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Dynamic portfolio rebalancing with lag-optimised trading indicators using SeroFAM and genetic algorithms

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ABSTRACT

Some common technical indicators, such as moving average convergence divergence (MACD), relative strength index (RSI), and MACD histogram (MACDH) are used in technical analyses and stock trading. However, some of them are lagging indicators, affecting the effectiveness in the stock trading and portfolio management. A forecasted MACDH (fMACDH) indicator for predicting next day price by a neuro-fuzzy network, Self-reorganizing Fuzzy Associative Machine (SeroFAM) which has been reported in the prior research work. In order to further reduce the lagging effect, two trading indicators are proposed in this paper: the optimised fMACDH indicator and the fMACDH-fRSI indicator. The optimised fMACDH indicator is derived to extend price forecasting to 1–5 days ahead as the prediction depth, using 1–5 days of historical price data as the input depth. The fMACDH-fRSI indicator is derived by combining the optimized fMACDH indicator and the forecasted RSI (fRSI) indicator. A genetic algorithm (GA) and the fitness functions are designed with the SeroFAM in this paper, which are utilised for optimising parameters of these two proposed indicators. Experiments have been conducted to evaluate and benchmark of the proposed trading indicators optimised by the GA. Two rule-based portfolio rebalancing algorithms are then proposed using the optimised fMACDH trading indicator tuned by the GA: the Tactical Buy and Hold (TBH) and the Rule-Based Business Cycle (RBBC) portfolio rebalancing algorithms. The TBH algorithm takes advantage of relative differences in risk levels to perform rebalancing during trend reversals. The RBBC portfolio rebalancing algorithm takes advantage of the offsets between the business cycles of different market sectors. Experiments have been conducted to evaluate the performance of both algorithms using two sets of portfolios consisting of different assets. The TBH portfolio rebalancing algorithm outperforms the equally weighted portfolio strategy by about 26 % – 27 %; as well outperforms the Buy and Hold strategy by 5 % – 40 %. The RBBC portfolio rebalancing algorithm outperforms the equally weighted portfolio strategy by 54 % – 55 %; it also outperforms 12 out of the 13 assets with the Buy and Hold strategy, by an average performance of about 166 %. The results are highly encouraging with consistent performances achieved in dynamic portfolio rebalancing.

1. Introduction

1.1. Technical indicators and portfolio management

Financial markets are the venue for trading securities in the form of bonds or equities. Bonds are loans made by an investor to a borrower with agreed interest rates and due dates. The investor can receive corresponding interest payments as investment returns, besides the principal of the loans. Equities commonly known as stocks are issued by corporations in financial markets to raise capital for funding their business (Hayes, 2021). Units of stock are represented by shares that are purchased by investors aiming profit making through dividends or capital gains.

Research interest in global financial market trading has been increased rapidly in recent years. With the rise of new trading platforms such as Robinhood, there has been greater access to the financial market nowadays. Many signs point to the rising influence of retail investors in financial markets, who make increasingly higher trading volumes compared to past years. Volatile changes in equities prices mean that equities trading comes with risks. Investing in equities can be extremely

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volatile. Usually, investors would choose to take on a certain level of risks if potential returns could match with the corresponding risks. It implies that the higher the risk, the higher the potential returns, which also implies higher potential losses for wrong investment decisions. Poor investment choices in high risk financial instruments such as stock options can lead to a total loss of initial principals. This has been exacerbated by the easy availability of leverage offered by some securities brokers. Some investors may suffer heavy financial losses if they fail at trading in the stock markets. Hence, there is a need for proper trading risk management.

Market risks and investor risks are main types of risks. Market risks are affected by market-wide factors from industrial level to international level that include the equity risk, interest rate risk, commodity risk and currency risk (Bandt & Hartmann, 2000; Ross, Westerfield, & Jordan, 2016). Investor risks are caused by human factor with erratic or irrational investment decisions made by investors (Barber & Odean, 2000). Camanho, Hau, and Rey (2022) study the global portfolio rebalancing behavior correlate to the investor risk aversion and exchange rate risk. These risks and potential returns may cause investors to change compositions of portfolios accordingly.

A typical retail investor would not have funds to invest in more than a handful of equities at a time. To gain a wider exposure to financial markets, several derivatives in the stock markets can be also considered for portfolio constructions, such as market index and Exchange-Traded Fund (ETF). A market index is a hypothetical portfolio of equities representing a financial market segment (Young, 2020). For example, the S&P 500 index measures performances of 500 large companies listed in the United States. Market indexes are typically a good gauge of the performance of the market. Various index funds are offered that aim to track the performance of the indexes. ETF is a portfolio that tracks a collection of assets, market indexes, or sectors, etc. ETF can be traded in financial markets like regular equities that offers investors access to a wide range of assets (Domash, 2011).

Modern portfolio theory is introduced to maximise returns within a period when minimising market risks through diversifications of investments in the portfolio management (Almahdi & Yang, 2017; Lekovic, 2018). It maintains a selectively diverse group of different securities with little correlations, to ensure good diversification in a portfolio. But good portfolio diversifications are usually not easily achievable by individual investor due to various factors, such as limited investment capitals compared to corporate investors or Asset Management Firms (AMFs) (Statman, 1987). Although AMFs usually have different portfolio management strategies, it may not achieve consistent performance in financial markets. Hence, there is a need for improved techniques on portfolio managements.

Technical analyses are commonly performed by AMFs and investors, which aim to predict future market or price trends with historical market data or trading information by technical indicators (Hoseinzade & Haratizadeh, 2019; Khan & Mehlawat, 2022). Market trends are the tendency of financial markets moving to certain direction within particular timeframes, that can affect investment behaviours (Alhnaity & Abbod, 2020; Fontanills & Gentile, 2001; Ngoc, 2014). There are three types of market trends in certain period of time: bullish market with asset prices expecting to rise; bearish market with asset prices expecting to fall; stagnant market with little to no growth in asset prices (Tsinaslanidis, 2018). Market trends are utilized for portfolio management by riding on bullish trends to capture more profits, and minimizing losses during bearish trends (Hurst, Ooi, & Pedersen, 2017).

There are various methods reported for market trend detections using technical analyses in financial trading, such as neuro-fuzzy systems (Chen, Rajan, & Quek, 2020; Tan & Quek, 2010), genetic algorithms (GA) (Aguilar-Rivera, Valenzuela-Rendon, & Rodriguez-Ortiz, 2015; Kaucic, 2010), machine learning (Padhi, Padhy, Bhoi, Shafi, & Yesuf, 2022), deep learning (Li & Bastos, 2020; Ozbayoglu, Gudelek, & Sezer, 2020; Troiano, Villa, & Loia, 2018), reinforcement learning (RL) (Pendharkar & Cusatis, 2018), and hybrid of few models (Alhnaity & Abbod, 2020). Some common technical indicators used in technical analysis include simple moving average (SMA), exponential moving average (EMA), relative strength index (RSI), and moving average convergence divergence (MACD) (Gunduz, Yaslan, & Cataltepe, 2017; Liu & Wang, 2019; Patel, Shah, Thakkar, & Kotecha, 2015). Agrawal, Khan, and Shukla (2019) introduce their research using the SMA for technical analysis with a long short-term memory (LSTM) deep learning method for prediction of stock market trends. A portfolio optimization model for trading gold and Bitcoin is reported using a LSTM model and an SMA-slope investment strategy to measure their daily price movements (Xue, Ling, & Tian, 2022). The asset re-allocations are conducted based on risk taking attitudes of investors and several technical indicators, such as moving average, Stochastics oscillator, etc. (Khan & Mehlawat, 2022). A support vector machine (SVM) recursive feature elimination method is presented to predict one-day ahead movement using RSI and two other technical indicators (Weng, Ahmed, & Megahed, 2017). Stock price trend is predicted by an optimised MCAD technical indicator, with considering historical volatility index and better accuracy achieved (Wang & Kim, 2018). Trading decisions in financial markets are predicted by means of LSTM and using technical indicators MCAD and moving average crossover (Troiano et al., 2018). An interval type-2 fuzzy logic system is presented for financial portfolio investment using two technical indicators, EMA and MACD, by comparing with the Buy and Hold strategy of stock market indexes of SP500, TOPIX, DAX, and FTSE100 (Takahashi & Takahashi, 2021). A LSTM model is trained to determine if profits or losses are predicted at a specific time with three technical indicators: SMA, RSI, and MCAD (Sang & Pierro, 2019). A SVM is used for technical analysis of Candlestick with GA and Imperialist Competition Algorithm optimising its parameters (Ahmadi et al., 2018). A set of the technical indicators are tuned with GA, such as the variable length moving average (VMA) derived from SMA, rate of change (ROC), dynamic support/resistance (dS&R), stochastic indicator, etc. (Kaucic, 2010).

Some technical indicators are considered as lagging indicators as historical price data are used in their computations, such as SMA, EMA, and MACD, etc. Trading decisions made using these indicators will lead to lagging behind actual price signals. MACD histogram (MACDH) is another lagging technical indicator that can be derived from MACD as a second-order trading signal of price actions (Fazeli & Houghten, 2019). MACD and MACDH can be used to determine trend reversals in stock analysis based on historical data (Tan, Zhou, & Quek, 2015). Tan and Quek report a self-reorganizing neuro-fuzzy network with online-reasoning capabilities, named Self-reorganizing Fuzzy Associative Machine (SeroFAM) (Tan & Quek, 2010), that is able to follow trajectory shifts in time-variant data streams such as stock prices. To decrease the lagging tendencies of current technical indicators, a forecasted MACDH (fMACDH) indicator is reported in the previous work for predicting next day price by the SeroFAM system (Tan et al., 2015).

1.2. Main contributions of this research

To further reduce the lagging tendencies of the fMACDH indicator in (Tan et al., 2015), two trading indicators are proposed and investigated in this paper: an optimised fMACDH indicator and a fMACDH-fRSI indicator.

The optimised fMACDH indicator is derived through exploring the forecasted price data by the SeroFAM neuro-fuzzy system for different input depth and prediction depth. The input depth refers to number of k days of historical price data from the current trading day as inputs, where $1 \leq k \leq 5$. The prediction depth refers to number of k days ahead to forecast price data from the current trading day. Several variables are identified to be optimal parameters tuned by the GA for the optimized fMACDH indicator, including the input depth, prediction depth, threshold values, EMA long period, short period and signal period, etc.

The proposed fMACDH-fRSI trading indicator is derived by the values combining both the optimized fMACDH indicator and the forecasted RSI (fRSI) indicator. It aims to synergise these two different approaches together, with hoping to benefit from their advanced features in prediction accuracy and investment gains. The parameters of the proposed fMACDH-fRSI trading indicator are optimised by the GA as well.

The GA and its fitness functions are designed specifically which will be presented in Section 3, for the parameter optimization for these two proposed trading signals. Experiments have been conducted for both proposed trading indicators by a portfolio with seven market index assets. Their performances will be evaluated and investigated.

