yielded by buy and sell signals. Trend indicators used are Relative Strength Index (RSI), MACD, and Stochastic. The research concluded that MACD gives an accurate signal, better profit, and higher return compare to Stochastic Oscillator. Whereas Stochastic Oscillator gave more signals, but the accuracy of the signals was not so good as compared to MACD.

Different strategies for trading agents were proposed by Vytelingum et. al. [26] using a framework. In their framework they proposed that trading agents for designing strategies should manage their capabilities through three layers, information, Knowledge, and behavioral layer. After that Yaman et al [27] used an approach that was based on an evolutionary algorithm for modeling autonomous trading agents. In this approach collection of trading agents were generated which were using different strategies using Evolutionary Programming. Yaman concluded that the result is far better when different agents are performing concurrently.

Isao Yagi proposed [28] a trading model to suppress an increase in market volatility. They found that if the impact on market price formation depends on the minimum number of orders in a rebalancing trade.

A reinforcement learning-based algorithm was proposed by Wenhong [29] where they used two different models for theoretical analysis to extend their fundamental behavior for trading. Secondly, they analyzed cooperative and competitive behavior to design a reinforcement model. The realistic liquidation problem was solved using this methodology but using the same mechanism we can combine different models for our problem.

3. PROPOSED STRATEGY DESIGN AND ANALYSIS

The purpose of this study is to design a trading strategy for autonomous agents in financial markets that can work in dynamic market conditions. Moreover, we aim to check their performance in an autonomous simulation environment. Real data is used from the stock market in this environment so that simulation could be close to the real-time market. We used double-check strategy as a bidding strategy in which buy or sell indications have been generated by the combination of MACD and Stochastic Oscillator. For MACD, the difference of longer-term moving average (26-Day EMA) from the short-term moving average (12-day EMA). Additionally, the exponential moving average of MACD of nine days was calculated to generate a signal line. Mathematically it is written as

$$MACD = EMA(C, n_x) - EMA(C, n_y)$$

where $x < y$

Here C is the closing price of that specific stock for which moving averages are calculated. Position of the signal line and MACD help in determining the bullish or bearish trends. The trend is bullish if the signal is below MACD and bearish otherwise. If we combine the centerline with the MACD indicator, then the line with crossover will indicate the trading strategy that confirms the momentum of the stock. A buy signal is generated when MACD crosses the nine-day EMA of the MACD from below, while a

sell signal is generated when MACD crosses the nine-day EMA of the MACD from above.

Trading signals generated by the crossover of MACD and signal line are interpreted in three different situations:

1. When $MACD - Signal = 0$, then it means that MACD has crossed the Signal. If we have positive MACD, it means MACD is above the signal line while if it's negative then it'll be below the signal line.
2. When $EMA(C, n_x) - EMA(C, n_y) = 0$, then it means that positive values increase which means upside momentum is increasing. Negative values increase as $EMA(C, n_x)$ diverges further below $EMA(C, n_y)$, this means downside momentum is increasing.
3. If we have equal relative price and MACD then the price graph will show higher highs or lower lows, but these will not be shown on the histogram. It also represents the strength of momentum.

Whereas, Stochastic Oscillator triggers the trading signal when the K value crosses over one-third of the moving average value known as D. It helps to identify overbought and oversold levels. The oscillator oscillates between 0 and 100. Usually, 80 taken as overbought, and 20 is an oversold indication. Mathematically it is written as:

$$K = 100 \frac{C - L}{H - L}$$

$$D = 3 - EMA(K)$$

Where C is the closing price, L is the lowest price in the last n days; H is the highest price in the last n days of the stock under consideration.

Combining SO and MACD results in better signals because stochastic measures the relationship between a stock's closing price and its price range over a certain period, while MACD analyzes the difference between moving averages diverging from and converging with each other. This combination evolves a strategy that confirms the trend with bullish MACD crossover and bullish stochastic crossover. It is caused whenever we have a condition that a slower moving average is left behind from a faster-moving average. As such things happen, it creates momentum in the market and prices tend to increase. Bullish of MACD depends on equilibrium and signal line. As the histogram value of MACD is above the equilibrium line or MACD line is above the signal line, MACD is bullish. The divergence of stochastic bullish happens as K value is above D that which also confirms the price turnaround.

The essential point of preference of this system is that as two different systems agreed, it will separate the signals. When we combine the two separate systems, it not only adds the advantages of both the systems

but also reduces the disadvantages that individual systems have. When MACD and Stochastic Oscillator systems are producing wrong signals about a stock at a particular time, this system will focus on the strongest signals and produces the right one. So, it will not only helpful in identifying the upward trending but also for downward trending. The focus on the strongest signals only is additionally the greatest shortcoming of this system. There will be very low chances of trading if we wait for the strongest signals only and we shall have to follow different markets to find regular signals for trading.

