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Building Intelligent Moving Average-Based Stock Trading System Using Metaheuristic Algorithms

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ABSTRACT Many studies have been proposed to prove that technical analysis can help investors make trading decisions. The moving average (MA) is a widely used technical indicator that plays an important role in this field since it directly reflects stock fluctuations. However, most studies ignore the parameter settings of the MA, which leads to underestimation of the potential of the MA. Therefore, this paper is the first attempt to remove all restrictions and extend the limits of the MA to take advantage of the MA's capability well. It also uses different kinds of MA, such as the weighted moving average (WMA) and the exponential moving average (EMA), to compose trading strategies. Our system proposes the global best-guided quantum-inspired tabu search algorithm (GQTS), which is better at searching than traditional algorithms, to optimize trading strategies based on the MA. Furthermore, an innovative 2-phase sliding window is invented to consider more investment situations in changeable stock markets. In summary, this paper intended to investigate the ability of MA and proposed dynamic and intelligent trading strategies based on MA, GQTS, and 2-phase sliding window to assist investors to make trading decisions. The experiments show that the proposed system flexibly discovers better trading points. Our system outperforms traditional methods and beats the buy-and-hold strategy to yield significant profits both in developed and emerging stock markets.

INDEX TERMS Technical analysis, moving average, metaheuristic algorithm, optimization, trading decision making, emerging market, two-phase sliding window.

I. INTRODUCTION

Choosing when to buy or sell stocks to make profits in the stock market is the most important issue for investors. Finding relatively low prices to buy at and higher prices to sell at is a challenging task; most individual investors buy high and sell low because the stock market is complex and most people invest based on their emotions. There are many analysis tools, such as fundamental analysis, chip analysis, and technical analysis [1], [2], to help investors time their trades. In recent years, many studies [3]–[6] have proposed to show that technical analysis can help investors make trading decisions and profit in developed and emerging financial markets [7], [8]. Technical analysis considers historical stock data and predicts future patterns and trends. The tools used in technical analysis are technical indicators. There are many well-known technical indicators, such as the moving average (MA), moving average convergence/divergence (MACD), and the relative strength index (RSI), that have been successfully applied in the trading system.

The MA is the most popular, basic, and widely used technical indicator in financial fields to help investors understand the situation of the stock market and decide when to buy or sell stocks. The MA uses time series data to reflect the stock price based on different parameter settings and shows the short-term fluctuations in the stock market as well as the long-term trend of the stocks. The conventional MA generates buy signals when the short-term fluctuation crosses above the long-term trend, which indicates recent bullish momentum on stocks. Conversely, sell signals are generated when the short-term MA crosses below the long-term MA, indicating recent bearish momentum. Most studies use numerous technical indicators to build trading systems, but the parameters associated with these technical indicators are set to unchangeable numbers.

Although the target stocks and investment situations vary in different Although the target stocks and investment situations vary in different countries, the parameters of the

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technical indicators used in trading remain unchanged. Most studies do not optimize the parameters of technical indicators because of the calculation's complexity. The main problem is moving beyond constant optimal values to find the appropriate combination of parameters that can be used flexibly in various stock markets. The main objective of this study is that not only considers traditional parameter values, but also extends the limit of the MA by using various optimal parameters, trading signals, and trading strategies to suit different situations and investment targets. Hence, this paper represents the first attempt to remove all restrictions on and extend the limit of the MA. In this regard, the study makes three main contributions. First, the parameter of the MA, which is the duration and traditionally set to 5, 10 or 20 days, etc., is extended to cover the period from one day to one year. This means that our approach can observe fluctuations in the MA that range from daily expected values to the annual trend. Second, in our method, buy and sell signals are not necessarily generated when the short-term MA crosses above or below the long-term MA; any crossing is applicable. This means our approach identifies the best trading signals based on the crossing of any two MAs, which optimized by our search algorithm, are able to adapt to different situations; thus our approach improves the lagging nature of the MA. Finally, the traditional trading strategy of the MA uses the same parameter to build buying and selling signals, whereas the proposed method extends the trading strategy so that buying and selling rules are based on various parameter settings. This paper also optimizes different kinds of MA, such as simple moving average (SMA), weighted moving average (WMA), and exponential moving average (EMA), and breaks their traditional settings as well.

Finding the optimal combination of parameters for the extended MA with targets and different investment situations is quite difficult. The metaheuristic algorithms [9], [10] can be applied to various optimization problems and can provide proper solutions within a reasonable time. Numerous metaheuristic algorithms have been proposed and have yielded promising results. Quantum-inspired evolutionary algorithms (QIEAs) [12] constitute an emerging branch of evolutionary computation (EC) [13]. QIEAs can be regarded as a type of estimation of distribution algorithm (EDA) [14], [15]. These optimization algorithms use different probabilistic models by estimating the distributions of individuals of previous generations to generate promising new individuals and then prevent premature convergence, which traditional algorithms commonly face. They are very competitive in optimization problems. The quantum-inspired tabu search (QTS) algorithm [16], [17] is a relatively new algorithm that applies a novel, effective, and efficient global search strategy. The QTS algorithm uses the best and worst solutions to simultaneously move individuals toward the best solution and away from the worst solution. This simultaneous guidance is why the QTS algorithm is quicker and more efficient than traditional heuristic algorithms. This paper also presents an improved QTS algorithm, called the GQTS algorithm, that uses the global best solution to enhance the intensification.

This paper uses a sliding window to avoid over-fitting and to dynamically alter the trading strategies according to the time period. The main functions of the sliding window are to process continuous stock data and to replace old data with new data as time progresses. The replacement interval is not necessarily the same length. To find the proper period, this paper adopts different window sizes. Unlike the traditional sliding window, which uses the closest stock price in the training period, this paper tests the sliding window year over year by using the same period in the previous year as training data because some stocks are subject to economic cycles. Therefore, this work investigates not only the traditional sliding window but also the year-over-year sliding window. Moreover, to suit various trading situations and numerous investors, this paper innovatively proposes a novel method, the 2-phase sliding window, which can consider multiple investment situations and can find the best one to help investors construct their trading strategies.