This paper aims to improve the performances of portfolio management using the optimised fMACDH indicator, GA and the SeroFAM neuro-fuzzy network. The overall framework developed in this research is shown in Fig. 1. Two rule-based dynamic portfolio rebalancing algorithms are proposed. One is the Tactical Buy and Hold (TBH) algorithm, that is a dynamic opportunistic strategy capitalising on the optimised fMACDH indicator and differences in risk. The other is the Rule-Based Business Cycle (RBBC) portfolio rebalancing algorithm, which is a dynamic strategy capitalising on the difference in market sector performance during different phases of business cycles.

Experiments have been conducted to evaluate the performances of both proposed portfolio rebalancing algorithms on two sets of portfolios consisting of ETF assets. The results will be analysed and discussed in Section 4.

As an overview, there are three main contributions in this paper.

a) Two trading indicators are proposed to further reduce the lag effects: the optimised fMACDH indicator and fMACDH-fRSI trading indicator, whose performances are evaluated and compared through the experiments.
b) The GA and fitness function are designed to tune the parameters of the optimised fMACDH indicator and fMACDH-fRSI trading indicator on the SeroFAM online learning neuro-fuzzy networks. It aims to achieve good performance on trend prediction and buy/sell signals generation for each individual asset in a portfolio.
c) Two dynamic portfolio rebalancing algorithms, i.e., the TBH and RBBC portfolio rebalancing algorithms are proposed using the optimised fMACDH indicator for the portfolio management.

Besides, we also use several methods to ensure an appropriate level of portfolio diversification to optimise the investment returns. We choose to invest in market index assets and ETFs for the portfolios, which allows us to invest in a wide range of securities with just a single asset. These index assets and ETFs have been carefully selected to ensure greater diversification of risks and market sectors.

The remaining parts of this paper are organized as follows. Section 2 introduces the prior works on the SeroFAM system and some commonly used financial technical indicators. Two proposed trading indicators and the designed GA are presented in Section 3, including the experiments to compare performances of the optimised fMACDH indicator and fMACDH-fRSI trading indicator. The proposed dynamic portfolio rebalancing algorithms are depicted in Section 4. Their experiment results are also analysed and compared. Section 5 concludes the findings of this paper and future research directives.

2. Prior works of SeroFAM system and technical indicators

2.1. SeroFAM system

Neuro-Fuzzy systems are hybrid networks by combining the advantages of both neural networks and fuzzy logic into a single system (Souza, 2020; Tung & Quek, 2010). Neural networks consist of large number of artificial neurons connected together that attempt to approximate human brains and imitate the function of neurons. Fuzzy logic performs humanlike reasoning based on imprecisely defined parameters to solve real-world problems. Mamdani model and Takagi-Sugeno-Kang (TSK) model are two main classes of fuzzy logic systems.

The Mamdani model (Mamdani & Assilian, 1975), also known as the fuzzy relational model, deals with rules for fuzzy inputs and fuzzy outputs. Relational links are drawn out from the input space to output space, generating a set of understandable output fuzzy rules. An example of Mamdani fuzzy rules is represented as following:

$$IF\ x\ is\ A \rightarrow THEN\ y\ is\ B \quad (1)$$

The TSK model (Takagi & Sugeno, 1985), also known as the fuzzy precision model, deals with rules in the form of fuzzy inputs and linear outputs. Compared to the Mamdani models, TSK rules are less understandable but tend to have greater precisions. An example of TSK rules is shown as follows:

$$IF\ x\ is\ SLOW \rightarrow THEN\ y = ax + b \quad (2)$$

Reported in the prior works, the SeroFAM system is an online learning neuro-fuzzy system based on the Mamdani model (Tan & Quek, 2010), by exploiting self-correcting nature of the Bienenstock-Cooper-Munro (BCM) theory (Bienenstock, Cooper, & Munro, 1982). The SeroFAM is constructed with five neuronal layers: input sensors layer, input fuzzy nodes layer, fuzzy rule base layer, output fuzzy nodes layer, and output actuators layer. The architecture of the SeroFAM system is shown in Fig. 2, that is adapted from the prior work (Tan & Quek, 2010). Given the number of input features as n, the crisp vector of input sensors layer to the SeroFAM is $X(t) = [x_1, x_2, \ldots, x_i, \ldots x_n]^T$. The number of input membership functions for x_i is P_i. For the number of output features as m, the crisp vector of output actuators is $Y(t) = [y_1, y_2, \ldots, y_j, \ldots y_m]^T$. The number of output membership functions for y_j is Q_j. Each membership

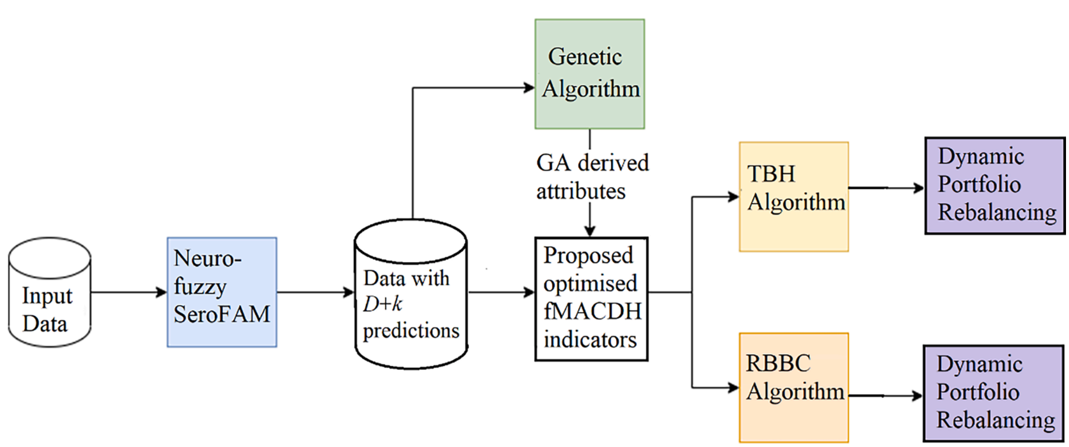

Fig. 1. Proposed Overall Framework.

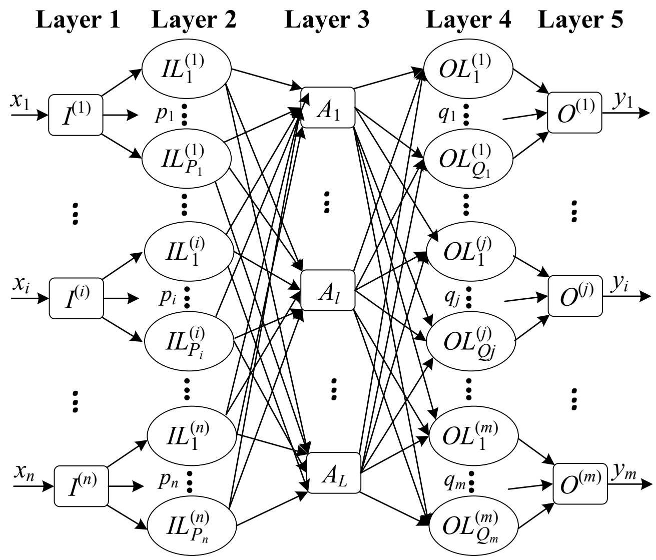

Fig. 2. Architecture of the SeroFAM system.

partition is a gaussian function $\mu(z)$. The predictions at any time t of the SeroFAM are given as the crisp vector $\hat{Y}(t) = [\hat{y}_1, \hat{y}_2, \dots, \hat{y}_j, \dots \hat{y}_m]^T$. Each layer performs operations in tandem to realize the Mamdani fuzzy rule model for fuzzy reasoning (Tan & Quek, 2010), as a rule as shown in Eq. (3).

$$If\left(x_1\ is\ IL^{(1)}_{p_1}\right)..\ \wedge ..\ \left(x_i\ is\ IL^{(i)}_{p_i}\right)..\wedge ..\ \left(x_n\ is\ IL^{(n)}_{p_n}\right)\rightarrow Then\left(y_j\ is\ OL^{(j)}_{q_j}\right) \quad (3)$$

where $IL^{(i)}_{p_i}$ denotes the p_i-th input membership functions within $[1, P_i]$ for input x_i; $OL^{(j)}_{q_j}$ denotes the fuzzy answer space shaped by the output membership partitions ($OL^{(j)}_1, \dots, OL^{(j)}_{Q_j}$) to different degrees.

For the SeroFAM system as a neuro-fuzzy system, each input sensor node in the first layer receives signals from the external environment, and relays to the second layer. In the second layer as input fuzzy nodes, each node $IL^{(i)}_{p_i}$ is derived from the p_i-th fuzzy membership function of the i^{th} input sensor node. The fuzzy rule base in the third layer consists of fuzzy premise nodes and fuzzy rule links, with a data pair $\{X(t), Y(t)\}$ at time t being derived. Each premise node A_l representing the "IF" part of a fuzzy rule uniquely identifies a localized fuzzy subspace in the input space. Next, the rule links articulate the associative mappings between these premise nodes at the third layer and the fuzzy consequent nodes at the fourth layer. Each node $OL^{(j)}_{q_j}$ at the fourth layer, i.e., output fuzzy nodes layer, represents the q_j-th fuzzy membership function for the j^{th} output actuator node in the last layer.

The SeroFAM utilises a single pass learning approach with a self-reorganizing fuzzy clustering method to define membership clusters (Tan & Quek, 2010). It allows unlearning of old rules and learning of new rules over time. After training and testing, the SeroFAM system was reported achieving competitive results compared to a TSK model-based neuro-fuzzy system. It illustrated the capability of the SeroFAM system for closely following price trends of the S&P 500 index.

In this paper, we will take advantages of benefits of the SeroFAM system, that will be employed to predict future price data for the two proposed trading indicators: the optimised fMACDH indicator and the fMACDH-fRSI indicator. Its online learning features make the SeroFAM system intrinsically useful for our desired goal in creating a real time trading system for portfolio managements.

2.2. fMACDH technical indicator

Typically, market trends can be estimated using historical trading data by statistical means in technical analyses. In general, investors tend to buy stock assets by driving share prices up rapidly in bullish markets. While investors tend to sell assets with stock prices being pushed down in bearish markets. As mentioned in Section 1, the lagging technical indicators of price signals inhibit the ability to make correct trading decisions. It affects the potential profits of the portfolio in trading, as stock prices have been risen or fallen before the buy or sell trading actions in the market. To illustrate it, assume that we currently hold 10 shares of a hypothetical stock H with daily price data shown in Fig. 3.

