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Empirical Study: Finding an Optimal Parameters in Collaboration with GridSearch and Windowing Trading Technique in FOREX

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Abstract: In the realm of finance, FOREX, also known as foreign exchange, is the act of exchanging currencies without the need for physical representation. The buying and selling of currencies are believed to provide benefits for certain individuals. Thanks to advanced technology and abundant data, people are attempting to develop various applications to predict the fluctuation of one currency against another in order to gain profits. In this study, the author employs a basic technical analysis approach, such as Average True Range (ATR) as to define stop loss level, and utilizes the sliding window technique, where certain parameters are modelled using Multiple Linear Regression (MLR) with related hyperparameters are estimated through GridSearch tuning, to minimize MSE. The aim of this research is to achieve a relatively high winning rate while considering the potential risks that traders may encounter.

Keywords: *Average True Rage, Forex, GridSearch, Hyperparameter Tuning, Sliding Window Technique*

1. Introduction

The current advancement in technology has opened up opportunities for everyone to engage in investing. Forex is one investment instrument that exhibits high volatility and risks, but also offers high returns, such as EUR/GBP, JPY/USD, GBP/USD, XAU/USD (for gold), and others. This has prompted many individuals to start trading foreign currencies through online platforms. The buying and selling process cannot be done directly but requires the services of an intermediary company (broker) or a bank. Brokers provide additional application facilities like MT4 and/or MT5 to enable traders to execute forex transactions. When engaging in forex trading, the exchange rate between one currency and another is influenced by various factors, such as the economic condition of a country, politics, society, global situations, and more, which can be projected into clear timeframe-based charts, whether in minutes, hours, days, weeks, or months.

Thanks to technological advancements and the availability of abundant data, people are attempting to develop various applications using Artificial Intelligence (AI) approaches to predict the rise and fall of currency pairs [6, 7, 8]. Apart from AI approaches, for the general public without an IT background, technical indicators are commonly used for forecasting [9, 10, 11]. Commonly used technical indicators include Moving Average, MACD, Relative Strength Index, Parabolic SAR, Bollinger Bands, Stochastic Oscillator, and others. These technical indicators essentially perform complex mathematical calculations to determine the upward or downward movement of a currency [15]. These technical indicators are already embedded in software like MT4, MT5, and TradingView, as features of the respective applications. By utilizing AI or technical indicators, individuals can create trading robots that automate currency trading transactions and potentially generate substantial returns.

Although the convenience offered by trading robots is appealing, it should be noted that trading robots have their own winning rate probability. The lack of knowledge about the winning rate probability of a trading robot can lead to significant losses if the probability is low, and this often occurs [14]. Through an empirical approach, the author proposes a new technique to achieve a relatively high winning rate by utilizing the windowing technique. This technique essentially uses the basic technical indicator such as ATR (Average True Range) and sliding window with a predefined range, which is then analyzed to identify the highest and lowest points of a currency's price within a window. These points are then used as references to determine whether the robot should initiate a buy or sell action and where the stop loss is located. There are several parameters that should be adjusted to achieve a high winning rate. Some of these parameters include the window distance (in the form of the number of candles), risk-to-reward ratio, ATR multiplier, and consecutive loss. To find the optimal configuration for these parameters, the author utilizes Multiple Linear Regression and the GridSearch tuning technique, to minimize MSE.

2. Related Work

Several studies have been conducted by numerous researchers to predict the fluctuations of foreign exchange

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rates and stock markets, employing both machine learning approaches and technical analysis. In this study [1], the research paper aims to compare the performance of hybrid soft computing and hard computing techniques in predicting average monthly forex rates one month in advance. The soft computing models utilized include a neural network trained with the scaled conjugate gradient algorithm and a neuro-fuzzy model employing a Takagi-Sugeno fuzzy inference system. Additionally, Multivariate Adaptive Regression Splines (MARS), Classification and Regression Trees (CART), and a hybrid CART-MARS technique were also considered. The findings indicate that the proposed hybrid models outperformed all individual techniques in accurately predicting forex rates. Empirical results also demonstrate that the hybrid hard computing approach exhibited improvements compared to our previous work involving the neuro-fuzzy approach. Research done by this author [1] investigated the feasibility of utilizing deep learning techniques for predicting exchange rates. The study conducted a systematic comparison between long short-term memory (LSTM) networks, gated recurrent units (GRUs), traditional recurrent network architectures, and feedforward networks. The evaluation focuses on the accuracy of directional forecasting and the profitability of trading model predictions. The empirical findings suggest that deep networks show promise in exchange rate forecasting, although the author also highlighted the challenges associated with implementing and fine-tuning these complex architectures. Interestingly, when considering trading profitability, a simpler neural network may perform equally well or even outperform a more intricate deep neural network.

