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Design Algorithmic Trading Strategies with Expert Advisor Using Linear Weighted Moving Average (LWMA) and Stochastic Oscillator Technical Indicators

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ABSTRACT

Earlier this decade, the financial sector saw a paradigm change, with automated trading (AT) systems gaining popularity as essential tools for traders and investors. This research explores deeply the design and implementation of Expert Advisors (EAs) for automated financial built using a combination of the Linear Weighted Moving Average (LWMA) and Stochastic oscillator technical indicators. The EAs are built using the programming language MetaQuotes Language 4 (MLQ4) at Metatrader 4 (MT4) platform, enabling automated trade execution. It implements a machine learning genetic algorithm, trained on historical data to optimize the parameters of the LWMA and Stochastic trading rules. The core strategy relies on the LWMA to identify the overall market trend direction while the Stochastic oscillator provides additional signals for timing entry and exit points based on momentum. The EAs were coded to generate automated buy and sell signals for algorithmic trading (AT) based on a set of defined rules using thresholds for each indicators. Extensive historical backtesting using Gold (XAU/USD) currency pair across multiple timeframes from 5-minute (M5) up to 4-hour (H4) charts was conducted using 5 years of price data from 2019 to 2023 for evaluation. The goal of this study is to assess if the EAs could potentially produce consistent profits over time while minimizing drawdowns in different market conditions. The results demonstrate that the system was able to generate annual returns ranging from 3.04% up to 232.19% depending on the aggression of the timeframe settings. Meanwhile, maximum drawdowns were controlled to reasonable levels between 0.5% to 8.27% which is below 10% of potential loss throughout the backtests. An hourly timeframe configuration provided a balanced blend between strong profitability and drawdown control based on the backtest analysis. All the timeframes used for the test show positive results and the M5 timeframe is the best chosen timeframe to trade using this EAs implementation.

1. Introduction

The financial trading scene has changed dramatically over the last several decades due to technological improvements and a rising interest in algorithmic and automated trading strategies. The development and execution of Expert Advisors (EAs) have acquired important meaning in this environment. An EAs is a software program that is designed to automatically execute trading options based on pre-defined algorithms, making it a crucial instrument for traders and investors in today's fast-paced financial markets. However, algorithmic trading can be costly because it requires significant investment in technology and requires continuous maintenance and updates to remain effective. Furthermore, the costs of data and access to market information can be high, which increases the transaction costs for transactions. On the other hand, traders often struggle with emotions that can undermine judgment and lead to bad decisions. By using algorithms, emotions can be removed from the decision-making process, creating a balance between the high cost of algorithmic trading. High investment costs and mathematical modeling required by these algorithms can make it difficult to compete with the market [1].

Algorithmic and automated trading have had a significant effect on the world of finance since their invention. Computing power, data analytics, and machine learning algorithms have all played a role in this technological advancement. Algorithmic trading, often known as automated trading or Algo trading (AT), is the use of computer programs that execute transactions according to specified requirements [2]. AT strategies rely on mathematical models and algorithms to analyze market data and identify profitable trading opportunities [3]. By automating the trading process, these strategies can take advantage of market inefficiencies and generate profits for investors. Besides, these programs use algorithms to analyze market data and make trading decisions according to predetermined criteria [4]. In addition, AT relies on computer algorithms to execute an immense number of transactions at highly rapid rates, which frequently takes advantage of small price differentials and market inefficiencies that human traders might not notice. These algorithms are frequently designed to execute specific strategies such as trend-following, arbitrage, or market-making, and they are capable of reacting to market fluctuations in real-time and making quick decisions about whether to buy or sell assets.

According to [5] trading process automation has resulted in quicker and more efficient transaction execution, resulting in greater trading volumes and liquidity. This has helped market players by increasing liquidity availability and improving price discovery [2]. AT goes a step further by completely eradicating human intervention from the trading process. Trading systems that are automated can watch markets 24 hours a day, execute transactions, manage risk, and even modify strategy depending on specified criteria. This automation trend has resulted in higher market liquidity, lower trading costs, and enhanced market efficiency.