Assume that there is a perfect hypothetical indicator capable of predicting the exact peaks and troughs of the stock prices without any lag. Under the ideal case, all shares would be sold on the 6th and 17th days at peak prices, and bought back on the 11th and 20th days at trough prices. At the end of the 25 days period, the total asset value of Stock H is as shown in Eq. (4), without considering the commission costs.

$$10\ shares\ initially \times \$15 \div \$5 \times \$23 \div \$2 \times \$27 = \$9,315 \quad (4)$$

Assume that there is another hypothetical indicator also capable of perfectly predicting the peaks and troughs of stock prices, but with a 1-day lag. It means that the trading of all shares will be sold 1-day after the peak prices, and bought back 1-day after the trough prices. Under this case, all shares are sold on the 7th and 18th days, and bought back on the 12th and 21st days as shown in Fig. 3. At the end of the same 25 days period, the total asset value of Stock H will be calculated in Eq. (5), without considering the commission costs.

$$10\ shares\ initially \times \$13 \div \$8 \times \$16 \div \$7 \times \$27 \approx \$1,002 \quad (5)$$

In this hypothetical scenario, the perfect indicator without lag outperforms the 1-day lagging indicator by a whopping 900 %. It shows the performance impact caused by the lagging indicator with even only one day lag. Hence, it is important to reduce laggings of technical indicators. In order to better understand the lagging effects, some commonly used technical indicators are described as follows.

2.3. Simple moving average (SMA)

SMA is a technical indicator to filter out noises from price signals and smooth the price signals. Given price signals $y(t)$ measured on Day t, the SMA can be calculated as shown in Eq. (6).

$$SMA = \frac{y(t_c) + y(t_c - 1) + .. + y(t_c - k + 1)}{k} \quad (6)$$

where t_c is denoted the current day and k is denoted the number of past days from the current day. For example, a 9-day SMA (i.e., $k = 9$) on Day 15 includes prices from the 7th day to the 15th day. It is shown that the SMA is derived from these historical data before the current day. As such, it is considered to be lagging the actual price signal. Ideally, a lag-free 9-day real moving average (RMA) value would contain price data

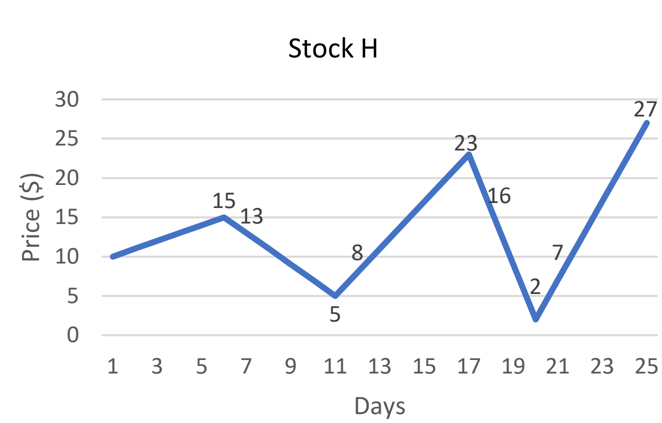

Fig. 3. Daily Prices of the Hypothetical Stock H.

from the past 4 days, the current day t_c, and the future 4 days, that is calculated in Eq. (7).

$$RMA = \frac{y\left(t_c + \frac{k-1}{2}\right) + .. + y(t_c) + .. + y\left(t_c - \frac{k-1}{2}\right)}{k} \quad (7)$$

Compared Eq. (6) and Eq. (7), it means that the SMA has a lag effect of about $\frac{k-1}{2}$ days. For a 9-day period, the lag effect of SMA is about four days.

2.4. Exponential moving average (EMA)

In order to help compensate for the lag effect of the SMA, the EMA is another moving average value to impart a higher weightage ω on recent prices near the current day t_c, shown in Eq. (8).

$$EMA_{t_c} = \omega(y(t_c)) + (1-\omega)EMA_{t_c-1} \quad (8)$$

where the weightage $\omega = \frac{2}{k+1}$. Although the mean lag effect of the EMA is the same as that of the SMA, the median lag effect of the EMA is lower than that of SMA. Generally, the EMA is capable of providing a more responsive indication of price trends and fluctuations.

2.5. Moving average convergence/divergence (MACD)

As a trend following momentum indicator, the MACD is built on the moving average indicators. The MACD investigates the differences between two moving averages of the price signal (Fernando, 2021). Typically, the EMA is used as the moving average indicator. The MACD value is computed by a long-term EMA, i.e., *EMA*(*long*), being subtracted from a short-term EMA, i.e., *EMA*(*short*), shown in Eq. (9), where the period lengths of long-term and short-term are 26 days and 12 days respectively.

$$MACD = EMA(short) - EMA(long) \quad (9)$$

A change in sign of the MACD represents a crossover between long-term and short-term EMA. It indicates the scenario of the short-term value becoming higher than the long-term value, or vice versa. Based on the values of MACD, a period of 9-day EMA of the MACD is computed in Eq. (10), that is called the MACD Signal Line. The crossovers of the MACD above the MACD Signal Line, or the MACD below the MACD Signal Line are the indications of *buy* or *sell* signals, respectively.

$$MACD\ SignalLine = EMA(MACD) \quad (10)$$

2.6. MACD histogram (MACDH)

The MACDH is a derivative of price that is designed to anticipate signals in the MACD. The MACDH can be derived from subtracting the MACD Signal Line from the MACD, as shown in Eq. (11).

$$MACDH = MACD - MACD\ SignalLine \quad (11)$$

Ignoring the lag effects, when the MACDH crosses over the zero axis, the momentum of the stock has peaked and is going to reverse in trend direction. As such, the MACDH can be used as an early indicator to identify trend reversals in price momentum of the underlying security (StockCharts.com, 2022).

However, the MACDH is susceptible to whipsaw effects (Murphy, 1999), where tiny fluctuations at the zero axis would indicate a change in trading signal frequently. It would trigger an excessive level of trading, resulting in higher losses on commission fees and lower return on investment (ROI). It needs to find a way to handle such issue.

2.7. MACDH$_{\%}$

In order to address the issue of tiny fluctuations near the zero axis, a notation MACDH$_{\%}$ is computed, as a variant of percentage price oscillator (Chen et al., 2020). The MACDH$_{\%}$ is derived from the MACDH as a percentage of EMA, as shown in Eq. (12).

$$MACDH_{\%} = \frac{MACDH}{0.5(EMA(short) - EMA(long))} \times 100\% \quad (12)$$

where the period lengths of long-term and short-term are 26 days and 12 days respectively. As the notation MACDH$_{\%}$ is in the form of a percentage, it allows investors to compare the MACDH$_{\%}$ values among different securities.

Next, we apply a whipsaw correction band as a dead-band by ignoring zero-axis crossovers within the range of the thresholds [-α, +α]. The trading signal $P(t)$ indicated by MACDH is changed only when the MACDH$_{\%}$ value exceeds the threshold range [$-\alpha$, $+\alpha$]. Otherwise, we still maintain our previous trading signal. The trading signal $P(t)$ is derived as shown in Eq. (13).

$$P(t) = \begin{cases} 1, & if\ MACDH_{\%} > \alpha \\ -1, & if\ MACDH_{\%} < -\alpha \\ P(t-1), & otherwise \end{cases} \quad (13)$$

where 1 represents a *buy* signal; and -1 represents a *sell* signal.

2.8. Forecasted MACDH (fMACDH)

To reduce the lagging effects of the abovementioned technical indicators, it is worth to explore an enhanced MACDH indicator with the forecast leads. A fMACDH indicator was reported by Tan et al. (2015) for predicting next day price using the SeroFAM neuro-fuzzy system. The computation of the fMACDH can be modified from the MACDH using the forecasted data.

First, the EMA shown in Eq. (8) is revised by integrating the forecasted price signal that is represented by a modified notation, the forecasted EMA (fEMA) in Eq. (14).

$$fEMA = \omega\widetilde{P}(t+1) + (1-\omega)EMA \quad (14)$$

where higher weightage ω is on the forecast signal $\widetilde{P}(t+1)$, and weightage (1- ω) on the EMA of historical signals.

Next, the fEMA is substituted the EMA and integrated into Eq. (9), Eq. (10), and Eq. (11). The fMACD, the fMACD Signal Line, and fMACDH can be computed by the modifications shown in Eq. (15), Eq. (16), and Eq. (17) respectively. The period lengths of long-term and short-term are kept unchanged being 26 days and 12 days.

$$fMACD = fEMA(short) - fEMA(long) \quad (15)$$

$$fMACD\ SignalLine = fEMA(fMACD) \quad (16)$$

$$fMACDH = fMACD - fMACD\ SignalLine \quad (17)$$

The fMACDH indicator were evaluated on ten US equities with good trading performances obtained in (Tan et al., 2015).

Finally, the notations MACDH, EMA, and MACDH$_{\%}$ in Eq. (12) and Eq. (13) are substituted by the corresponding forecasted notations. The forecasted MACDH$_{\%}$ (fMACDH$_{\%}$) and the revised trading signal $P(t)$ are modified with forecast leads, as shown in Eq. (18) and Eq. (19) respectively.

$$fMACDH_{\%} = \frac{fMACDH}{0.5(fEMA(short) + fEMA(long))} \times 100\% \quad (18)$$

$$P(t) = \begin{cases} 1, & if\ fMACDH_{\%} > \alpha \\ -1, & if\ fMACDH_{\%} < -\alpha \\ P(t-1), & otherwise \end{cases} \quad (19)$$

3. Proposed two trading indicators

3.1. Optimised fMACDH indicator

In order to further enhance the trading signals with less lagging effects, the optimised fMACDH indicator is proposed by extending to integrate additional k days forecasted prices as the prediction depth, with the corresponding k days historical price data as the input depth, where $1 \le k \le 5$. To derive the optimised fMACDH indicator, the notation of fEMA in Eq. (14) needs to be modified to integrate number of k days forecast price data. The modified $fEMA_{t+k}$ is calculated using Eq. (20).

$$fEMA_{t+k} = \omega \widetilde{P}(t+k) + (1-\omega) fEMA_{t+k-1} \tag{20}$$

Correspondingly, the computations of the fMACD in Eq. (15), the fMACD Signal Line in Eq. (16), and the fMACDH in Eq. (17) are also required to be modified by substituting the modified $fEMA_{t+k}$ in. As such, the modified notations of the $fMACD_{t+k}$, the $fMACDSignalLine_{t+k}$, and the optimised fMACDH indicator (i.e., $fMACDH_{t+k}$) will be derived from Eq. (21), Eq. (22), and Eq. (23) respectively.

$$fMACD_{t+k} = fEMA_{t+k}(short) - fEMA_{t+k}(long) \tag{21}$$

$$fMACD\ SignalLine_{t+k} = fEMA_{t+k}(fMACD) \tag{22}$$

$$optimised\ fMACDH_{t+k} = fMACD_{t+k} - fMACD\ SignalLine_{t+k} \tag{23}$$

With these updated notations to cater for number of k days forecast price data, the $MACDH_{\%}$ in Eq. (18) and the trading signal $P(t)$ in Eq. (19) are also required to be modified and computed accordingly, shown in Eq. (24) and Eq. (25) respectively. In order to enable better flexibility and parameter tuning in forecasting using GA, the threshold value α in Eq. (19) has been revised into two separate threshold values: upper bound threshold α, and lower bound threshold β. In this case, the whipsaw correction band is applied by ignoring zero-axis crossovers within the range of the thresholds $[\beta, \alpha]$, as shown in Eq. (25). The trading signal $P(t)$ for the optimised fMACDH is changed only when the optimised $fMACDH_{\%}$ value exceeds the threshold range $[\beta, \alpha]$. Otherwise, we still maintain our previous trading signal.