The objectives of this study are that discover the potential of MA and combine it with computational intelligence techniques to build dynamic and intelligent trading strategies that can provide investors to make trading decisions. This paper proposes a state-of-the-art approach to moving average (MA) analysis by extending the limit of the MA to find solutions that can significantly improve its ability to forecast trends and break its nature as a lagging indicator. We furthermore propose a novel algorithm, GQTS, to optimize trading strategies based on SMA, WMA, and EMA, and use a new technique, a 2-phase sliding window, to build further suitable trading strategies. The proposed method can automatically optimize the best trading strategy based on the MA and can be applied to developed and emerging stock markets with impressive results. As these results reveal, our trading strategies can beat stock market yields and outperform traditional methods. The remainder of this paper is organized as follows: Section II briefly reviews the literature. Section III provides background information on technical indicators and sliding windows. Section IV presents the details of the proposed trading system. Section V discusses the experimental results, and we draw our conclusions in section VI.

II. RELATED WORK

In this section, two types of related studies are described: previous methods for building automated trading systems and previous work on the QTS algorithm.

Recently, numerous studies [18] that combine technical analysis with computational intelligence have been proposed to construct trading rules or trading strategies and show promising results in different stock markets. There are other studies [19], [20] that not only combine the technical indicators but also use other information, such as stock news, to find trading signals. Frequently used optimization techniques include genetic programming (GP), genetic algorithms (GAs), particle swarm optimization (PSO), fuzzy theorems, artificial neural networks (ANNs), machine learning (ML), and hybrid methods. Some studies [21]–[32] have used fuzzy theorems, ANNs, ML, and technical indicators such as the MA and MACD to help define the trend of a stock and then predict its price to help investors make trading decisions. In [22], [23], daily closing prices and a back-propagation neural network are used to predict stock prices. This system performs well with input variables that are the only highly correlated element, stock closing prices over the past N days. In [24], technical indicators such as moving average indicators and moving average volume indicators are combined with fuzzy theory to compose trading rules. It is concluded that trading systems based on the pure price trend are better than those based on the pure volume trend or hybrid price-volume trends. In [28], [29], they used the MA technique to reflect the trend of the stock market and then used a support vector machine (SVM) to identify appropriate trading signals. In [30], the author uses PSO to improve the ability of support vector regression (SVR) and proposes adaptive SVR to predict stock prices more accurately. Some studies [31], [32] construct trading rules based on feedback laws; these studies only observe stock price, not fundamental values. In addition, some studies [33]–[37] used hybrid models that combine evolutionary methods and fuzzy theorem to predict stock price or improve the portfolio selection problem.

Some [38]–[43] studies have focused on using GAs, GP, genetic network programming, and EDAs to construct or create new trading rules based on technical indicators such as the MA, the RSI, MACD, the rate of change (ROC) or price and volume information to help investors decide when to buy or sell stocks. In [38]–[40], the authors use GP, which is based on a tree structure, and technical indicators, such as the MA and the ROC, as input variables to generate new trading rules. This method outperforms the buy-and-hold strategy, which is a common benchmark in this area. The trading rules they create, such as when the 3-month moving average is less than the lower trend line or when the 2-month moving average is less than the 10-month moving average, are combinations of different technical indicators that use logical operations, such as and, greater than, and than less. In [43], pattern recognition techniques and technical indicators such as the MA, MACD, and the RSI are used as input variables; then, a GA kernel is used as the core optimization method to identify optimal trading strategies. Additionally, several studies have used EC, PSO, and ANNs [44]–[48] to find combinations of technical indicators or optimize the weights of different technical indicators, such as the MA, MACD, the RSI, and bias, to put many technical indicators into a trading strategy. In [44], the authors use a biclustering algorithm to discover effective technical trading patterns that contain a combination of indicators from historical financial data series. In [45], several technical indicators (the MA, MACD, the RSI, stochastic oscillators (STOs), the commodities channel index (CCI), and the William percent range (%R) are used, and PSO is used to calculate the weight of each indicator, then determine whether to buy, sell or hold the particular stock. In [46], the QTS algorithm is used to find the optimal combination of trading strategies based on eleven technical indicators, including the MA, MACD, the RSI, and the %R, with three common periods (variables) for each indicator. In [48], trading rules are generated using ten different technical indicators, including MA, RSI, KD and so on. The author then uses a grouping genetic algorithm to discover useful trading strategies. In [49], the author investigates many technical indicators to select the most accurate indicators for forecasting stock price.

Basically, the methods described above all use the technique of technical analysis and produce great results. However, the parameters of the technical indicators remain the same when these methods are applied in different situations. Therefore, several studies have used EC to optimize the parameters of technical indicators [50]–[54] to suit different investment situations. In [50], PSO is employed to optimize the parameters of the MA, and the duration parameters are bounded by 5 to 50 days. The results show that the parameter of the MA does not like traditional sets and leads to substantial profits and reductions in losses in unfavorable market conditions. In [51], a multi-objective evolutionary algorithm is used to find the proper parameter settings for MACD and the RSI, and the obtained results perform better than the results of the buy-and-hold strategy. Reference [52] addresses the main problem, which is that one use of an indicator is to determine the appropriate parameters. A multi-objective GA is adopted to optimize the parameters for MACD, the RSI, the double exponential moving average crossover (DEMAC), and the moving average RSI. The results show that the optimized parameters beat the indicators with typical parameters and outperform the buy-and-hold strategy most of the time. [53] uses multi-objective optimization to find the appropriate parameters for the EMA, the RSI, MACD and the %R. The results show that optimized indicators produce excess returns compared to the common parameter settings and produce better returns than the buy-and-hold strategy. In [54], the author uses dynamic multi-objective algorithms to build a decision model that optimizes the parameters of RSI and MACD on profit making in automated trading in the foreign exchange market.