The efficacy of utilizing Twitter posts for stock price prediction is shown in this research [2]. Initially, various models were trained on the Sentiment 140 Twitter dataset. Support Vector Machines (SVM) emerged as the top performer, achieving an accuracy of 0.83 in sentiment analysis. Consequently, SVM was employed to forecast the average sentiment of daily tweets during market hours. Subsequently, the sentimental analysis was conducted on one year's worth of tweets containing keywords such as "stock market," "stocktwits," and "AAPL" to predict the corresponding stock prices of Apple Inc. (AAPL) and the Dow Jones Industrial Average (DJIA). The two models, Boosted Regression Trees and Multilayer Perceptron Neural Networks were employed to forecast the closing price difference for AAPL and DJIA. The findings illustrate that neural networks outperform conventional models significantly in the prediction of stock prices.

Meanwhile, predicting stock reversal by employing fundamental and technical analysis is performed in this work [3]. The study explored the significance of news information and time series descriptors derived from technical analysis in predicting trend reversals in the coming days. It assesses the performance of various classification models trained on four different sets of data: technical indicators indicating short-term overbought or oversold conditions, news sentiment descriptors reflecting the financial community's opinion, historical time series highlighting recurring price trends, and a combination of the aforementioned factors. The findings, based on an 11-year dataset of U.S. S&P 500 stocks, demonstrate that strategies incorporating historical news sentiment values and stock price indicators generally outperform other tested combinations. As a result, news information proves valuable in trend reversal strategies and should be taken into account.

The work [4] presents a novel hybrid approach for predicting intra-day stock prices by integrating time-series analysis and sentiment analysis. Specifically, it focuses on leveraging the long short-term memory (LSTM) architecture for analyzing the time-series patterns of stock prices, and the Valence Aware Dictionary and sEntiment Reasoner (VADER) for sentiment analysis. LSTM is an advanced type of recurrent neural network (RNN) architecture that effectively captures patterns in sequential time-series data, particularly in cases where the data spans long sequences, while mitigating the issue of gradient vanishing commonly encountered in traditional RNNs. On the other hand, VADER is a sentiment analysis tool designed to analyze sentiments expressed in social media and news articles using lexicons and predefined rules. The study combines the results from both techniques to forecast intra-day stock movements, resulting in the development of the LSTM-VADER model, which represents a novel fusion of LSTM and VADER for stock price prediction. The dataset utilized in this study comprises closing prices of stocks and recent news articles collected from diverse online sources. When applied to stock prices of companies listed on the Bombay Stock Exchange (BSE), this approach demonstrates noticeable improvements compared to previous research endeavors.

This study of [5] presents an advanced approach to model and predict volatility using high-frequency data. It introduces a forecasting model based on Realized GARCH, which incorporates multiple time-frequency decomposed realized volatility measures. The inclusion of various timescales enables a closer approximation of traders' behavior at different investment horizons. Additionally, the proposed methodology incorporates the impact of jumps by utilizing a recently proposed jump wavelet two-scale realized volatility estimator. The authors propose realized Jump-GARCH models estimated in two versions using maximum likelihood and an observation-driven estimation framework of generalized autoregressive score. To evaluate the forecasting performance, the authors compare the results using several popular realized volatility measures on data related to foreign exchange rate futures, specifically focusing on the period encompassing the recent financial crisis. The findings highlight the significance of distinguishing jump variation from integrated variation in achieving accurate volatility forecasts. Moreover, the multiscale decomposition of volatility provides valuable insights into the underlying process. It shows that the high-frequency component of the spectra, representing very short investment horizons, contains most of the information for predicting future volatility. Importantly, the newly proposed models exhibit superior statistical performance compared to both popular and conventional models, demonstrating their effectiveness in both one-day and multi-period-ahead forecasting scenarios.