$$optimised\ fMACDH_{\%} = \frac{optimised\ fMACDH_{t+k}}{0.5(fEMA_{t+k}(short) + fEMA_{t+k}(long))} \times 100\% \tag{24}$$

$$P(t) = \begin{cases} 1, & if\ optimised\ fMACDH_{\%} > \alpha \\ -1, & if\ optimised\ fMACDH_{\%} < \beta \\ & P(t-1),\ otherwise \end{cases} \tag{25}$$

3.2. Optimal prediction depth

Theoretically, by integrating additional k days forecasted prices, we could further reduce the lagging tendency of the trading signal $P(t)$. However, it is also incurred a penalty in the form of a loss in forecast accuracy, as we try to predict future prices in several more days. It is a tradeoff between the forecast leads and the forecast accuracy. By integrating additional forecast leads, we should be able to perform the *buy* and *sell* trading actions closer to the peaks and troughs of price signals, thus increasing the investment returns. However, the drop in forecast accuracy will result in additional inaccuracies in the trading signal $P(t)$, reducing the investment returns. Thus, it is necessary to find the optimal point at which the two trends intersect, thus creating minimum lags and maximum returns on the investment on assets.

In this research, we perform a grid search in experiments, to find the optimal forecast parameters for the optimised fMACDH indicator. The parameters used for the experiments are shown in Table 1.

Table 1
Experiment parameters for searching optimal prediction depth.

Fixed Parameter (s)	• Training-Testing data split for SeroFAM: 80 – 20. • Commission rate per transaction: 0.1 % • Initial investment: USD$300,000.
Variable Parameter(s)	• Prediction depth (Number of k days ahead to forecast price data): 1 to 5 days ahead. • Input depth (Number of k days historical price data as the input): 1 to 5 days back
Target Variable	• Final net asset value (NAV) based on trading signal

To ensure that the experiments are generalisable and broadly applicable to all financial markets, several different major market indexes have been chosen, shown in Table 2. These market indexes represent different levels of risk and market capitalization.

For each combination of the prediction depth and the input depth, the final net asset value (NAV) of investment is computed based on the trading signals derived from the optimised fMACDH indicator. This process is repeated for each of the market indexes in Table 2. We then calculate the percentage change in ROI, as benchmarked to the regular MACDH indicator. The average changes in ROI across all market indexes are listed in Table 3.

Observed the results of this experiment in Table 3, it seems that there is a decreasing trend in ROI as prediction depth increases. This indicates that beyond the prediction depth being '1′, the additional returns by the reduction of trading signal lag are insufficient to offset the reduction of the prediction accuracy.

Additionally, we observe that the changes in ROI are less effected by different input depth values. It illustrates the strength of the SeroFAM as an online and single-pass model. The use of BCM theory and time-varying adaptive modelling enables the SeroFAM to self-reorganize and adapt to local concept drifts or shifts. As such, it is likely unnecessary to pass in much historical data as the input depth, unlike other models. Instead, the SeroFAM is able to make accurate predictions just based on the 1-day historical data.

Observed from the experiment results, the settings of the input depth being '1' and prediction depth being '1′ are the optimal values that give the highest ROI. Therefore, for the next experiments in this paper, the input depth and prediction depth are set to be '1 day' each.

3.3. Designed GA for tuning the optimised fMACDH indicator

Presented in Eq. (20) – Eq. (23), several parameters are needed when deriving the optimised fMACDH indicator and its derivatives from several notations such as EMA, $fEMA_{t+k}$, $fMACD_{t+k}$, $fMACDSignalLine_{t+k}$, shown in Table 4.

Conventionally, traders rely on the indicator MACDH(12, 26, 9), which refers with a "short" EMA period of 12 days, "long" EMA period of 26 days and a period of 9 days for the MACD Signal Line. This is a

Table 2
Market indexes for experiments of two proposed trading indicators.

Index	Descriptions
^DJIA	Dow Jones Industrial Average: stock performance of 30 large companies listed on US stock exchanges
^GSPC	S&P 500: stock performance of 500 large companies listed on stock exchanges in the U.S.
^FTSE	FTSE 100: stock performance of 100 large companies listed on London Stock Exchange
^HSI	Hang Seng Index: stock performance of 50 large companies listed on Hong Kong Stock Exchange
^IXIC	Nasdaq Composite: includes almost all stocks listed on Nasdaq Stock Exchange
^N225	Nikkei 225: stock performance of 225 large, publicly owned companies on Tokyo Stock Exchange
^STI	Straits Times Index: stock performance of top 30 companies listed on the Singapore Stock Exchange

Table 3
Average percentage changes in ROI of the optimised fMACDH indicator.

Input Depth (days) → Prediction Depth (days) ↓	1	2	3	4	5
1	28 %	17 %	26 %	28 %	25 %
2	2 %	26 %	26 %	20 %	8 %
3	3 %	9 %	2 %	7 %	2 %
4	8 %	15 %	13 %	11 %	12 %
5	9 %	1 %	14 %	0 %	10 %

Table 4
Parameters for the optimised fMACDH indicator and its derivatives.

Parameter	Description	Conventional Value
Long period	Number of days for "long" EMA and $fEMA_{t+k}$ period	26 Days
Short period	Number of days for "short" EMA and $fEMA_{t+k}$ period	12 Days
Signal period	Number of days for $fMACDSignalLine_{t+k}$	9 Days
α	Upper bound threshold for *Buy* Signal	0
β	Lower bound threshold for *Sell* Signal	0

remnant from the olden days, when the working week used to be 6 days. These period settings were represented two weeks, one month and 1.5 weeks respectively (DayTrading.com, 2022).

As mentioned in Section 2.2, the zero-axis crossover is typically taken to be a *buy* or *sell* signal. However, depending on the volatility of the security, the trading signal could potentially oscillate near the zero axis. This could create many false buy or sell signals. It will result in additional commission costs, as we take *buy* or *sell* actions more than necessary. That is the reason why the parameters of thresholds α and β are proposed for.

These parameters in Table 4 will be tuned by the GA, in order to reduce the lag of the trading signal. Each individual security asset has its own unique characteristics. It would need to own a unique set of fine-tuned parameters to achieve optimal performance separately. Thus, we can potentially achieve better ROI by tuning the optimised fMACDH parameters for each asset in the portfolio, before using dynamic portfolio rebalancing algorithms to better manage the portfolio.

For the configurations of the designed GA, we set the bounds for the "long" EMA period, "short" period and signal period to be [1, 50] days in the GA search space. We also enforce the restriction that the "long" EMA period has to be greater than the "short" EMA period. The range of the upper bound threshold α is restricted in the range of [0, 1]. The range of lower bound threshold β is restricted in the range of [-1, 0]. The chromosome incorporates these five variables as an array in the following order: (Short period, Long period, Signal period, α, β). The values are all encoded as the double data type.

Next, we need to design a fitness function for the GA to evaluate the fitness values of generated chromosomes. As we are attempting to reduce the amount of lag of our trading indicators, the fitness function will naturally be related to the amount of lag of our trading indicators. We will explain the methodology to design the fitness function next.

3.4. Price signal peaks and troughs

Firstly, we have to definitively pinpoint the peaks and troughs of a price signal. Given an example on the S&P 500 index, ˆGSPC, its 5 years historical price data (2016 – 2020) is shown in Fig. 4. It is observed that the price data shows many short-term fluctuations. If attempting to capture every short-term peak and trough, it can lead to several issues. Each buy or sell trade made incurs a certain amount of commission costs. It would result in excessive commission costs. In fact, it is only benefitable if the profit between a buy transaction at a trough and a sell transaction at a peak is higher than the commission costs of two transactions. Additionally, due to the lag of the trading indicators, it is impossible to predict short-term trends accurately. Thus, it leads to poor trading profits.

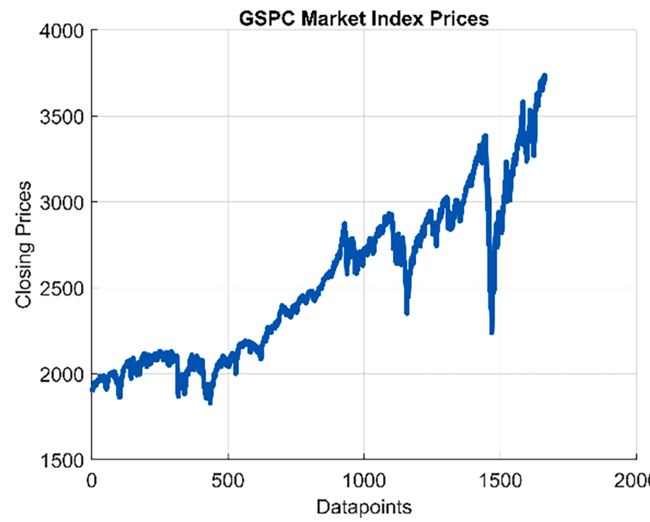

Fig. 4. 5-year price data of ˆGSPC index.

If ignoring the short-term price fluctuations, it is observed a clear long-term trend in the price data that can be ridden on for profit making. Therefore, in this paper we will ignore the short-term price fluctuations, and focus on the underlying long-term trend.

As shown in Eq. (26), the first order RMA of the price signal can be calculated over a 25-day period, i.e., the current day and ± 12 days as short EMA period. It is followed by the second order RMA of the price signal over a 9-day period that is computed in Eq. (27).

$$P^{'}(t) = RMA_{25\ day}(P(t)) \tag{26}$$

$$P^{''}(t) = RMA_{9\ day}(P^{'}(t)) \tag{27}$$

The derived price signal of ˆGSPC index after the second order RMA computation is plotted in Fig. 5. It is shown a substantially less noisy price signal after the second order RMA, that clearly shows the long-term trends of the ˆGSPC index.