In general, studies that attempt to find combinations of technical indicators or optimize the parameters of technical indicators to produce positive results. In addition, they all use the MA as a tool, which makes the MA the most frequently used tool since it is the technical indicator that most directly reflects stock market trends. However, the MA is still bound by some constraints in these methods, such as a duration of 5 to 50 days. Buying and selling use the same parameters, and the signals occur only if the short MA goes up or down to the long MA. Since the MA is the most significant technical indicator, this paper challenges the limit of the MA and pushes it to determine how effective the MA is.

When we optimize the MA without many restrictions, the complexity increases rapidly. Therefore, this paper proposes a novel optimization method called the GQTS algorithm, which is based on the QTS algorithm and has a powerful search ability to help discover the optimal parameter of the MA efficiently. Compared with other traditional evolutionary algorithms [9]–[11], such as GAs, PSO, the tabu search, and QIEAs [55]–[57], and the quantum-inspired electromagnetism-like mechanism (QEM) [58], the QTS [16] algorithm shows much better performance on both the 0/1 knapsack problem and the traveling salesman problem. Moreover, the QTS algorithm has been applied to many combinatorial optimization problems and used in real world application, such as function optimization [17], [59], deployment in wireless sensor networks (WSNs) [60], wormhole attack detection [61], stock selection [62], stock trading [63], [64], and reversible circuit synthesis [65]. The QTS algorithm demonstrates better results than other traditional optimization methods for these optimization problems. This is why this method uses the QTS algorithm as the basic search algorithm and improves its ability to search. GQTS improves QTS by using the global best strategy to update the probability, which has a better ability for exploitation. In addition, many studies [54], [66], [67] use sliding windows to find the appropriate training and testing size. In [66], this study uses the sliding window and ML to predict the trend of a stock price. The results show that the sliding window decreases the computational burden and addresses the overfitting problem. Therefore, in this study, we adopt a sliding window, improve it, and then invent a novel method called the 2-phase sliding window to address more complex stock market trading situations.

In summary, to the best of our knowledge, this study is the first attempt to remove all restrictions on the MA and then use the GQTS algorithm, which searches faster than the QTS algorithm, and a 2-phase sliding window to optimize the use of the MA, thereby identifying the optimal strategy based on the MA. It generates the best buy and sell signals in various investment situations.

III. PRELIMINARY

In this section, the concept of the MA and other popular variations on the MA, such as the WMA and the EMA, is described. This section explains how these indicators are calculated and how they generate trading signals. In addition, it briefly introduces how the traditional sliding window works.

A. MOVING AVERAGE

The MA is the most basic technical indicator and the most widely used by investors. It has been regarded as one important piece of information for making trading decisions in financial markets. The traditional trading strategy based on the MA generates a signal when the short-term MA crosses the long-term MA. When the short-term MA crosses above the long-term MA, there is a bull market, which is a buy signal. Conversely, when the short-term MA crosses below the long-term MA, there is a bear market, which is a sell signal. Basically, there are three well-known kinds of MA: the SMA, WMA, and EMA.

1) SIMPLE MOVING AVERAGE, SMA

The equation for the SMA is as follows:

$$MA_t(n) = \frac{p_{t-(n-1)} + \ldots + p_{t-1} + p_t}{n} \tag{1}$$

where $MA_t(n)$ represents the average of the n days prior to the closing price and p_t is the closing price on day t. The duration (n) is generally in one of the three major categories: short-, intermediate-, and long-term. This parameter usually considers 5 or 10 days short-term, 20 or 60 days intermediate-term, and 120 or 240 days long-term. These periods represent approximately one week, two weeks, a month, a season, half a year, and a year, respectively.

2) WEIGHTED MOVING AVERAGE, WMA

The WMA is an average that gives different weights to stock price data on different days. This indicator is calculated by Equation (2).

$$WMA_t(n) = \frac{1 \cdot p_{t-(n-1)} + \ldots + (n-1) \cdot p_{t-1} + n \cdot p_t}{1 + 2 + \ldots + (n-1) + n} \tag{2}$$

The WMA is an average that gives different weights to stock price data on different days, and the weights usually decrease linearly. The older a data point is, the smaller the weight assigned to it is. In contrast, higher weights are assigned to more recent data. This can help investors analyze recent stock trends.

3) EXPONENTIAL MOVING AVERAGE, EMA

The EMA weights the closing prices exponentially. This indicator is calculated by Equation 3.

$$EMA_t(n) = EMA_{t-1}(n) + \alpha \times [p_t - EMA_{t-1}(n)]$$
$$\alpha = 2/(n+1) \tag{3}$$

The EMA is a commonly used type of MA. This indicator is calculated by Equation (3). The weights of the data points decrease exponentially, which means this index assigns greater weight to the most recent data and substantially less weight to the older data. The EMA is also a basic indicator used in MACD calculations [59].

Investors can use the MA to easily understand the trend of a stock because it reflects the average stock price. However, the drawback is that the MA is a lagging indicator. Using its traditional parameters, the MA generates buy or sell signals that exceed the highest or lowest point at which such signals occurred. This study significantly improves the usability of the MA by removing the restrictions on it.