AT, on the other hand, has brought new risks to the world of finance. The utilization of fast-speed algorithms in trading with high frequencies has been related to significant fluctuations in prices and market instability. To guarantee market stability and protect investors, authorities must strictly monitor and control AT [6]. Furthermore, the utilization of automated trading algorithms poses ethical problems, especially when these algorithms have the potential to produce profound market conditions [7]. It is of the utmost importance for market players and regulators to evaluate the potential risks and advantages of AT and to implement suitable controls to limit risks and preserve financial market integrity [8] . Herein This study focuses on the design and implementation of an AT system applying EAs to generate a more accurate prediction of the Financial Market's features.

The idea for this study is derived from the increasing demand for smart and efficient trading solutions in financial markets. Traditional manual strategies for trading are frequently limited by human factors such as emotions, failure, and speed of response. EAs, for example, provide an attractive option by helping traders create and execute trading strategies with speed and accuracy. This enhances trading efficiency and reduces the possibility of human mistakes. The important role of financial industry experts has changed greatly as a result of market evolution. As financial markets become more complex and multifactorial, central banks' role as mega regulators has increased [9] . This shows the significance of understanding the historical progression of market index results and the requirement for continuous financial market monitoring. The study of volatility metrics such as structural unpredictability and Eigen-entropy gives insights into the developing dynamics of financial markets [10] . In addition, research indicates that emerging markets, such as the Moroccan financial market, have experienced both periods of efficiency and inefficiency [11] . This indicates the dynamic nature of financial markets and the need for expert advisors to respond to changing market conditions. EAs are frequently seen as possessing specialized knowledge in their respective fields. Yet, these experts must acknowledge the changing nature of financial markets and maintain their expertise and strategies up to date. Financial systems grow increasingly market-based, and bank-based technologies may become less effective. As a result, while establishing risk management methods, expert advisors must take into consideration the growing financial structure.

This research paper discusses the complexities of designing an automated trading strategy that brings together two important elements of automated trading: technical indicators and expert advisors. Technical indicators are mathematical calculations that are applied to historical price and volume data and act as useful tools for analyzing market trends, momentum, and probably reversal points. EAs, on the other hand, are computer programmers who execute trading strategies according to specific requirements, allowing traders to automate the decision-making and execution processes. The main purpose of this study is twofold. Firstly, it aims to create, implement, and rigorously test an AT strategy that use combination of technical indicators. It also seeks to assess the effectiveness of various risk management techniques incorporated within expert advisor strategies to mitigate potential losses, and enhance and consistent the performance of profit. Next, the second objective of the research is to test an automated trading strategy in the forex market and analyze the historical performance of these strategies through backtesting to make a higher and consistent profit.

2. Research methodology

Designing an EAs for trading involves a lot of important processes and strategies to ensure its effectiveness and consistency. Every trading plan should start with a personal trading method. A trading strategy, also known as a trading algorithm, is a set of rules that sets specific entry and exit points. It starts with an idea, which is then coded, analyzed, back-tested, optimized, and run through a comprehensive walk-forward analysis before coming live. The whole process can take a few months to complete, but the result should be an effective trading algorithm that can be used with one of the existing trading systems or as a starting point for the development of a new system. Figure 2 show the lifecycle of Algorithmic Trading System methodology (Trading Strategies: Algorithmic Trading Strategy * AlgorithmicTrading.Net, n.d.)