Next, the local maximum and minimum values of the second order RMA will be calculated over a 33-day period, as each price data point contains information in the current day and ± 16 days. The calculations

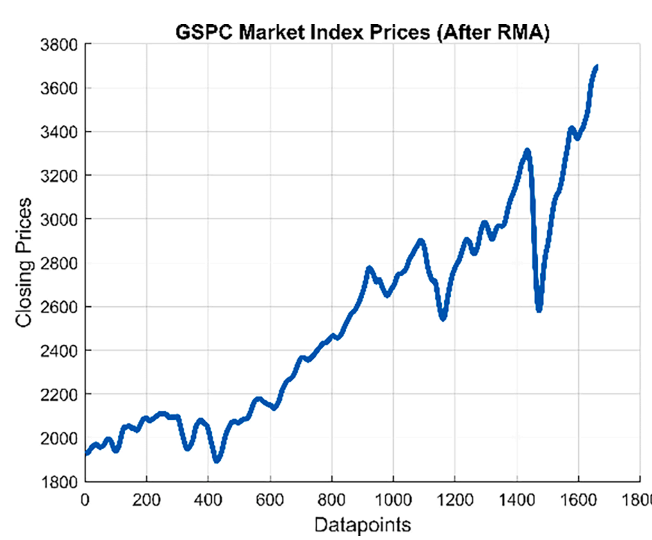

Fig. 5. Price data of ˆGSPC index after RMA.

are shown in Eq. (28) and Eq. (29).

$$P''_{max}(t) = \max(P''(t-16), P''(t-15), \cdots P''(t+15), P''(t+16)) \quad (28)$$

$$P''_{min}(t) = \min(P''(t-16), P''(t-15), \cdots P''(t+15), P''(t+16)) \quad (29)$$

Finally, the price at time t is considered as a peak when the $P''(t)$ is equal to the local maximum value. While it is considered as a trough, when the $P''(t)$ is equal to the local minimum value. The value of $PeakTroughs(t)$ is derived in Eq. (30).

$$PeakTroughs(t) = \begin{cases} 1, & if\ P''(t) = P''_{max}(t) \\ -1, & if\ P''(t) = P''_{min}(t) \\ 0, & otherwise \end{cases} \quad (30)$$

where '1' represents a peak and '-1' represents a trough in the price signal.

3.5. Calculating lag

After the peaks and troughs of the price signal have been found by Eq. (30), we can then calculate the lag of our trading indicator in relation to the price signal. For each peak in the price signal, it should ideally be followed by a sell signal. Conversely, for each trough in the price signal, it should ideally be followed by a *buy* signal. Since our trading indicator is ultimately still a lagging indicator, we do not consider the negative lag. It means that it is impossible for our trading signal to lead a buy/sell signal.

The finite state machine of the proposed lag algorithm for calculating lag is shown in Fig. 6. For each buy/sell signal from the trading signal, the total number of trading signals will be increased by 1.

It is possible to miss a peak or trough. It occurs when a peak happens, followed by a trough closely, without any sell signal in between. Conversely, a miss also happens when a trough occurs, followed by a peak closely, without any *buy* signal in between. The number of missing peak or trough will be recorded. But such situations are rare.

There are likely to be the occurrence of false positives and false negatives in the trading signals. When this happens, we incur additional commission costs as we buy or sell unnecessarily. Hence, we need to keep watch on the total number of buy/sell signals from our trading signals.

3.6. GA fitness function

Next, the fitness function of the GA is designed in this paper. In the GA optimisation process, the higher the value calculated by the fitness function, the greater the fitness of the chromosome.

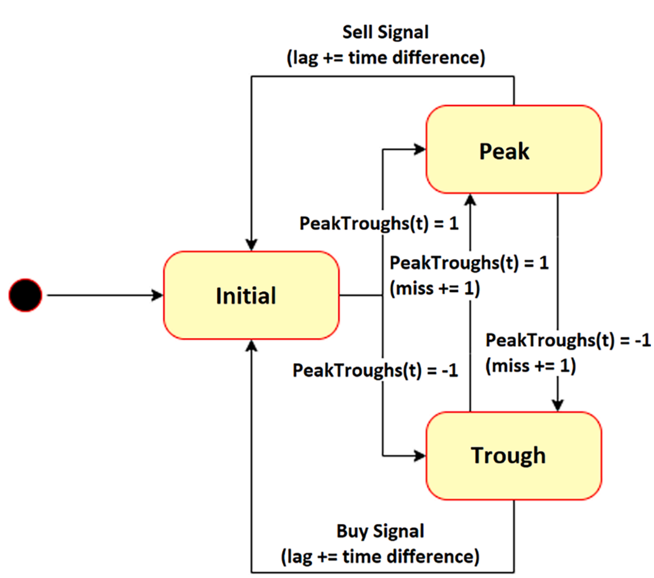

Fig. 6. Finite State Machine of lag algorithm for calculating lag.

We focus on reducing the amount of lag of the trading signals. Thus, we start with the inverse of the lag calculated by the lag algorithm. The average lag calculated can range from $[0, \infty]$. As shown in Eq. (31), the denominator is added by 1 in order to avoid division by zero potentially.

$$Fitness\ Step\ 1 = \frac{1}{1 + avgLag} \quad (31)$$

Next, we want to penalize any miss by the trading signals. Missing a sell trading at a peak or a buy trading at a trough could potentially lead to a large loss in returns. We either fail to capitalize in a price rise or fail to liquidate our portfolio before the stock rapidly falls in value. Hence, the denominator of the function is multiplied by the number of misses of buy/sell trading, shown in Eq. (32).

$$Fitness\ Step\ 2 = \frac{1}{(1 + avgLag) \times (1 + miss)} \quad (32)$$

Finally, we want to penalize either having too many buy/sell signals, or too few trading signals. Ideally, we want to only trade the same number of times as the number of peaks/troughs denoted by n. The excessive deviations from n should be severely penalized. Hence, we will use a Gaussian function, to ensure that the total number of trading signals are within a certain range of n, shown in Eq. (33):

$$Fitness\ Function = \frac{\exp\left(-\frac{(total\ \ trading - n)^2}{2 \times n^2}\right)}{(1 + avgLag) \times (1 + miss)} \quad (33)$$

where the total trading refers to the number of trading times. Therefore, the designed fitness function for the GA is obtained as shown in Eq. (33). This fitness function will be employed to evaluate the generated chromosomes of the GA when tuning the parameters of the optimised fMACDH indicator and the trading signal.

Several experiments have been conducted to utilise the developed GA for parameter tuning. The GA configurations for all of the experiments in this research are shown as follows.

- Population size: 200.
- Max number of generations: 100.
- Max number of stall generations: 20.
- Two-point crossover employed.
- Crossover probability: 0.8.
- Mutation probability: 0.01.

3.7. Experiment on GA tuning for the optimise fMACDH indicator

Seven major market indexes shown in Table 2 are employed in the experiments to evaluate the performances of GA optimising parameters of the proposed fMACDH indicators. The data window for these market indexes in the experiment are from 3rd January 2005 to 26th February 2021.

In this experiment, the GA is utilized to tune parameters shown in Table 4 of the optimised fMACDH indicator for each individual index. The number of real-valued variables incorporated in each chromosome are five. The best performing set of parameters derived by the GA for the optimize fMACDH indicators in these seven major market indexes are shown in Table 5.

For the set of parameters optimised by the GA of each index, an initial investment of USD\$300,000 is given and invested accordingly to the trading signal $P(t)$. The commission rate of 0.1 % is used for each trading transaction. The best result is chosen and benchmarked. The final NAV in the experiment of seven market indexes are shown in Table 6.

The experiment results of the optimised fMACDH indicator by the GA will be benchmarked to three trading methods.

Table 5
GA derived attributes for Optimize fMACDH Indicator with seven market indexes.

Index	Short period	Long period	Signal period	α	β
ˆDJIA	16	44	42	0.0005370555861	−0.001113480843
ˆFTSE	3	48	30	0.004308625046	−0.00446683314
ˆGSPC	39	49	22	0.0000791	−0.0001480196065
ˆHSI	9	32	45	0.00240068358	−0.002323139163
ˆISIC	26	48	33	0.0002666334854	−0.0007584818714
ˆN225	3	45	3	0.002220960537	−0.002483342771
ˆSTI	10	49	19	0.001121727976	−0.001688737134

Table 6
Performance benchmarks of the GA optimised fMACDH indicator.

Index	Buy and Hold	Regular MACDH	Ideal lag-free MACDH	Optimised fMACDH
ˆDJIA	$547,423.35	$392,602.67	$326,745.25	**$628,649.94**
ˆFTSE	$289,248.49	$206,654.54	$220,628.07	**$451,287.65**
ˆGSPC	**$588,971.61**	$401,033.68	$330,992.55	$562,633.72
ˆHSI	$347,873.70	$286,138.57	$309,344.85	**$455,201.48**
ˆIXIC	**$924,879.95**	$456,847.08	$530,269.45	$790,412.77
ˆN225	$582,028.39	$353,648.69	$261,790.56	**$863,937.10**
ˆSTI	$260,684.40	$306,755.87	$232,781.23	**$446,279.59**

- Trading by a passive investment strategy, i.e., Buy and Hold strategy, where an investor buys and holds a stock for a significant period of time. It means that all initial funds are invested on Day 1, and only sell on the last day.
- Trading by a regular MACDH indicator, which is derived in Eq. (8) to Eq. (13) based on the EMA, MACD, MACD Signal Line, $MACDH_{\%}$, with 26-day long period, 12-day short period, and 9-day signal period.
- Trading by an ideal lag-free MACDH, which is derived by the similar way as the regular MACDH indicator, following Eq. (8) – Eq. (13), except for calculations of the EMA are replaced by the ideal lag-free RMA in Eq. (8), Eq. (9), Eq. (10) and Eq. (12). The time setting is the same as that of the regular MACDH indicator, i.e., 26-day long period, 12-day short period, and 9-day signal period.

Observed in Table 6, the fMACDH indicator optimised by the GA is the best performing trading indicator for five out of seven market indexes. While the Buy and Hold strategy achieves the best performance for the indexes of ˆGSPC and ˆIXIC, the performance of the optimised fMACDH indicator achieves the second best performance for these two indexes.

It is also observed that the optimised fMACDH by the GA outperforms both the regular MACDH and ideal lag-free MACDH indicators on every index. Particularly, the optimised fMACDH significantly outperforms the ideal lag-free MACDH indicator by about 150 % to 300 %. The ideal lag-free MACDH indicator incorporates ideal future data in its calculations, albeit with the standard time setting of 26-day long period, 12-day short period, and 9-day signal period. It serves as a “best case scenario” with minimal lag for the MACDH indicator. As such, the optimised fMACDH indicator by the GA shows great promise in reducing the trading signal lag and improving ROI.

3.8. GA for parameters tuning of the proposed fMACDH-fRSI indicator

Besides the technical indicators presented in Section 2.2, the RSI is another popular momentum indicator. It measures magnitude of recent price changes to evaluate overbought or oversold conditions in the price signal (Fernando, 2021), that indicates a possible reversal in trend. The RSI is calculated in Eq. (34) and Eq. (35).

$$RSI = 100 - \frac{100}{(1+RS)} \tag{34}$$

$$RS = \frac{Average\ Gain}{Average\ Loss} \tag{35}$$

Typically, 14-day RSI period is used. An asset is considered overbought when RSI is over 70 (denoted by γ), and oversold when RSI is under 30 (denoted by δ).