B. SLIDING WINDOW

In the stock trading system, stock prices change every day. We use the sliding window method because it can adapt to the dynamic environment. The sliding window concept involves

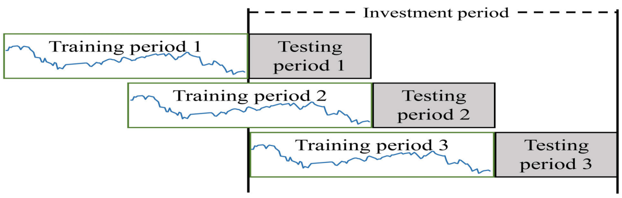


FIGURE 1. Sliding window mechanism.

handling a series of continuous data. Data are substituted by repeatedly replacing obsolete data with recent data. Figure 1 shows the sliding window mechanism. This method separates the investment period into multiple sections of the testing period. Then, it uses historical data that are closer to the testing period as a reference to identify proper trading rules. This period is called the training period. The sizes of the training and testing periods are generally a month, a quarter year, half a year, and a year for the stock problem. In this paper, they are represented simply by M, Q, H, and Y, respectively. The training size is greater than or equal to the testing size because the strategy cannot look for a similar situation and find a proper trading rule when it trains without a long enough history. For example, it is difficult to use the events of the past week to predict the events that will occur over the whole year. On the contrary, the training period cannot use very early data as input because the old data has lost its reference value. For example, it does not need to use ten years or more of historical data to predict the trend for one day. There are ten combinations of training and testing periods: MM, QM, HM, YM, QQ, HQ, YQ, HH, YH, and YY. With MM as an example, assume that January is the first training period and that the following month, February, is the testing period. Once February has been tested, it becomes the training period, and the subsequent month, March, becomes the testing period. This alternating mechanism is the main characteristic of the sliding window. In addition, We also adopt year-on-year sliding windows such as M*, Q*, H* that use the same period in the last year as the training data. With M* as an example, assume that January 2018 is the training period, then January 2019 is the corresponding testing period.

IV. PROPOSED METHOD

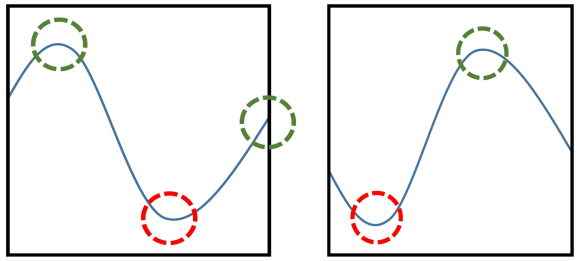
This section details the proposed automated trading system based on various MAs. This paper proposes a novel method to extend the limit of the MA to remove traditional restrictions and minimize the drawbacks of the MA. Therefore, the GQTS algorithm, which is more effective than the QTS algorithm and other traditional algorithms, is proposed to identify the optimal trading strategy based on the MA. In addition, to deal with such a complex stock trading problem, the innovative 2-phase sliding window is invented in this paper to consider multiple situations. The pseudocode for the proposed automated trading system based on the MA is shown in Algorithm 1.

Algorithm 1 Automated Trading System Based on the MA, the GQTS Algorithm, and a 2-Phase Sliding Window

$TrainingP \leftarrow 0, t \leftarrow 0, phase \leftarrow 0,$
while $TrainingP \leq Last_P$ **do**
  while $phase \leq 2$ **do**
    if phase **then**
      Holding funds at beginning
    else
      Holding stocks at beginning
    end if
    Initialize quantum population $Q(t)$
    while not termination-condition **do**
      $t \leftarrow t + 1$
      Produce trading rule set N by multiple measurements of $Q(t-1)$
      Calculate profit
      Select the best solution in past generations (s^{Gb}) and the worst solution among N (s^{w}).
      Update $Q(t)$
    end while
    $phase \leftarrow phase + 1$
  end while
  Change the initial state of the testing period to match the best trading strategy
  Use the best strategies to trade in the corresponding testing periods
  $TrainingP \leftarrow TrainingP + 1$
end while

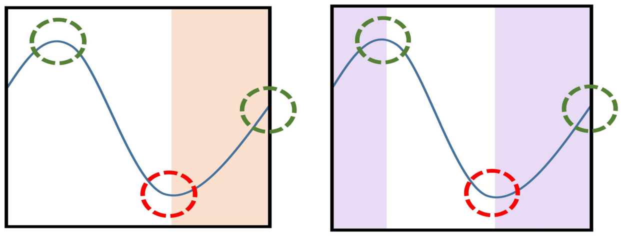
A. TWO-PHASE SLIDING WINDOW

The traditional sliding window holds funds at the beginning of the training period. This approach is not considered comprehensively. An example is shown in Figures 2-4, where the green dotted circle represents a sell signal and the red dotted circle represents a buy signal. Figure 2 shows two stock trends in the training period. Figure 2(a) shows that the stock rises at the beginning; the trading strategy is to buy at the red dotted circle and to sell in the two green dotted circles. While funds are being held, there is no trading until the buy signal occurs, and then selling occurs on the last day of the period. The holding period is the orange area in Figure 3(a). In a given stock trend with stocks held during the holding period (purple area), a greater return results because of the additional holding period, as shown in Figure 3(b). In this case, when the stock rises at the beginning, it is more appropriate to train the trading rules by holding stocks at first. However, holding stocks at first is not always suitable. Figure 2(b) shows a trend that decreases at the beginning. Figure 4(a) shows that the strategy of holding funds at the beginning is better in this trend. Conversely, Figure 4(b) shows that holding stocks is not as good as holding funds at the beginning. This situation also considers investors may have their own stocks before using our system. Therefore, the profit is actually affected whether funds or stocks are held at the beginning, but the traditional sliding window does not consider these situations. In our research, we propose a 2-phase sliding window to train both situations, holding funds and stocks at the beginning, and then choose the best strategy for the corresponding testing periods. In addition, the beginning of the testing period



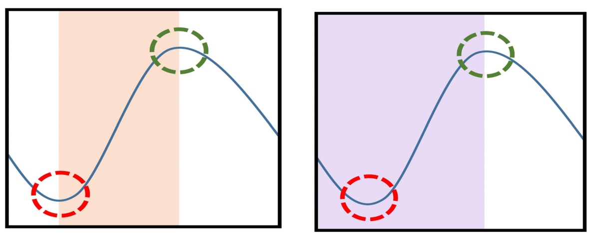
(a) (b)

FIGURE 2. Two stock trends: (a) Rising and (b) falling at the beginning.