International enterprises commonly utilize the Forex exchange market to facilitate their business operations. Nevertheless, investment carries inherent risks, necessitating accurate Forex information for informed decision-making. The simple moving average (SMA) technique is a widely employed and well-established method for time series forecasting. The empirical investigation done by the researcher [12] conducted a performance analysis of EUR/USD Forex rates by incorporating the simple moving average technique along with key financial factors such as the Dollar Index (DX), US Interest Rate (federal funds rate), Inflation Rate (IR), and real Gross Domestic Product (GDP). Four distinct Forex datasets are utilized, namely Forex, Forex with factors, Forex with SMA, and Forex with factors and SMA, in order to forecast Forex rates. Research efforts focus on employing Multilayer Perceptron (MLP) and Linear Regression (LM) models for forecasting EUR/USD Forex rates. The results, evaluated using mean square error (MSE), demonstrate a significant performance improvement when financial factors and the simple moving average are incorporated into the Forex datasets.

The application of two hybrid models for stock market timing based on the technical analysis of Japanese Candlestick patterns using Support Vector Machine (SVM) and heuristic algorithms done by this study [13], namely Imperialist Competition and Genetic Algorithm. In the first model, SVM is combined with the Imperialist Competition Algorithm (ICA) to optimize the SVM parameters for stock market timing. The second model incorporates SVM with the Genetic Algorithm (GA), where GA is used for feature selection and optimization of SVM parameters. Two approaches, namely Raw-based and Signal-based, are devised to generate the input data for the models, drawing from relevant literature. To assess the performance, the Hit Rate is used as a measure, representing the percentage of accurate predictions for time periods ranging from 1 to 6 days. The findings indicate that the SVM-ICA model outperforms the SVM-GA model and even surpasses the standard feed-forward static neural network presented in the literature.

On the other hand, in this research, Multiple Linear Regression (MLR) will be utilized. MLR is employed to model the final data, which is the outcome of testing the raw data (obtained through TradingView) using predefined parameters. Generally, MLR can be defined as follows:

$$y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n \tag{1}$$

Here, y is the target variable to be predicted, b_0 is the intercept (constant value), b_1, b_2, ..., b_n are the regression coefficients that depict the relationship between each independent variable (x_1, x_2, ..., x_n) and the target variable, and x_1, x_2, ..., x_n are the independent variables. Technically, while implementing this function, it requires some hyperparameters, such as intercept and whether the coefficients are forced to be positive number. To achieve a better model, the author employs GridSearch technique to minimize Mean Square Error (MSE). Meanwhile, to determine the appropriate level for placing the stop loss, the author utilizes the Average True Range (ATR). Generally, the ATR formula can be expressed as follows:

- Calculate the True Range (TR) for each period:

$$TR = Max[(HP - LP), |HP - CPP|, |LP - CPP|] \tag{2}$$

TR represents the difference between the highest price (HP) and lowest price (LP) values within a given period, and CPP is the closing previous price.

- Compute the ATR using a moving average:

$$ATR = SMA(TR, n) \tag{3}$$

ATR represents the average value of the True Range over n periods, calculated using the Simple Moving Average (SMA) method. Due to the requirement of a specific period length for utilizing ATR and considering that some initial candles may not have ATR values, the author initiates a default ATR value of 20. This value can be modified as desired. The SMA can be defined as follows:

$$SMA = (PP_1 + PP_2 + \cdots + PP_n)/n \tag{4}$$

In the formula PP_1 refers to the closing price in first period, PP_2 is the second, and PP_n is the n-th period. SMA is used to smooth out price data and form a trend line. It helps in identifying the overall direction of price movement over a specific time period. Shorter SMAs (with fewer periods) are more responsive to recent price changes, while longer SMAs (with more periods) are slower to react to price changes.