The MACDH and RSI are often used together by analysts to get a more complete technical picture of a financial market. These two indicators are trend-following momentum indicators. Whilst the MACDH calculates the moving trends of the price signal, The RSI calculates the average price gains and losses over a period of time. These are two different approaches that can synergise well together.

Therefore, a new trading signal, fMACDH-fRSI is proposed in this paper by combining the fMACDH indicator and the forecasted RSI (fRSI). The parameters of the proposed fMACDH-fRSI indicator will be optimised by the GA. The experiments will be the conducted to compare its performances to those of the optimised fMACDH indicator.

3.9. Forecasted RSI (fRSI)

The fRSI indicator is proposed by making some minor modifications to the RSI calculation in Eq. (34) and Eq. (35). The calculation of the relative strength (RS) value in the Eq. (35) will be modified into the Eq. (36) as follows:

$$RS = \frac{Average\ Gain}{Average\ Loss} = \frac{Total\ Gain}{d} \div \frac{Total\ Loss}{d} = \frac{Total\ Gain}{Total\ Loss} \tag{36}$$

where d is the days of calculating the RSI. Typically, a value of 14 days is used for d. The proposed forecast RS (fRS) is modified to include the total gain/loss in d-1 days and the predicted gain/loss on Day $d+1$ ($predGain_{d+1}$) or ($predLoss_{d+1}$). The computation of the fRS is shown in Eq. (37). Next the proposed fRSI is computed in Eq. (38).

$$fRS = \frac{Total\ Gain_{d-1\ days} + predGain_{d+1}}{Total\ Loss_{d-1\ days} + predLoss_{d+1}} \tag{37}$$

$$fRSI = 100 - \frac{100}{(1+fRS)} \tag{38}$$

3.10. Modified trading signal of the fMACDH-fRSI

The trading signal will be modified for the proposed fMACDH-fRSI indictor. Firstly, we calculate both the optimised $fMACDH_{\%}$ value using Eq. (24) and the fRSI using Eq. (38) respectively. We then calculate modified trading signal $P(t)$ by combining both the optimised $fMACDH_{\%}$ and fRSI values, shown in Eq. (39).

$$Modified\ P(t) = \begin{cases} 1, & if\ fMACDH_{\%} > \alpha\ and\ fRSI > \gamma \\ -1, & if\ fMACDH_{\%} < \beta\ and\ fRSI < \delta \\ P(t-1), & otherwise \end{cases} \tag{39}$$

For the proposed fMACDH-fRSI indicator, the parameters to be tuned and optimised by the GA are listed in Table 7. The fRSI includes 3 additional parameters: the fRSI period length, the *buy* signal threshold γ, and the *sell* signal threshold δ. Thus, there are eight different parameters for tuning by the GA. Similar to those of the optimised fMACDH parameters, the GA search space for the fRSI period is set to be [1, 50]. The GA search space for γ and δ are set to be [0, 100], with the restriction as $\gamma > \delta$. The chromosome incorporates these eight real-valued variables as an array in the following order: (Short period, Long period, Signal period, α, β, fRSI period, γ, δ). The values are all encoded as the double data type.

Table 7
Parameters of the proposed fMACDH-fRSI indicator for GA tuning.

Parameter	Description	Conventional Value
fMACDH Long period	Number of days for "long" EMA and $fEMA_{t+k}$ period	26 Days
fMACDH Short period	Number of days for "short" EMA and $fEMA_{t+k}$ period	12 Days
fMACDH Signal period	Number of days for $fMACDSignalLine_{t+k}$	9 Days
α	Upper bound threshold for fMACDH *Buy* Signal	0
β	Lower bound threshold for fMACDH *Sell* Signal	0
fRSI period	Period over which to calculate fRSI	14 Days
γ	Threshold for fRSI *Buy* Signal	70
δ	Threshold for fRSI *Sell* Signal	30

3.11. Experiment on GA for the optimise fMACDH-fRSI indicator

In this experiment, the GA is performed to optimize the proposed fMACDH-fRSI indicator for each individual market index. The best performing set of parameters derived by the GA for the optimised fMACDH-fRSI indicators in these seven market indexes are shown in Table 8.

For the set of parameters optimised by the GA of each market index, an initial investment of USD$300,000 is given and invested accordingly to the modified trading signal $P(t)$. The commission rate of 0.1 % is used for each transaction. The best result is chosen and benchmarked.

The experiment results of the proposed fMACDH-fRSI indicator tuned by the GA are benchmarked to the proposed optimised fMACDH indicator tuned by the GA. The final NAV in the experiment of each of the 7 indexes are shown in Table 9. The data window for these indexes in the experiment are from 3rd January 2005 to 26th February 2021.

It is observed from the comparison results in Table 9, the proposed optimised fMACDH indicator outperforms the proposed fMACDH-fRSI indicator on each of the seven market indexes. It is obvious that the proposed fMACDH-fRSI indicator does not perform better than the proposed optimised fMACDH indicator.

The reason could be a result of the fMACDH and the fRSI indicator having to agree before a trading signal is sent for the combined fMACDH-fRSI indicator. As such, the proposed fMACDH-fRSI indicator attempts to "play it too safe", by making too few buy and sell trades. As a consequence, while the markets and assets perform very well, the combined fMACDH-fRSI indicator fail to take advantage of the uptrend. The fMACDH-fRSI indicator does not realize as much profit as the fMACDH indicator. Instead, focusing on a single indicator tends to achieve better results. Thus, in the remainder of this paper, we will be focusing on the optimising fMACDH indicator in the next experiments.

4. Proposed algorithms for dynamic portfolio rebalancing

4.1. Algorithms

4.1.1. Tactical Buy and Hold (TBH) algorithm

The TBH algorithm is an active opportunistic rule-based investment strategy, whereupon an investor capitalizes on trend reversal opportunities to buy or sell financial asset within a single portfolio. This strategy represents more traditional investing values, where we invest in riskier securities when the market is performing well, and fall back to safer securities when the market does not perform well. The TBH algorithm is shown in Algorithm 1.

Table 9
Performance benchmarks of the proposed fMACDH-fRSI indicator.

Market Index	Optimised fMACDH	Proposed fMACDH-fRSI
ˆDJIA	**$628,649.94**	$466,295.21
ˆFTSE	**$451,287.65**	$391,014.89
ˆGSPC	**$562,633.72**	$398,047.91
ˆHSI	**$455,201.48**	$294,393.78
ˆIXIC	**$790,412.77**	$771,362.03
ˆN225	**$863,937.10**	$453,907.59
ˆSTI	**$446,279.59**	$343,845.97

Algorithm 1. Proposed TBH algorithm.

```
Input: fMACD, fMACD Signal Line, trading signal P(t),
    Buy Signal, Sell Signal, Classifications of Assets in
    Portfolio as High Risk, Medium Risk, Low Risk
Output: Portfolio Allocation across Time Period
Initialize optimized fMACDH, Sell/Buy Signal of Each Asset
Optimized fMACDH ← fMACD – fMACD Signal Line
for Daily calculation for every asset in portfolio: do
  for Update fMACDH value for each asset: do
    if Buy Signal = TRUE then
      Sell/Buy Signal of this Asset ← 1
    else if Sell Signal = TRUE then
      Sell/Buy Signal of this Asset ← 2
    else
      Sell/Buy Signal of this Asset ← 0
    end if
  end for
  for Every stock or index asset in portfolio: do
  if Sell/Buy Signal of high risk assets = 2 then
    Sell high risk assets and Buy medium risk assets
    Rebalance Portfolio Allocation
  end if
  if Sell/Buy Signal of medium risk assets = 2 then
    Sell medium risk assets and Buy low risk assets
    Rebalance Portfolio Allocation
  end if
  if Sell/Buy Signal of medium risk assets = 1 then
    Sell low risk assets and Buy medium risk assets
    Rebalance Portfolio Allocation
  end if
  if Sell/Buy Signal of high risk assets = 1 then
    Sell medium risk assets and Buy high risk assets
    Rebalance Portfolio Allocation
  end if
   end for
end for
Algorithm 1. Proposed TBH portfolio rebalancing algorithm
```

Algorithm 2. Proposed RBBC algorithm.

```
Input: fMACD, fMACD Signal Line, trading signal P(t),
     Buy Signal, Sell Signal,Cash, Holdings.
Output: Portfolio Allocation across Time Period
Initialize optimized fMACDH, HoldValue, HoldNum,
```

(*continued on next page*)

Table 8
GA derived attributes for Optimize fMACDH-fRSI Indicator with seven market indexes.

Index	Short period	Long period	Signal period	α	β	fRSI period	γ	δ
ˆDJIA	10	26	28	0.002252167029	31.52047141	63	79	7079
ˆFTSE	12	43	42	0.002192555334	39.16703667	26	34	4339
ˆGSPC	18	29	12	0.0008638833761	26.47932283	39	30	8709
ˆHSI	8	49	20	0.004083955948	28.04870465	42	82	9033
ˆISIC	5	15	31	0.003795819996	28.34001711	48	5	8232
ˆN225	15	34	21	0.001832321073	30.71265346	41	69	8998
ˆSTI	2	50	21	0.007373710633	20.62889137	33	28	12,551

(*continued*)

```
        New Buy Signals, BuyAmt.
Optimized fMACDH ← MACD – MACD Signal Line
for Daily calculations in trading for the portfolio: do
  for Update fMACDH value for each asset: do
    if Sell Signal = TRUE then
      Sell all our holdings of the asset
    else if Buy Signal = TRUE then
      if Currently not holding the asset then
      NewBuy Signals ← NewBuy Signals + 1
      end if
    else
  HoldValue ← HoldValue + value of asset holdings
  HoldNum ← HoldNum + 1
      end if
  end for
  BuyAmt ← (HoldValue + Cash)/(HoldNum + NewBuy Signals)
  for Every NewBuy Signals: do
      Purchase worth BuyAmt of asset
      if insufficient cash then
  Sell equal amounts of all held assets
      end if
  end for
  if Cash > 0 then
    Spread Cash equally among all buy signals
  end if
end for
```

Algorithm 2. Proposed RBBC portfolio rebalancing algorithm

The TBH algorithm makes use of the different levels of risks of each asset in a portfolio, to determine the allocation of assets when a trend reversal signal is received. The proposed optimised fMACDH trading indicator is employed for determining the trend reversal signal. When the value of the optimised fMACDH$_{\%}$ goes above the upper bound threshold α, it indicates an anticipatory peak and thus a *buy* signal. When the value of the optimised fMACDH$_{\%}$ goes below the lower bound threshold β, it indicates an anticipatory trough, and thus a *sell* signal.

When a trend reversal signal from any of the assets in the portfolio is detected, the TBH algorithm will then perform asset rebalancing and reallocation. When a *sell* signal is detected from any of the portfolio assets, the portfolio will be reallocated to a lower risk asset. This is because in a bearish market, the likelihood of losses is greater. Investors tend to try to minimize risks and losses (Lim, Cao, & Quek, 2022). Likewise, when a *buy* signal is detected from a higher risk asset, the portfolio assets will be reallocated from a lower risk asset to the higher risk asset. In general, the risk is highly correlated and proportional to profitability. In a bullish market, there is greater probability of making a profit. Hence, holding assets with higher risks is likely to result in higher returns.