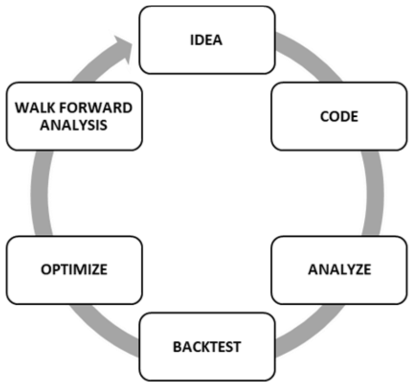

Figure 1. Trading Algorithm Design Method.

a. Selection of Technical Indicators

Choosing proper technical indicators was the initial stage of designing our strategy. These indicators were chosen for their relevance and potential to provide meaningful insights into price fluctuations. The study from [12] and [13] shows that moving averages and fractions below the moving average subset have become a popular formula for forex forecasting and modeling. The moving average was used by previous researchers as the main formula for the study because it was very significant and logical. So in our study we proposed a specific type of moving average called a linear weighted moving average. We are proposed LWMA and combination with stochastic oscillators as the technical indicators used for the design and analysis of these EAs. One of the most popular technical indicators by Forex traders is the moving average. It is a lagging indicator that is extremely useful for verifying that a pattern has begun or going to occur. Most of the well-known technical indicators are the Simple Moving Average (SMA), Exponential Moving Average (EMA), and Moving Average Convergence Divergence (MACD) but we are just focusing on using LWMA. Besides that, we also combine both LWMA with stochastic indicators to improve and better EAs. The equations that apply are presented in Equations (1) - (4). The LWMA indicator's values are calculated using the following formula:

$$LWMA_i = \frac{Sum}{Sum\,Weight} \tag{1}$$

$$Sum = \mathrm{Pr}ice_i \times N + \mathrm{Pr}ice_{i-1} \times (N-1) + \ldots + \mathrm{Pr}ice_{i-N+1} \times (1) \tag{2}$$

$$SumWeight = N + (N-1) + \ldots x + 1 = N \times \frac{(N+1)}{2} \tag{3}$$

where:

$LWMA_i$ is the value of the current period calculation.

$\mathrm{Pr}ice_i$ is the source (Close or other) price of any period participating in the calculation.

N - is the number of periods, over which the indicator is calculated.

The second technical indicator that we use in this research is stochastic oscillators. The Stochastic Oscillator is a momentum indicator that reflects the speed and strength of price change. The stochastic oscillator can be calculated by subtracting the period's low from the current closing price, dividing by the total range for the period, and multiplying by 100.

$$\%K = \left(\frac{C - L14}{H14 - L14}\right) \times 100 \tag{4}$$

Where,

C = The most recent closing price.

L14 = The lowest price traded of the 14 previous trading sessions.

H14 = The highest price traded during the same 14-day period.

%K = The current value of the stochastic indicators.

b. Design and Development of Expert Advisors(EAs)

Traders that use EAs benefit from automated decision-making and trade execution based on a set of rules. Our EAs were programmed using the MQL4 on the MT4 platform. The EAs were designed to take into consideration making higher profits return and in addition to low potential losses also can produce consistent results for both of these factors. The signal is given by the specified momentum technical indicators, such as LWMA crossover and overbought/oversold conditions from the Stochastic Oscillator. The whole operation of this system trading of these EAs is shown in Figure 3 for better understanding. As mentioned earlier this trading system uses two technical indicators which is LWMA and Stochastic. The concept of this trading system for open and close positions is as follows: -

Open position.

Open positions in the market are established according to a set of specific conditions within the trading system. The first condition takes into account the position of the LWMA crossover relative to the current market price. Whether the LWMA crossover is positioned above (Buy position) or below the price (Sell position) is crucial, as it indicates the prevailing trend direction. The second condition involves monitoring the Stochastic Oscillator, a momentum oscillator. When the Stochastic exceeds the commonly recognized threshold of 80, signifying an overbought condition (Sell position), or falls below the threshold of 20, indicating an oversold condition (Buy position), it triggers consideration for initiating a trade. The third and most comprehensive condition requires the alignment of both LWMA and Stochastic conditions. An ideal scenario for opening a position occurs when the Stochastic signifies overbought conditions (sell position) while the LWMA is positioned crossover below the price, or when the Stochastic signals oversold conditions (Buy position) while the LWMA is positioned above the price. This combination of technical indicators ensures a more robust and well-informed approach to market entry.