In practice, ATR cannot be directly used as is; there needs to be a multiplication factor to ensure that the distance between the opening price and the stop loss is not too close. In this study, the following formula is employed:

$$SL_b = (CP - (ATR\_MLP \times ATR)) \tag{5}$$

SL_b refers to stop loss for buying position, CP is the previous closing price, and ATR_MLP is an ATR multiplier factor. On the other hand, for selling position can be defined as:

$$SL_s = (CP + (ATR\_MLP \times ATR)) \tag{6}$$

SL_s is stop loss for selling position. As for taking profit level (TP) can be expressed as follows:

$$TP_b = \left(OP - \left(\frac{RW_{MLP} \times MP}{R_{MLP}}\right)\right) \tag{7}$$

Where TP_b is taking profit level (price) for buying position, OP is opening price (or closing previous price), RW_{MLP} and R_{MLP} are reward and risk multiplier factors, respectively.

$$TP_s = \left(OP + \left(\frac{RW_{MLP} \times MP}{R_{MLP}}\right)\right) \tag{8}$$

TP_s refers to taking profit for selling position.

3. Methodology

This research was conducted using an empirical approach, utilizing a dataset obtained for XAU/USD trading on the daily timeframe. It is also applicable to foreign currency trading and stocks. For a more detailed explanation of the underlying process, it will be elaborated in several sub-sections.

3.1. Proposed Workflow Model

The process involves reading data within a specific window range, extracting the highest and lowest prices within that range, and evaluating them using other parameters. The sliding window on the daily timeframe then continues, and the search for highest and lowest prices is repeated until the latest data is reached.

The evaluation results are recorded and sorted based on promising accuracy levels, while considering several aspects that traders need to consider, such as risk-to-reward ratio, consecutive losses, and others (Fig. 1).

Fig. 1. Proposed Workflow Model

3.2. Defining Parameters

To obtain the winning percentage, several parameters that need to be considered are the window length, risk, reward, ATR multiplier, and consecutive loss. As previously explained, window length is used to determine the lowest and/or highest prices within a price range, which consists of multiple candles. If the length of window range is too narrow, it is highly likely to result in local minima or maxima on a price chart (Fig. 2).

Fig. 2. Window too short, implies skipping profits.

Once the highest/lowest prices are determined, the long or short position can be opened. After identifying the entry price for a long/short position, it is crucial to determine the placement of the stop loss. This is related to the acceptable risk level for a trader compared to the potential profit. For example, a position is established with a Risk: Reward ratio of 2:1, which means the trader accepts twice the risk to achieve a single unit of profit. Setting a larger risk does not guarantee a higher winning percentage, and vice versa. Although trend reversals often require a wider stop loss range (higher risk), it eventually leads to profitable outcomes. A commonly used technique is utilizing the Average True Range (ATR), which provides an estimate of the average price range movement over a specific period. With this price range, a trader can place their stop loss in a measured manner. On the one hand, setting a high reward ratio does not necessarily result in high net profit, as it trades-off with potential losses that may lead to a negative net profit. Similarly, consecutive losses primarily affect a trader's mindset. Successive losses can disrupt a trader's strategy as it frequently prompts intervention in already opened positions, contradicting the pre-designed strategy. A high number of consecutive losses does not indicate a negative net profit, and vice versa. However, it mainly pertains to a trader's psychology and their readiness to accept predetermined consecutive losses. Hence, all the aforementioned parameters need to be carefully set, which involves data modeling of winning rates (explained in phase 3.4). The initial configuration for each parameter is presented in Table 1 below, and these values can be modified as needed.

Table 1. Initial Configuration Parameters

Window Length	*Risk*	*Reward*	*ATR Multiplier*
[5, 10, 12, 15, 20]	[1, 2]	[1, 2, 3, 4, 5]	[1, 2, 3, 4]

The dataset used for this research consists of XAU/USD trading data across various timeframes, including 15 minutes, 30 minutes, 1 hour, and daily timeframes, sourced from the TradingView website. However, it is not limited to foreign currency trading and includes stocks and futures. It is important to note that each timeframe has its own specific time range, which is due to the limitations of accessing data through the website.