Figure 1: Flow Chart for Bidding Strategies

4.IMPLEMENTATION OF TRADING STRATEGY

For experimenting with autonomous trading agent strategy, we used simulation environment of Jacarkoo Trading Agent Platform (JTAP). The basic structure of JTAP is the client-server, and simulation duration is controlled using the same clock maintained by the server. We used the clock of 365 days to represent whole year trading. Furthermore, there are 10 rounds in each day while 500 milliseconds will make one round. JTAP used the double auction mechanism for trading. The single non-divisible asset is always there in every market that is the stocks of the market. For our experimentation, we used the stocks from the Karachi stock exchange with high and low range prices for one year of each stock. To study the outcome of different strategies in a non-sophisticated

manner, we used a double-check strategy with a single stock price movement. Our strategies are based on financial indicators as we are using real-world techniques and data for simulation. We used different strategies for simulation using different settings of parameters and in this way, the optimized technique can be approached. In these simulations, four trading agents were used. To ensure a controlled environment and to perform a relative study of trading agent strategies, trading agents have the same amount of budget available at the beginning of the trade simulation. At a particular time, all trading agents will have the same price for a certain stock but on a single stock, agents can have different prices for each shout.

Input: n ; $currentPrice$; $buyQuantity$; $sellQuantity$

Output: buy , $sell$, $quantity$, $price$

$doubleMACD = EMA(12) - EMA(n)$.

$signal = (MACD \times 0.2) + MACD_n \times 0.8$

$$K = 100 * \frac{marketClosingPrice - low}{high - low}$$

$$K_1 = 100 * \frac{marketClosingPrice - low_1}{high_1 - low_1}$$

$$K_2 = 100 * \frac{marketClosingPrice - low_2}{high_2 - low_2}$$

$$D = \frac{K + K_1 + K_2}{3}$$

if ($macd < signal$ & $signal < 0$ &

$traderBalance > currentPrice \times buyQuantity$

& $d > 80$)

$creatanewShout$; $Shout.setBid(false)$;

$shout.Price = currentPrice + margin$;

$shoutQuantity = sellQuantity$

else if ($macd > signal$ & $signal > 0$ & $Inventory > 0$ & $d < 20$)

$creatanewShout$;

$Shout.setBid(true)$;

$shout.Price = currentPrice - margin$;

$shoutQuantity = buyQuantity$;

This pseudo-code is an implementation of Double Check Strategy (integration of MACD and SO). In theory a 26-day EMA is subtracted from the 12-day EMA, the resulting calculation is a MACD. For performance comparison of different trading agents with different parameter settings we have replaced 26-day EMA by n .

Another indicator used is the Stochastic Oscillator (SO). SO is an indicator based on momentum and used to produce high-low ranges for n periods. This

type of indicator uses closing price for statistical analysis. After analysis, the indicator calculates a percentage value representing by k that is momentum.

To calculate d, we have used 3 periods moving average of k. To make the buying or selling decision, the value of d is very helpful. For example, if a trading agent wants to buy the stock, then needs to check i) is the MACD line below the signal line ii) is the signal in the negative range, and iii) is the value of d above 80. If all these are 'Yes' then the agent can bid for buy. For a selling event, the agent needs to check i) is MACD line above signal line ii) is signal in the positive range, and iii) is the value of d below 20. If the decision is to buy, then the further agent needs to check for available balance so that transaction could be made. An asset is deemed to be overbought once the Stochastic Oscillator approaches the 80 levels. Likewise, if the Stochastic Oscillator approaches 20, it is an indication that the asset may be getting oversold. Following are the results based on seven different shares generated using JTAP.

4.1 MCB

Figure 2: This is a graphical representation of the results generated for Double Check Strategy in comparison with MACD, Relative Strength Index (12 days), and Stochastic Oscillator during the simulation based on JTAP. This result is based on MCB's share price in the year 2004.

Table 1. Profit/loss of MCB shares

	Balan ce	Share Value	Tran sacti ons	Profit/ Loss
DC	82.3	2146.2	47	122.86 %
MACD	19.1	2146.2	192	116.54 %
RSI	978.5	0	680	-2.14%
SO	1024.8	0	311	2.83%

From table 1, we can interpret that while keeping the lowest transactions DC gives the highest profit which is 122.86. Whereas MACD gives 116.54% profit and RSI gives a negative return, which is -2.14. So, gives 2.83% profit.

4.2 NBP

Figure 3: This is a graphical representation of the results generated for Double Check Strategy in comparison with MACD, Relative Strength Index (12 days), and Stochastic Oscillator during the simulation based on JTAP. This result is based on NBP share price in the year 2004

Table 2. Profit/loss of NBP shares

	Balan ce	Share Value	Tran sacti ons	Profit/ Loss
DC	11.5	2362.8	25	137.43 %
MACD	114.6	1999.2	101	111.39 %
RSI	634.6	0	184	-36%
SO	693.0	0	128	-30.6%

From table 2, we can interpret that DC gives 137.43% profit, MACD gives 113.39% profit whereas RSI and so gives negative returns, that is -36, -30.69% respectively. The transaction remains the lowest for DC.