Close position

The process of closing positions is meticulously governed by a predetermined target profit level. This strategy ensures that when a position attains a specified profit threshold, it is promptly closed to lock in those gains, safeguarding the trader's returns. Crucially, in instances where the targeted profit level is not reached, the system refrains from an immediate position closure. Instead, it diligently maintains the position till the trade meets stop loss. This approach empowers the system to stay dynamically engaged in the market.

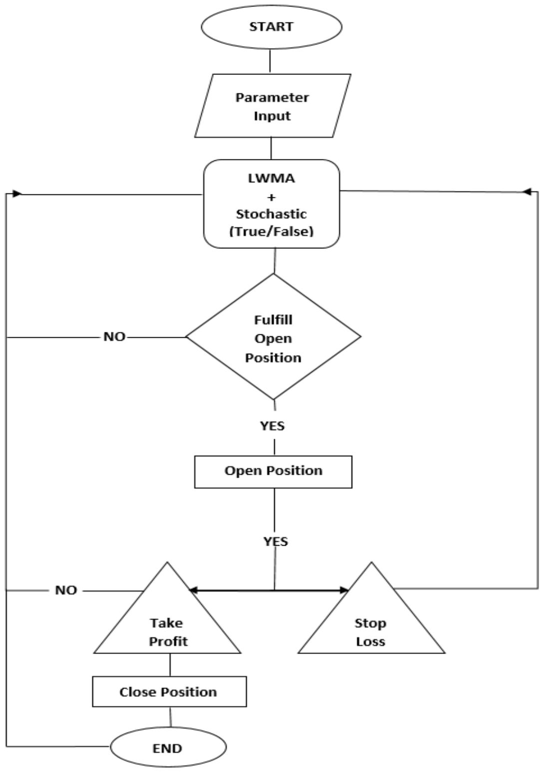

Figure 2. Flowchart System Expert Advisor.

c. Data Sources and Historical Data

To conduct comprehensive backtesting, we sourced historical data from reputable data providers. High-quality historical price and volume data were essential for the accuracy of our backtesting results. We ensured that the historical data encompassed a variety of market conditions, including different timeframes. To investigate the effects of the different input data on the prediction model, different data inputs were tested on the system. We are used the historical data from Dukascopy Bank SA [14] and test to pair currency of Gold (XAU/USD). The period chosen for testing purposes is within 5 years, from 2019 to the current date of 2023 (1 Jan 2023 to 30 Nov 2023). The original research involves using the raw close and open price as input.

3. Results and Discussion

The purpose of this testing is to determine how profitable and loss of the trading system, which has been developed, is when implemented in transactions using historical data from Dukascopy Bank SA [14] and was tested on a strategy tester at MT4 platform. The method employed for conducting this testing is referred to as backtesting, which is a feature provided by MLQ4 for evaluating the EAs using past price data. This testing will be conducted on currency pair namely Gold (XAUUSD). The time frames used are M5, M15, H1, and H4. M5 represents a 5-minute time frame, where each bar on the chart represents 5 minutes and M15 stands for 15-minute intervals. While H1 and H4 stand for 1-hour and 4-hour intervals. Testing is carried out on these four different timeframes because they are the most commonly used in trading, especially for traders who prefer profit and trade in a short and long time. Meanwhile, the survey done by [15] on Malaysian traders shows that H1 has higher numbers of trade followed by M5 and M15 timeframe which have the same numbers and second highest of traders chosen in their trading, and H4 at fourth place. The process of backtesting is executed by utilizing the tools available within Metatrader's Strategy Tester. The testing is conducted within 5 years from 2019 to the current 2023 year, from 1 Jan 2023 to 30 Nov 2023. The initial capital used in this testing is USD 1000, USD 0.05 started entry, 4 pips for take profit, and 2 pips for stop loss. The full description of the data used for testing and the results of the testing of these currency pairs are summarized as shown in Table 1.

Table 1. Profit and drawdown Gold (XAU/USD) using strategy tester from years 2019 till 2023.