3.3. Acquiring Data

The raw data obtained from the scraping process through the TradingView website cannot be directly used for this research. This study requires data in the form of parameter values such as window length, risk, reward, ATR multiplier, consecutive loss, and winning rates (which have been defined in the previous process, except for **consecutive loss** and **winning rates**), as well as information such as closing price, low price, and high price within a specific time range (data from the TradingView website). Each parameter will be mapped individually and tested with raw data to obtain the consecutive losses and winning rates. In this testing, XAUUSD trading data on the daily timeframe is used, but it is not limited to other trades and different timeframes. Below are some examples of the processed data, as shown in Table 2.

Table 2. Data sample (WL: window length, AM: ATR multiplier, CL: consecutive loss, WR: winning rates)

WL	*Risk*	*Reward*	*AM*	*CL*	*WR*
5	1	1	1	6	0.7231
5	1	1	2	7	0.6441
…	…	…	…	…	…
10	2	1	2	3	0.8702
10	2	3	4	11	0.5465
…	…	…	…	…	…
20	1	2	3	12	0.5794

The highest/lowest point of a candle within a range is essentially used to determine buy/sell positions. However, in its determination, the author compares it with the price of the candle in the previous range (if any). If the highest-lowest price in the current range is greater/smaller and no similar position is opened, then the highest/lowest price will be updated, and this will serve as a reference for taking a buy or sell position. The general overview of the data acquisition phase can be seen in Fig. 3, and the details of the logic occurring within the 'Test Raw Data' can be observed in Fig. 4.

Fig. 3. Grand design from defining parameters to testing raw data.

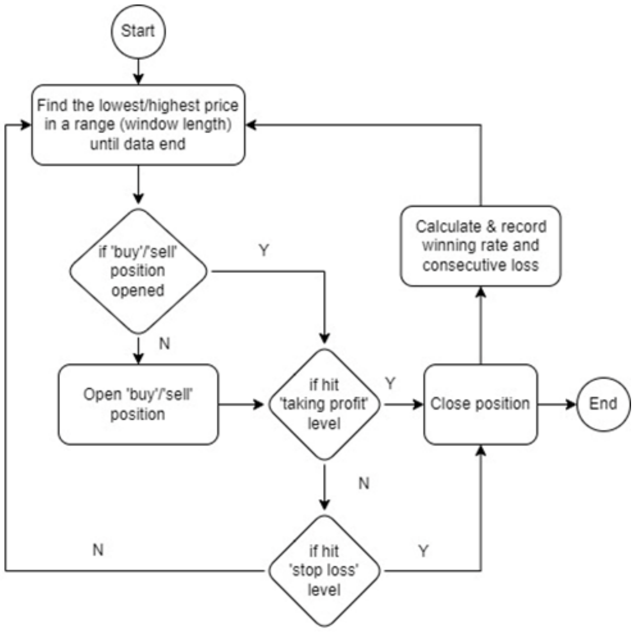

Fig. 4. Details logic for testing raw data

3.4. Modeling Data and Hyperparameter Tuning

After completing the data acquisition phase, the next step is to model the data using the MLR approach. In this case, we utilize the MSE as the objective function to measure the prediction error of the MLR model. Our goal is to find the optimal values for the independent variables (x) that yield the minimum MSE. The author uses LinearRegression library, available on scikit-learn, and it has two hyperparameters that need to be determined, such as 'intercept' and 'positive'. The intercept hyperparameter is used to determine whether the model will include an intercept term. By default, if set to True, the model will consider the intercept in its calculations. If set to False, the model will not have an intercept, and the regression line will pass through the point (0, 0). On the other hand, the 'positive' hyperparameter determines whether the coefficients are forced to be negative or not. To tune the hyperparameters of the MLR, the author employs GridSearch on the dataset obtained from step (3.3). The outcome of this step is a model with the minimum MSE, which serves as a reference for evaluation purposes in step (3.5). From January 7th, 1833, to February 22nd, 2023, using a daily timeframe, the data has been effectively modeled. The objective function derived from this data can be defined as follows:

$$y = 0.648 + 0.007x_0 + 0.147x_1 - 0.085x_2 - 0.041x_3 - 0.003x_4 \quad (9)$$

Where y is (predicted) or expected accuracy, and $x_0, x_1, \dots, x_4$ are independent variables (window length, risk, reward, ATR multiplier factor, and consecutive loss).