4.2. RBBC portfolio rebalancing algorithm

Ideally, when investing, we would like to find two perfectly negatively correlated stocks, similar to the two stocks shown in Fig. 7. It would allow us to easily achieve large returns on our investment, by

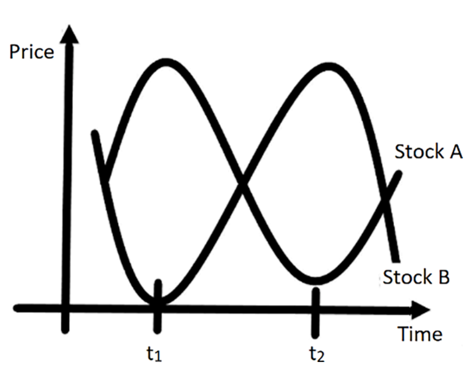

Fig. 7. Two negatively correlated stocks.

reallocating the assets from Stock A to Stock B at time t_1, and reallocating the assets from Stock A to Stock B at time t_2. However, in the real world, it is impossible to find such perfectly negatively correlated stocks. Instead, we can invest in a basket of portfolios that follow different price cycles, with the hope to capitalize on these differences in price movements.

Stock markets have typically been a leading indicator of the business cycle (Management, 2016). Different sectors tend to perform better at different phases of the business cycle. The relative performance of different market sectors at different phases of the business cycle is shown in Table 10, where the market sectors from top to bottom at the vertical axis are in the order from Economically Sensitive to Economically Insensitive. A higher percentage indicates that a particular market sector is performing better during this phase. Clearly, all market sectors follow the same trend, performing well at the early stage of the business cycle and underperforming during a recession. However, sectors like Consumer Discretionary tend to outperform the rest during the early cycle. While economically insensitive sectors like Consumer Staples tend to outperform the rest during a recession cycle (Management, 2016).

As such, the RBBC portfolio rebalancing algorithm is proposed to exploit these differences in cyclical action of various market sectors, by investing into a basket of assets from different market sectors. Similar to the TBH algorithm, the *buy* and *sell* signals are computed using the proposed optimised fMACDH indicator. However, for RBBC portfolio rebalancing algorithm, there is no clear hierarchy of high or low risk securities. Therefore, we reallocate the portfolio using a different method.

The pseudocode for the RBBC portfolio rebalancing algorithm is shown in Algorithm 2. In the RBBC portfolio rebalancing, there are three states assigned to each asset in the portfolio at each time period: *buy*, *sell* and *hold*. At each time period, for an asset having a *sell* signal, all holdings of such asset will be sold.

Next, we wish to purchase into positions on assets with the *buy* signals, which we are not currently already holding in the portfolio. In the meantime, we do not sell any existing holdings of assets that also have *buy* signals. Hence, we spread out the value of all assets and cash equally into the new and existing holdings with the *buy* signals.

For example, at time period *t*, we are currently not holding any of Stock *C*, that has a *buy* signal now. We are holding USD$500 of Stocks *D*, *E* and *F*, which have the *hold* signals. We have USD$100 in cash at the moment. Hence, we will invest $\frac{(500+100)}{4} = USD\$150$ into Stock *C*, by selling off Stocks *D*, *E* and *F* in equal numbers to make up the shortfall in cash.

This strategy ensures that we stay in or even add onto winning positions. While it triggers to sell of all losing positions, and also redistribute stagnant positions.

4.3. Experiments for TBH and RBBC portfolio rebalancing algorithms

Market indexes are hypothetical portfolio of equities and not directly purchasable, For the experiments to evaluate the proposed TBH and

Table 10
Relative performance of different market sectors at different phases.

	Early cycle	Mid cycle	Mature cycle	Recession
Consumer Discretionary	**36 %**	14 %	**4 %**	−16 %
Materials	29 %	11 %	18 %	−15 %
Industrials	29 %	16 %	9 %	**−20 %**
Technology	29 %	**20 %**	5 %	**−20 %**
Financials	28 %	15 %	10 %	−16 %
Consumer Staples	22 %	13 %	14 %	**−1%**
Healthcare	20 %	16 %	16 %	−7%
Energy	17 %	17 %	**23 %**	−14 %
Utilities	**13 %**	**11 %**	14 %	−3%
Overall Average	24 %	15 %	9 %	−14 %

(Source: Beaumont Capital Management, 2016)

RBBC portfolio rebalancing algorithms, we will be trading in various ETFs. ETFs can represent different markets, sectors, or even different commodities. We have chosen to two different sets of ETFs for the experiments. The first set of ETFs are chosen based on varying levels of risk shown in Table 11. The second set of ETFs are chosen on the basis of different market sectors shown in Table 12.

The second set of ETFs include the ˆAGG for hedging purposes, as well as 12 other ETFs. These ETFs represent broad market sectors each, as defined by the Global Industrial Classification Standard (Hayes, 2020).

Under the same experiment configurations of the GA engine, the optimised fMACDH trading indicator is tuned for each asset in the portfolio individually. The best performing set of parameters derived by the GA for these two sets of ETF portfolio are shown in Table 13 and Table 14.

These best performing parameters are chosen for the experiments of the proposed TBH and RBBC portfolio rebalancing algorithms. An initial investment of USD$1,000,000 is split equally among all assets. The commission rate of 0.1 % is used for each transaction. Results of each proposed algorithm are benchmarked against two portfolio strategies; one is the Buy and Hold strategy; the other is the popular $1/N$ portfolio strategy, i.e., equally weighted portfolio strategy, where the total capital is equally rebalanced and invested to each portfolio asset at each rebalancing date (DeMiguel, Garlappi, & Uppal, 2009). The $1/N$ portfolio strategy is reported as an effective strategy, where many prior works in the literature conduct rebalancing equally the portfolio once a month (Bernoussi & Rockinger, 2022; Bessler, Taushanov, & Wolff, 2021; Lee, 2020; Zhou & Palomar, 2020). The $1/N$ portfolio strategy with equally rebalancing quarterly is also discussed (Zhou & Palomar, 2020).

4.4. Experiment results of the TBH algorithm

For the first set of ETFs selected for dynamic portfolio rebalancing experiment in March 2017 – March 2021, the experiment results of the TBH algorithm are shown in Table 15. Its performance comparisons over the Buy and Hold strategy, the $1/N$ portfolio strategy with equally rebalancing monthly, and the $1/N$ portfolio strategy with equally rebalancing quarterly are also shown in the same table. For all the experiments, the commission rate of 0.1 % is used per trading transaction.

It is observed from Table 15, we can see that the TBH algorithm outperforms the Buy and Hold strategy of each ETF by 5 % – 40 %. It is a significant improvement in ROI. It is also noted that the TBH algorithm only outperforms the Buy and Hold strategy of ˆSPY by 5 %. The TBH portfolio rebalancing algorithm outperforms the $1/N$ portfolio strategy by about 26 % – 27 %.

Fig. 8 shows the TBH algorithm at work over this period in March 2017 – March 2021. The lighter coloured lines show the price signal of each ETF, while the darker coloured lines denote when the TBH algorithm is currently holding onto shares of the corresponding ETFs. It is observed in Fig. 8 that the TBH algorithm is able to successfully switch from higher risk to lower risk assets when the market is predicted to perform poorly. At the big drop in the ˆSPY price at about datapoint 550, the TBH algorithm chooses to reallocate its assets from the ˆSPY to the ˆAGG. It avoids a large fall in portfolio NAV at that time. It is also observed that the proposed TBH algorithm is generally able to sell at the peaks and repurchase at the troughs.

Shown in Fig. 8, we observe whilst price of the ˆSPY changes quite significantly over this period, the prices of the ˆAGG, ˆVGK and ˆVWO do not vary greatly. Hence, it affects the ability of the TBH algorithm to increase returns from switching between assets of different risks, especially with the commission costs involved. This explains the minimal

Table 11
First set of ETFs selected for dynamic portfolio rebalancing experiment.

ETF Ticker	Tracks	Risk (Relative)
ˆAGG	U.S. investment grade bonds	Very low (Used for hedging)
ˆSPY	S&P500 market index	Low
ˆVGK	FTSE market index	Medium
ˆVWO	Various emerging markets globally	High

Table 12
Second set of ETFs selected for dynamic portfolio rebalancing experiment.

ETF Ticker	Market Sector
ˆAGG	U.S. investment grade bonds, included for hedging
ˆGLD	Gold spot price, included for hedging
ˆVAW	Materials sector
ˆVCR	Consumer Discretionary sector
ˆVDC	Consumer Staples sector
ˆVDE	Energy sector
ˆVFH	Financials sector
ˆVGT	Information Technology sector
ˆVHT	Health Care sector
ˆVIS	Industrial sector
ˆVNQ	Real Estate sector
ˆVOX	Communication Services sector
ˆVPU	Utilities sector

Table 13
GA derived attributes for the first set of ETF portfolio.

ETF Ticker	fMACDH Short period	fMACDH Long period	fMACDH Signal period	α	β
ˆAGG	1	35	47	0.002877357	−0.001810002
ˆSPY	13	46	30	0.001110505	−0.002115682
ˆVGK	5	45	36	0.005499194	−0.003570893
ˆVWO	2	3	43	0.00206	−0.002580471

Table 14
GA derived attributes for the second set of ETF portfolio.

ETF Ticker	fMACDH Short period	fMACDH Long period	fMACDH Signal period	α	β
ˆAGG	1	35	47	0.002877357	−0.001810002
ˆGLD	1	10	9	0.008566634	−0.007571127
ˆVAW	19	40	35	0.000732225	−0.000931759
ˆVCR	16	48	34	0.001024174	−0.001867539
ˆVDC	1	38	49	0.007226696	−0.00735962
ˆVDE	16	45	20	0.000797459	−0.000671206
ˆVFH	10	33	38	0.001534005	−0.001928799
ˆVGT	13	39	40	0.00258925	−0.003643088
ˆVHT	20	44	46	0.000712891	−0.00118471
ˆVIS	8	24	41	0.00282611	−0.002165171
ˆVNQ	7	38	17	0.002724131	−0.000237593
ˆVOX	13	47	48	0.001974847	−0.001535438
ˆVPU	3	14	46	0.001601159	−0.00378873

Table 15
Experiment result comparisons of the TBH algorithm (March 2017 to March 2021).