Timeframe	Years	LWMA & Stochastic Net Profit (%)	LWMA & Stochastic Drawdown (%)
M5	2019	29.06%	8.27%
	2020	232.19%	1.88%
	2021	131.93%	1.61%
	2022	163.72%	0.78%
	2023	122.20%	1.95%
M15	2019	20.07%	3.30%
	2020	92.49%	1.60%
	2021	45.38%	1.66%
	2022	44.65%	1.38%
	2023	47.53%	1.61%
H1	2019	10.99%	2.10%
	2020	24.94%	1.29%
	2021	13.47%	1.28%
	2022	10.57%	1.65%
	2023	9.83%	1.62%
H4	2019	3.38%	1.10%
	2020	7.62%	0.50%
	2021	3.69%	0.63%
	2022	3.04%	0.84%
	2023	7.91%	0.52%

The results show the performance of EAs using a combination of LWMA and stochastic indicators across four different timeframes (M5, M15, H1, and H4) from 2019-2023. The M5 timeframe produced the highest net profit percentages rather than other timeframes, ranging from 29.06% in 2019 to 122.20% in 2023. Even produces higher profit, it also comes with the lowest maximum drawdowns as low as below 10% of potential risk to loss. The H4 timeframe had the lowest drawdowns, with a maximum of only 1.1% in 2019. This timeframe also produced much lower profits only 3.38% to 7.91% (2019-2023) but yet still produced profit. Specifically looking at the performance on the M5 timeframe, we see the EAs were able to capitalize on short-term price fluctuations to generate triple-digit and over 100% percentage profit returns for 4 years which is 2020 (232.19%), 2021(131.93%), 2022 (163.72%) and 2023 (122.20%). However, short-term trading is inherently risky, as evidenced by the over 8% drawdown seen in 2019.

The expert advisor aggressively trades on the 5-minute chart, which can produce outsized returns but also low losses when trends rapidly reverse. These results demonstrate the development of an expert advisor that uses technical indicators to produce consistent profits each year, meeting the goal of higher and more stable returns. The best balance appears to be the H1 timeframe which maintained profits of 9.83% to 24.94% with maximum drawdowns of only 1.28% to 2.10%. Minimizing risk is also evident in the low drawdown percentages across all timeframes, especially on higher timeframes like H4. The more moderate results on the H1 and H4 timeframes demonstrate how utilizing higher timeframes can reduce risks and smooth out returns. The hourly chart provides a balance where there is still an opportunity to capture reasonable gains in the 10-25% range yearly while limiting drawdowns to below 2%. The H4 takes an even more conservative approach, yielding single-digit returns but only 0.5-1.1% max drawdowns showing the preservations of capital. The use of timeframes from M5 to H4 allows fine-tuning of the advisor's risk profile. The expert advisor succeeds in combining indicators for profitable trading while controlling risk through the conservative use of higher timeframes. Further optimization could focus on tweaking parameters to smooth returns and drawdowns. Overall, these results validate the strategy of using a double indicator approach to develop an expert advisor with consistent, low-risk performance.

4. Conclusion

The results of the reverse test highlight the promising performance of the newly developed Expert Advisors (EAs) using a combination of linear weighted average moving averages (LWMAs) and stochastic indicators for algorithmic trading (AT). The system, which proves continuous profitability year by year, effectively contains maximum draws to levels below 10% and affirms the efficiency of its technical approach. The advisor's adaptability to various market conditions and its ability to trade at relatively low volatility are notable strengths. Although it is acknowledged that real-world trading may pose additional challenges, the findings suggest a positive potential for the strategy. The research introduces a new approach to automated financial transactions, incorporating a genetic algorithm that learns machine learning to optimize indicator parameters. Through extensive historical testing with Gold (XAU/USD) currency pairs over several timescales, the study emphasizes the adaptability and balanced performance of the system, especially on an hourly scale. The focus on both profitability and risk management provides valuable insights for algorithmic traders, making the study beneficial to investors, retail traders and academics engaged in algorithmic trading research.

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