4.3 NML

Figure 4: This is a graphical representation of the results generated for Double Check Strategy in comparison with MACD, Relative Strength Index (12 days), and Stochastic Oscillator during the simulation based on JTAP. This result is based on the NML share price in the year 2004.

From table 3, we can interpret that DC gives 52.24% profit, MACD gives 46.4% profit whereas RSI gives

negative returns, which is -35.19, and SO gives 6.85% profit. Transactions remain the lowest for DC.

Table 3. Profit/loss of NML shares

	Balan ce	Share Value	Tran sac tions	Profit/ Loss
DC	1533.3	0	62	52.24 %
MACD	95.71	1368.2	135	46.4%
RSI	648.18	0	312	-35.1%
SO	1068.5	0	262	6.85%

4.4 OGDC

Figure 5: This is a graphical representation of the results generated for Double Check Strategy in comparison with MACD, Relative Strength Index (12 days), and Stochastic Oscillator during the simulation based on JTAP. This result is based on OGDC share price in the year 2004

Table 4. Profit/loss of OGDC shares

	Balan ce	Share Value	Tran sac tions	Profit/ Loss
DC	1121.9	443.2	42	56.52%
MACD	1232.1	0	124	23.22%
RSI	528.5	0	226	-47.1%
SO	741.7	0	198	-55.6%

From table 4, we can interpret that DC gives 56.52% profit, MACD gives 23.22% profit whereas RSI and SO give negative returns, that is -47.15 and -55.68% respectively. Transactions are lowest for DC.

4.5 PSO

Figure 6: This is a graphical representation of the results generated for Double Check Strategy in comparison with MACD, Relative Strength Index (12 days), and Stochastic Oscillator during the simulation based on JTAP. This result is based on PSO share price in the year 2004

Table 5. Profit/loss of PSO shares

	Balan ce	Share Value	Tran sac tions	Profit/ Loss
DC	302.9	1260.8	21	56.38%
MACD	116.2	1260.8	27	37.71%
RSI	823.2	0	104	-16.78%
SO	7938.5	0	68	-6.15%

From table 5, we can interpret that DC gives 56.38% profit, MACD gives 37.71% profit whereas RSI and SO give negative returns, that is -16.78 and -6.15% respectively. Transactions remain the lowest for DC.

4.6 UBL

Figure 7: This is a graphical representation of the results generated for Double Check Strategy in comparison with MACD, Relative Strength Index (12 days), and Stochastic Oscillator during the simulation based on JTAP. This result is based on the UBL share price in the year 2004.

Table 6. Profit/loss of UBL shares

	Balanc e	Share Value	Transa ctions	Profit/ Loss
DC	1144.9	0	42	14.49%
MACD	1075.7	0	112	7.58%
RSI	490.3	0	302	-50.9%
SO	587.6	0	204	-41.2%

From table 6, we can interpret that DC gives 14.49% profit, MACD gives 7.58% profit whereas RSI and SO give negative returns, that is -50.97 and -41.24% respectively. Transactions remain the lowest for DC.

4.7 BYCO

Figure 8: This is a graphical representation of the results generated for Double Check Strategy in comparison with MACD, Relative Strength Index (12 days), and Stochastic Oscillator during the simulation based on JTAP. This result is based on BYCO's share price in the year 2004.

Table 7. Profit/loss of BYCO shares

	Balan ce	Share Value	Transac tions	Profit/ Loss
DC	694.3	394.9	47	8.94%
MACD	14.05	956.2	192	-2.97%
RSI	974.2	0	680	-2.57%
SO	554.1	561.3	311	11.5 %

From table 7, we can interpret that DC gives 8.94% profit where MACD and RSI give negative returns, that is -2.97, -2.57% respectively SO gives 11.54% profit.

5. CONCLUSION

In this study, we have proposed an algorithm that is helpful for different trading strategies. These strategies are based on technical indicators that are used in all the financial markets for trading and analysis. At the start of each day, agents start the trading based on previous and running data to make the decisions of buying, sell or hold. Different signals are generated based on different technical indicators that are used by these agents to make the decision.

We used data from the Karachi stock exchange and used different parameters to make different strategies and run them on the JTAP simulator. Based on the signals produced during the simulation we have concluded that if momentum-based strategies are combined with trend following strategies then we can have better profits. We compare the Double Check (DC) Strategy with MACD, RSI, and SO strategies applied on seven different shares. The high and low price of all shares taken for 365 days. From the result, it is evident that while keeping the lowest transactions DC gives higher profit most of the time. This shows that when we combine the MACD and SO then mostly it generates better profit. Furthermore, in volatile market conditions, we can have stable returns. In the future, these indicators can be produced using deep learning algorithms that can take raw data and direct us to make buy, sell or hold decisions.

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