(a) (b)

FIGURE 3. Different holding periods with a stock trend that rises at the beginning: Holding (a) funds and (b) shares.



(a) (b)

FIGURE 4. Different holding periods with a stock trend that falls at the beginning: Holding (a) funds and (b) shares.

inherits the status (holding stocks or funds) at the end of corresponding training periods.

B. TRADING STRATEGY BASED ON THE MA

This study uses the MA as the basis for a trading rule. The MA is a very important technical indicator, but previous studies have usually ignored the potential of technical indicators and merely used traditional parameter settings. Our MA not only includes all the traditional parameters but also expands the restrictions on the parameters and the principle of generating trading signals. Furthermore, different kinds of MA, i.e., the SMA, WMA, and EMA, are employed in the proposed automated trading system.

Traditionally, there are three restrictions when the MA generates a trading signal. First, the duration of the MA usually set to 5, 10, 20, 60, 120, or 240 days, which represents approximately a week, a fortnight, a month, a season, a half year, or a year on the stock market, respectively. These parameter settings seem reasonable, but in the real stock

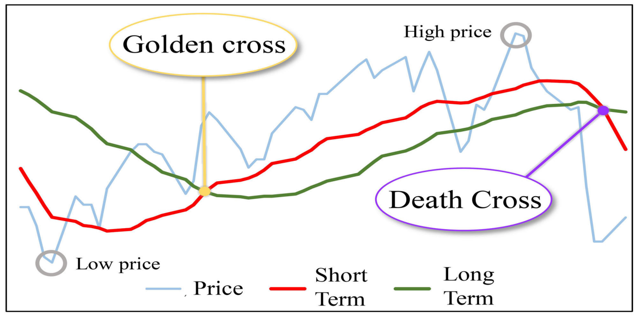


FIGURE 5. Trading points and low/high prices.

market, the opening day can be influenced by terrible weather, disasters, national holidays, and other unexpected situations. Therefore, it is not always open 5 days per week, and other parameters are also affected. Second, the golden cross and the death cross restrict the parameters that should use short- and medium-duration MAs or medium- and long-duration MAs. For example, MA (5, 20) and MA (60, 240) can be used to generate traditional trading signals, but MA (5, 240) and MA (20, 60) are not appropriate. Third, the golden cross and the death cross are set to be the same. This means that MA (5, 20) is used for both buying and selling. In other words, when MA (5) crosses above MA (20), a buy signal is generated, and when MA (5) crosses below MA (20), a sell signal is generated. With these restrictions, the MA has a shortcoming: the timing usually misses buying at the low points and selling at high prices. This is why the MA is known as a lagging indicator and is shown in Figure 5.

Our method removes the above three restrictions and proposes a new intelligent trading strategy based on the MA. First, in our system, the parameter of the MA is extended so that the duration can range from 1 to 256 days, from MA (1) to MA (256). In other words, these parameters can be chosen from one day's MA, which reflects the daily price, to the MA for 256 days, which covers any year's opening day. Second, trading signals are generated when any two MAs cross, which is applicable to many different situations in the stock market. It not only includes all the examples of the traditional setting but also expands to a large number of strategic possibilities, such as MA (2, 248), MA (167, 14), and MA (43, 5). Finally, the rules for buying and selling can be different. For example, choosing MA (47, 45) for buying and MA (63, 139) for selling is one solution employed by our intelligent system to flexibly find low prices at which to buy stocks and relatively high prices at which to sell. In addition, this method optimizes different types of MA, such as the SMA and the WMA, to search for optimal trading signals. Sample trading rules based on the MA are shown in Equations 4, 5, 6, and 7. t is the date used to calculate the MA.

$$SMA_{buy,t}(n_1, n_2), \quad SMA_{sell,t}(n_3, n_4)$$
$$n_1,\ n_2,\ n_3,\ n_4 \in [1, 256] \tag{4}$$
$$WMA_{buy,t}(n_5, n_6), \quad WMA_{sell,t}(n_7, n_8)$$

TABLE 1. Example of encoding MA (47).

2^7	2^6	2^5	2^4	2^3	2^2	2^1	2^0	value
0	0	1	0	1	1	1	0	46

$$n_5,\ n_6,\ n_7,\ n_8 \in [1, 256] \tag{5}$$

$$EMA_{buy,t}(n_9, n_{10}), \quad EMA_{sell,t}(n_{11}, n_{12})$$

$$n_9,\ n_10,\ n_11,\ n_12 \in [1, 256] \tag{6}$$

$$Trading \begin{cases} buy, & if\ MA_{buy,t}(d_1) > MA_{buy,t}(d_2) \\ & \&\ MA_{buy,t-1}(d_1) \leq MA_{buy,t-1}(d_2) \\ & d_1, d_2 \in [1, 256] \\ sell, & if\ MA_{sell,t}(d_3) < MA_{sell,t}(d_4) \\ & \&\ MA_{sell,t-1}(d_3) \geq MA_{sell,t-1}(d_4) \\ & d_3, d_4 \in [1, 256] \end{cases} \tag{7}$$

C. GLOBAL BEST-GUIDED QUANTUM-INSPIRED TABU SEARCH (GQTS) ALGORITHM

Since this trading system does not restrict the parameters of the MA, the search space is large, and an effective search algorithm is required to identify the optimal trading strategies. The QTS algorithm, which is more effective than the traditional metaheuristic algorithm [13], is adopted. However, there is a drawback when QTS solves this trading problem: the best solution in each generation is used to update the probability in the QTS algorithm, which decreases the ability of the QTS algorithm to intensify the search. Therefore, this system improves the ability of the QTS algorithm to intensify the search by using the global best solution, which is the best solution in the past generations, to update the probability. Some examples are given to make the proposed algorithm easier to understand.