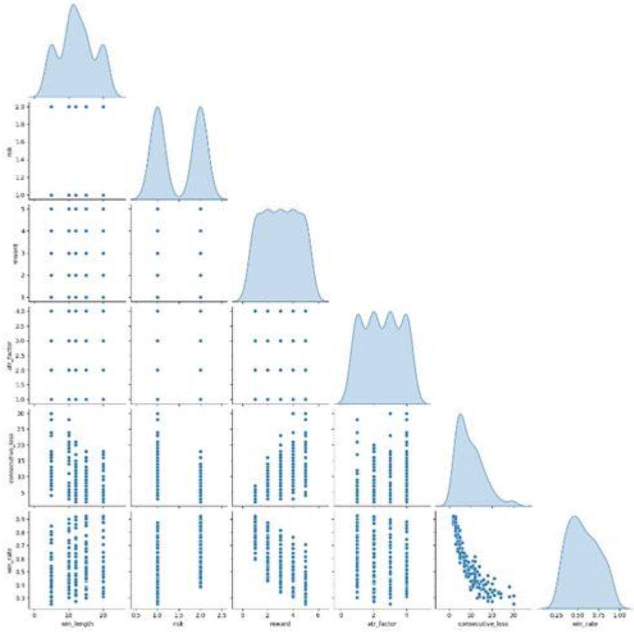

Fig. 5. The relationship between variables in the dataset

3.5. Evaluation

The results obtained from step (3.2) can actually be used directly, allowing a trader to search for configurations that yield high winning rates. However, not all traders can accept high-risk settings and significant consecutive losses. As a comparison, this can be seen in Table 2 below. Therefore, an evaluation is needed to determine the number of configurations acceptable to a trader in order to achieve the desired accuracy. For example, if a trader desires an accuracy of 0.8 with minimal risk, using the predefined linear function (9) above, the trader can determine the necessary values for profit, window length, and/or consecutive loss. These will serve as the reference configurations during trading. For example, using (9), and with parameters window length 20, risk and reward ratio 1:2, ATR multiplier factor 2, and acceptable consecutive losses equal to 5, then the expected accuracy will be **0.613**. Similarly, a trader can determine the desired accuracy and utilize (9) to calculate the values of each required parameter to achieve the desired accuracy.

4. Discussion and Results

By utilizing test data from February 23, 2023, to June 26, 2023, on a daily timeframe, and employing the predefined configuration in step (3.5), an accuracy of 0.6667 and a consecutive loss of only 1 were obtained. The following are the transaction details for the testing data:

Table 3. Performing experiment using data

Position	OP	SL	TP	Status
Buy	1826.67	1786.67	1906.67	OK
Sell	1978.97	2039.03	1858.86	NOT OK
Buy	1956.45	1891.16	2087.02	RUNNING
Sell	2050.31	2110.96	1928.99	OK
Sell	1957.55	2007.34	1857.97	RUNNING

Fig. 6. Illustrating the trading positions of XAUUSD, where the green upward arrow represents the opening position for a buy trade, the orange downward arrow represents the opening position for a sell trade, the black star and the blue dot signify taking profit for the buy and sell, respectively.

5. Conclusion

Based on the above experimental results, it can be concluded that the proposed approach can be used as a reference for trading XAUUSD on the daily timeframe. For forex trading such as AUDUSD, JPYUSD, GBPUSD, and others, further simulations need to be conducted to obtain an optimal and acceptable configuration for traders. This research can be improved in the future by incorporating additional technical indicators and/or combining fundamental analysis, especially in the case of stock trading, such as PBV, P/E, EBT, NPM, and other financial attributes.

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Author contributions

Notarista Magdalena Silaban: Conceptualization, Methodology, Software, Data curation, Writing-Original draft preparation, Software, Validation, Visualization, Investigation, Writing-Reviewing and Editing. **Drs. Tuga Mauritsius, M.Si, Ph.D :** offering insights into the theoretical framework, supervised the data collection and analysis, ensuring the integrity and accuracy of the findings, and provided critical feedback.

Conflicts of interest

The authors declare no conflicts of interest.

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