No.	ETF Assets	Investment Strategy	Final NAV	TBH over Buy and Hold or 1/N Strategy
1	ˆAGG	Buy and Hold Strategy	$1,044,372.71	143 %
2	ˆSPY	Buy and Hold Strategy	$1,422,598.88	105 %
3	ˆVGK	Buy and Hold Strategy	$1,047,199.80	143 %
4	ˆVWO	Buy and Hold Strategy	$1,183,860.64	127 %
5	All four ETFs	$1/N$ Portfolio Strategy Rebalancing Monthly	$1,186,133.79	126 %
6	All four ETFs	$1/N$ Portfolio Strategy Rebalancing Quarterly	$1,184,411.68	127 %
7	All four ETFs	**TBH Algorithm**	**$1,498,505.11**	–

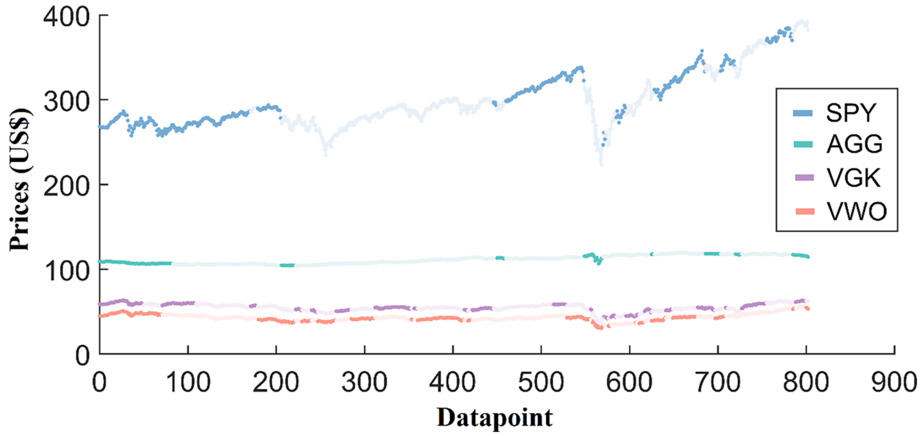

Fig. 8. Results of the TBH algorithm on four ETFs (March 2017 to March 2021).

gain in returns over the Buy and Hold strategy of the ˆSPY.

In addition, the ˆSPY, ˆVGK and ˆVWO prices seem to be highly correlated, despite being in different market sectors. In order to investigate the asset correlations in these four ETFs, the values of the asset correlations are calculated and shown in Table 16. It is observed that the asset correlations of the ˆSPY, ˆVGK and ˆVWO are high, with about 0.77 – 0.87 in correlation values between the ˆSPY v.s. ˆVGK, the ˆVGK v.s. ˆVWO, and ˆSPY v.s. ˆVWO. Hence, it indicates that the differences in price action of the different ETFs may not be sufficient for the TBH trading algorithm to achieve much higher performance, due to the commission loss. It is observed many trades between ˆVGK and ˆVWO despite little to no change in the stock price in Fig. 8.

The proposed TBH algorithm using the optimized fMACDH indicator shows promising results, consistently beating the $1/N$ portfolio strategy, as well as the Buy and Hold strategy of each individual ETF. However, due to the nature of global markets today, markets of differing risk levels may not necessarily show sufficient price variation that the TBH algorithm can take advantage of. This could potentially affect the performance of the TBH trading algorithm. As such, the RBBC portfolio rebalancing algorithm is developed, that focuses on taking advantage of the variation in different market sectors as a result of the business cycle.

4.5. Experiment results of the RBBC portfolio rebalancing algorithm

In this experiment, the second set of ETFs is selected for dynamic portfolio rebalancing experiment in March 2017 – March 2021. The experiment results of the RBBC portfolio rebalancing algorithm are shown in Table 17. Its performance comparisons over the Buy and Hold strategy, the $1/N$ portfolio strategy with equally rebalancing the portfolio monthly, and the $1/N$ portfolio strategy with equally rebalancing quarterly are also shown in the same table. For all the experiments, the commission rate of 0.1 % is used per trading transaction.

Observed from Table 17, the proposed RBBC portfolio rebalancing algorithm performs tremendously well, with over 200 % returns on the initial investment of USD$1,000,000. It outperforms the Buy and Hold strategy for 12 out of the 13 ETFs used, by an average performance of about 166 %. The sole outlier is the ˆVGT, which tracks technology sectors. It has performed freakishly well over this period. Such performance from a single stock is unlikely to persist over long periods of time.

Table 16
Correlation values matrix among ˆAGG, ˆSPY, ˆVGK and ˆVWO.

ETF ticker	ˆAGG	ˆSPY	ˆVGK	ˆVWO
ˆAGG	–	0.03	0.12	0.13
ˆSPY	0.03	–	0.87	0.77
ˆVGK	0.12	0.87	–	0.85
ˆVWO	0.13	0.77	0.85	–

Table 17
Experiment result comparisons of the RBBC Portfolio Rebalancing (March 2017 – March 2021).

No.	ETF Assets	Investment Strategy	Final NAV	RBBC over Buy & Hold and 1/N Strategy
1	ˆAGG	Buy and Hold Strategy	$1,046,766.48	192 %
2	ˆGLD	Buy and Hold Strategy	$1,366,529.92	147 %
3	ˆVAW	Buy and Hold Strategy	$1,206,029.88	166 %
4	ˆVCR	Buy and Hold Strategy	$1,841,292.95	109 %
5	ˆVDC	Buy and Hold Strategy	$1,163,349.93	172 %
6	ˆVDE	Buy and Hold Strategy	$720,342.87	279 %
7	ˆVFH	Buy and Hold Strategy	$1,173,195.58	171 %
8	ˆVGT	Buy and Hold Strategy	$2,140,824.12	94 %
9	ˆVHT	Buy and Hold Strategy	$1,451,148.76	138 %
10	ˆVIS	Buy and Hold Strategy	$1,261,922.20	159 %
11	ˆVNQ	Buy and Hold Strategy	$1,054,527.47	190 %
12	ˆVOX	Buy and Hold Strategy	$1,391,426.57	144 %
13	ˆVPU	Buy and Hold Strategy	$1,047,154.04	192 %
14	All 13 ETFs	$1/N$ Portfolio Strategy Rebalancing Monthly	$1,296,731.90	155 %
15	All 13 ETFs	$1/N$ Portfolio Strategy Rebalancing Quarterly	$1,306,427.78	154 %
16	All 13 ETFs	**RBBC Algorithm**	**$2,006,569.53**	–

The RBBC portfolio rebalancing algorithm also outperforms the $1/N$ portfolio strategy by about 54 % – 55 %. Thus, we believe that the proposed RBBC portfolio rebalancing algorithm would ultimately outperform for all the ETFs over a longer trading period.

The RBBC portfolio rebalancing algorithm at work is shown in Fig. 9. The lighter coloured lines show the price signal of each ETF, while the darker coloured lines denote when the RBBC portfolio rebalancing algorithm is currently holding onto shares of the corresponding ETFs. Observed in Fig. 9, despite tracking different market sectors, the 13 ETFs tend to follow the same general trend, with the RBBC algorithm choosing to buy and sell groups of ETFs at approximately the same time. However, there are definitely some variations in the price action of different market sectors, and the RBBC portfolio rebalancing algorithm is able to cycle between different sectors depending on the market conditions. It allows the RBBC portfolio rebalancing trading algorithm to perform well compared to the Buy and Hold strategy of a single ETF.

Overall, the RBBC portfolio rebalancing trading strategy shows great promise in taking advantage of differences in relative performance of different market sectors.

5. Conclusions and future works

In this paper, we first investigate various approaches of

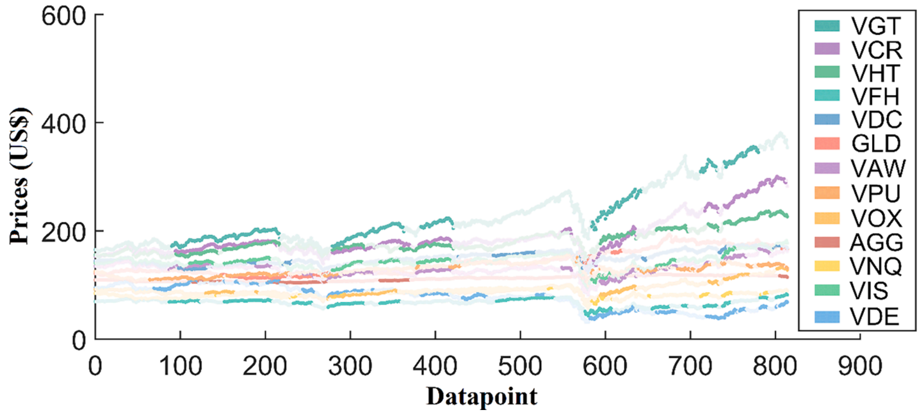

Fig. 9. Results of the RBBC portfolio rebalancing algorithm on 13 ETFs (March 2017 to March 2021).

counteracting the lagging tendency of financial technical indicators. Two trading indicators are proposed and evaluated: the optimised fMACDH indicator and the fMACDH-fRSI indicator.

The optimised fMACDH indicator is derived by extending to forecast stock prices by additional 1–5 days as the prediction depth. The corresponding 1–5 days of historical price data are needed as the input depth. The evaluation has been performed on the average percentage change in investment returns as benchmarked to the regular MACDH indicator. The parameter settings for the prediction depth and the input depth are configured as '1′, i.e., one-day, respectively to get better final NAV of investment.

The fMACDH-fRSI indicator is proposed by combining the optimized fMACDH indicator and the fRSI indicator. The trading signal is modified to be relevant to both the computed fMACDH value and the computed fRSI value.

The trade-off between the additional forecast leads and forecast accuracy has been studied for further reducing the indicator lag by optimizing the parameters with the GA. The GA and its fitness function have been designed and derived in this paper. The designed GA has been employed to tune and optimise the parameters of these two proposed indicators: the optimised fMACDH indicator and the fMACDH-fRSI indicator. The experiments have been conducted to compare their performances, where the proposed optimised fMACDH indicator outperforms the proposed fMACDH-fRSI indicator on each of the seven market indexes.

Using the proposed optimised fMACDH indicator and GA, two different rule-based trading strategies have been proposed to implement dynamic portfolio rebalancing algorithms: the TBH and RBBC portfolio rebalancing algorithms. Two sets of the ETF assets have been chosen for experiments to evaluate the performance of the TBH and RBBC portfolio rebalancing algorithms. The experiment results illustrate that both portfolio rebalancing algorithms perform significantly well. They generally outperform the $1/N$ portfolio strategy, as well as the Buy and Hold strategy despite an increase in commission costs.

For future works, more approaches to reduce indicator lags can be explored. The integration of other forecast leads, such as from more accurate TSK models, can be explored. Alternatively, the use of other trading indicators can be explored.

Additionally, whilst the SeroFAM system is an online learning model, the current optimised fMACDH indicator is an offline model, as it relies on the GA for optimising the parameters. Other online means of parameter optimisation can be explored and integrated into the SeroFAM system. It would enable the creation of a fully online trading system, capable of continually re-learning new fMACDH parameters and ensuring minimal indicator lag.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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