1) REPRESENTATION

The encoding scheme is an important step in a system. In the GQTS algorithm, binary strings are used to represent numbers to allow the encoding method to solve both numerical and combinatorial optimization problems. Table 1 shows how MA (47) is encoded as an example. Furthermore, the proposed method extends the parameters of the MA. A sample trading strategy is shown in Table 2. A trading strategy includes rules for buying and selling; therefore, we define MA(d_1, d_2)·MA(d_3, d_4) as a the trading strategy in which d_1, d_2, d_3, and d_4 are the durations of the MA. $MA(d_1, d_2)$ is in charge of determining when to buy, and $MA(d_3, d_4)$ is in charge of determining when to sell. Our method differs from the traditional approach; the values of d_1, d_2, d_3, and d_4 can be any numbers within a year. The rules for buying and selling on the opening day can also be different.

2) INITIALIZATION

A quantum matrix (Q) is used to store the probability of each measurement, just as each quantum has different probabilities of seeing different states. Q is used for determining the solution in the GQTS algorithm. $Q(0)$ can be expressed as

$$\begin{bmatrix} q_1^1 & q_1^2 & \cdots & q_1^n \\ q_2^1 & q_2^2 & \cdots & q_2^n \\ \vdots & \vdots & \ddots & \vdots \\ q_d^1 & q_d^2 & \cdots & q_d^n \end{bmatrix},$$

where n signifies the length of the binary string that represents the duration and d represents the buy and sell rules of the MA. Initially, there is no information in the solution space, so the q_i^k in Q are set to $\frac{1}{\sqrt{2}}$, where i represents the bit corresponding to the variable and k represents the corresponding rule. This means that each q_i^k has the same probability of being selected to maintain the variability of the strategy. The square of q_i^k is the probability of measuring the state at 0 or 1.

TABLE 2. Encoding a trading strategy that contains MA(47,122)·MA(9,243).

	2^7	2^6	2^5	2^4	2^3	2^2	2^1	2^0	value
n_1	0	0	1	0	1	1	1	0	46
n_2	0	1	1	1	1	0	0	1	121
n_3	0	0	0	0	1	0	0	0	8
n_4	0	1	1	1	0	0	1	0	242

Algorithm 2 Procedure Measure (s)

```
for i = 1 to d do
    for k = 1 to n do
        r ∈ random number U[0,1]
        if r < |q_i^k|^2 then
            x_i^k ← 1
        else
            x_i^k ← 0
        end if
    end for
end for
```

3) MEASUREMENT

This section is inspired by quantum computing; the measurement involves using the GQTS algorithm to generate a new solution. To build the solution, we compare the random variable r_i^k with the probability, which is the square of q_i^k in Q and determine x_i^k, which is the state of this bit. The pseudocode is given in Algorithm 2. Measuring maintains the variability of the trading strategy in the early phase and tries to jump out of a local optimum in the late phase. However, after numerous iterations, Q converges. The first bit of the probability of q_1^0 may become 0.1. This means that the first bit has a 90% probability of becoming 1, but it also means that first bit still has a 10% chance to become 0. Q prevents the GQTS algorithm from converging prematurely.

4) FITNESS

The fitness represents the return during the period of the trading strategy. Clearly, fitness in trading stock is determined by the profit. Consequently, if the trading strategy involves buying at a relatively lower price and selling at a higher price during same period, that strategy is fit. The fitness is calculated using Equations 8, 9, and 10.

$$Share = \left\lfloor \frac{started\ fund}{buying\ price} \right\rfloor \tag{8}$$

$$Remaining\ fund = \lfloor started\ fund - (Share \times buying\ price) \rfloor \tag{9}$$

$$Return = \lfloor Share \times selling\ price + Remaining\ fund) \rfloor \tag{10}$$

To compare the fitness of each strategy on the last day of the investment period, if stock is held on the last day of investment period, we compare it with the return of the stock based on the closing price.

5) UPDATING

The QTS algorithm records the best and worst strategies in the same generation. The best strategy is the one that obtains the highest return, and the worst strategy is the one that obtains the lowest return. The QTS algorithm uses these two strategies to update Q and then has the next generation move forward to the best solution and away from the worst solution simultaneously. The GQTS algorithm uses the global optimum solution, which is the best solution for the past generations, for guidance while finding a better trading strategy and improving its ability to intensify the search.

The GQTS algorithm compares the corresponding bits of the global best strategy and the worst strategy. Only two states are compared in the most- and least-profitable solutions: the same state (00 or 11) and different states (01 or 10). If they are in the same state, then it is unnecessary to change the probability q_i^k in Q. If they are in different states, then we update the weights of the q_i^k using a rotation angle θ. The equation for the update is shown in Equation 11, where GB is the global best strategy for the previous generations and W is the worst strategy for this generation.

$$\begin{cases} IF\ GB_i^k \neq W_i^k\ AND\ GB_i^k = 0, & THEN\ q_i'^k = q_i^k - \theta, \\ IF\ GB_i^k \neq W_i^k\ AND\ GB_i^k = 1, & THEN\ q_i'^k = q_i^k + \theta, \end{cases} \tag{11}$$

6) TERMINAL CRITERION

The stock trading problem is very complex; stock prices can involve different levels of complexity in periods of different lengths. For instance, a longer trading period becomes more complex and requires more iterations for the algorithm to convergence. Therefore, this paper sets a dynamic terminal condition, which is to stop when continuous generations have the same solution. Conversely, if this condition is not satisfied, the algorithm goes back to step 3, measurement.

To sum up, the exploration and exploitation characteristics of GQTS algorithm are that GQTS using the quantum matrix (Q) to represent the probability of selected bits to show the exploration of GQTS, and GQTS using the global best solution which means the best solution in the past generation rather than the current generation to update the Q matrix show the exploitation of GQTS. We initialize each bit to set them has 50% to be selected or not, which means GQTS can try different solutions to explore the solution space in the early stage and still have the probability to jump out at the late stage, and GQTS using both global best solution and worst solution simultaneously to update the matrix to intensify its search. Hence, GQTS has great abilities both in exploration and exploitation.

In summary, our proposed method removes the restrictions on the MA and extends the parameters of the MA to obtain more possible solutions for more different stock market situations. Then, to efficiently and effectively identify the optimal trading strategy, the GQTS algorithm, which is better able to intensify the search than the QTS algorithm, is used. Furthermore, a 2-phase sliding window is used for solving the dynamic trading problem and to consider more investment situations for higher profits.

V. EXPERIMENTS

In this section, the performance of the proposed automated trading system, as based on the MA, is evaluated for U.S. and Taiwan's stock markets. Taiwan's economic growth mostly depends on international trades, meaning that different stock market fluctuations affect Taiwan's stock market, such as the US, Japan, China, Hong Kong, Singapore, and even stock markets in Europe and Australia. In other words, Taiwan's stock market situation can represent a major part of the world's stock market situations, and thus, is worth of study. The proposed trading system is implemented in C++. The stock price data in the experiment are from Yahoo Finance, Google Finance, and Taiwan Economic Journal (TEJ). In the experiments, the Taiwan 50 ETF (0050) is chosen as an important investment target. The Taiwan 50 ETF is an exchange-traded fund that combines the weighted prices of the top fifty stocks in terms of market capitalization. The Taiwan 50 ETF is a good representative index because its fluctuations reflect 70% of Taiwan's stock market and it is recommended by the government. A comparison of the QTS and GQTS algorithms is presented in section V-A. The performance of the 2-phase sliding window is demonstrated in section V-B. The results of the proposed strategies based on the MA and comparisons with the traditional MA are described in section V-C. In section V-D, an experiment that evaluates the SMA, the WMA, and the EMA is described. The performance during the testing period is discussed in section V-E.

A. COMPARISON BETWEEN THE QTS AND GQTS

The experimental results are based on the best run of thirty independent runs. The algorithm population is 300, and the terminal criterion is that our method cannot find a better solution after thirty iterations. The size of the sliding window is MM. The investment period is from 2011 to 2017. Figure 6 compares the annual returns of the GQTS and QTS

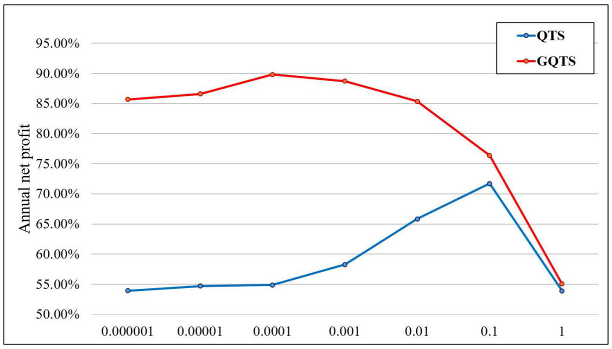


FIGURE 6. Annual net profit of the QTS and GQTS algorithms for different values of θ.

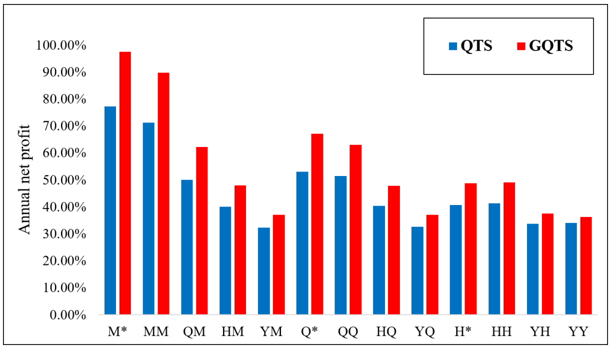


FIGURE 7. Performance of the QTS and GQTS algorithms over all sliding window periods.

algorithms for different rotation angles (θ). The angle ranges from 0.000001 to 1. The results show that the GQTS algorithm produces the highest profit at an angle of 0.0001. Because the GQTS algorithm is guided by the global optimum solution, it needs a small angle to prevent premature convergence. In contrast, the QTS algorithm performs the best at an angle of 0.01. The QTS algorithm performs well at a larger angle. This result shows that the GQTS algorithm performs better than the QTS algorithm for these different angles. Hence, we set GQTS with the 0.0001 angle and QTS with 0.1 angle for the rest of the experiments. Moreover, Figure 7 shows that the GQTS algorithm provides more annual net profit than the QTS algorithm does in every sliding window period. These experiments can find GQTS algorithm is more stable than the QTS algorithm does.

B. EXPERIMENT WITH THE 2-PHASE SLIDING WINDOW

The traditional sliding window only considers one situation: training the algorithm with only one fund and testing the best strategy during the testing period. The proposed 2-phase sliding window trains the algorithm with both funds and stocks and then determines which is best to trade during the testing period and alters the beginning state, which is to hold fund or stocks, according to the best trading strategy. The experiment presents the effectiveness of the 2-phase sliding window in Figure 8. The experimental results show that the GQTS algorithm with the 2-phase sliding window can yield more profit than the GQTS algorithm with the traditional sliding window over different periods.

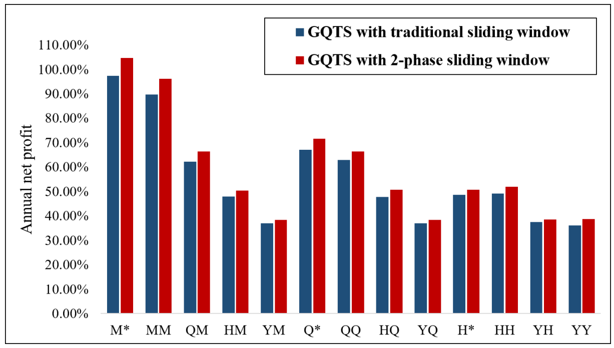


FIGURE 8. Performance of 2-phase sliding window for all the sliding window periods.

C. COMPARISON BETWEEN THE PROPOSED METHOD AND THE TRADITIONAL MA

Figure 9 show that during 2011 to 2019, the proposed trading strategies based on the MA which extend the limit of the MA and use the GQTS algorithm to optimize the parameters outperform the MA with traditional parameter settings and restrictions. The experiments also show that our MA can beat the stock market, represented by the buy-and-hold strategy. Our method yields more profit than the traditional method. In addition, we analyze the proposed method and the traditional MA (5, 20) in the experiments. Figure 10 shows the timing of buying and selling with these two trading strategies. It finds that MA (5, 20) lags the most, which could cause it to miss the relative lowest price at which to buy and the highest points at which to sell. On the contrary, our trading strategy, which yields MA_{buy} (38, 6) and MA_{sell} (99, 34) in this period, removes the restrictions on the MA, extends the use of the MA and identifies relative lows at which to buy and highs at which to sell. It also shows that different buying and selling strategies discover better trading points and that it is not always necessary to determine when the short-term MA crossing the long-term MA represents a buy or sell signal. In the experiment, according to statistics, only 6,843 out of 179,280 $\cong$ 3.82% optimal MA trading strategies use traditional rules. This reveals that over 96.1% of MA trading rules escape the traditional restrictions, and were used in the optimal strategies. Based on the experimental results, the proposed intelligent trading strategy removes the restrictions of the traditional MA, which its advantage is that it enables the MA to be more suitable in different investment situations. The proposed intelligent trading strategy, as based on the MA, can automatically optimize the best trading strategies by computational intelligence techniques through advanced personal computers. Thus, as the optimal parameters will automatically change based on the different investment targets and situations, investors will not need to remember the parameters of MA by rote. In this paper, we focus on push the limit of MA, and the limitation is that there are still several

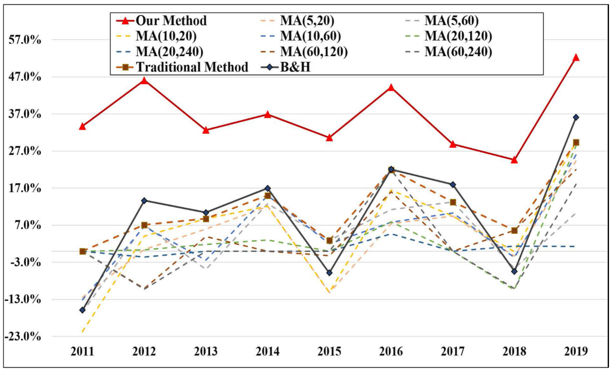


FIGURE 9. Performance of the proposed method, the traditional MA, and B&H strategy.

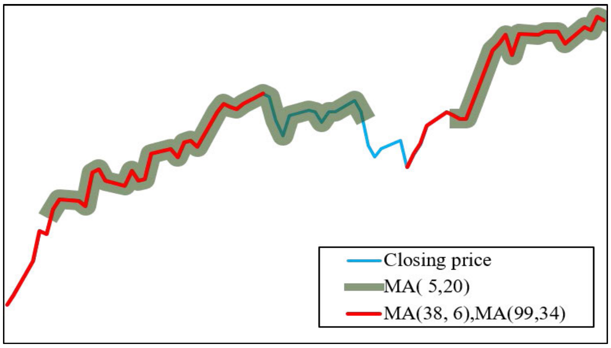


FIGURE 10. Comparison between the traditional MA and the proposed MA.

technical indicators that show potential we have yet to use. Hence, in future work, the proposed model can consider more technical indicators to optimize their parameters based on the success of extending MA.

D. EXPERIMENTS WITH THE SMA, WMA, AND EMA

The proposed method also optimizes different kinds of MA (the SMA, the WMA, and the EMA). The WMA and the EMA change the weight of the daily closing price. They use higher weights for recent closing prices and lower weights for older data. The WMA and the EMA change the weight of the daily closing price. They use higher weights for recent closing prices and lower weights for older data. The WMA linearly decreases the weight, whereas the EMA decreases it exponentially. The investment period is from 2011 to 2019.

In the experiments, the GQTS algorithm with the 2-phase sliding window optimizes the different types of MA for different investment targets, including the Taiwan 50 ETF (ETF) and the top three companies in terms of market capitalization: Taiwan Semiconductor Manufacturing Co., Ltd. (TSM), which is the world's largest dedicated independent semiconductor foundry, Hon Hai Precision Industry (HNHPF), and Chunghwa Telecom (CHT). These three companies can also trade on US stock exchanges (ADR stocks). In addition, we analyzed the correlation coefficients between the ETF and the top 50 companies. The correlation coefficients between ETF with TSM, CHT and HNHPF are +0,983, +0.926, and +0.749 respectively, meaning that they are highly correlated with ETF and found that TSM (2330) has the greatest positive correlation coefficient to ETF which means these two stock price time series move in a very similar direction. On the contrary, Yulon Motor Co. (2201) has the greatest negative correlation coefficient to ETF, −0.862, which means these two price fluctuations move mostly in opposite directions. In addition, the correlations between ETF with AU Optronics (2409) and Cheng Shin Rubber Industry (2105) are the closest to zero, both positively and negatively, which are +0.023 and −0.061, respectively, which reveals that neither have apparent correlation between their stock prices with ETF. Hence, 2201, 2409, and 2105 are also chosen as investment targets to test the proposed method. The experimental results are shown in Figures 11-17, which show that the proposed intelligent MA strategy is still very suitable for all seven different industries/ETF and reach a consistent result. This experiment also tests the proposed method in Dow Jones Industrial Average (DJIA) and NASDAQ Composite (IXIC) from 2015 to 2019.

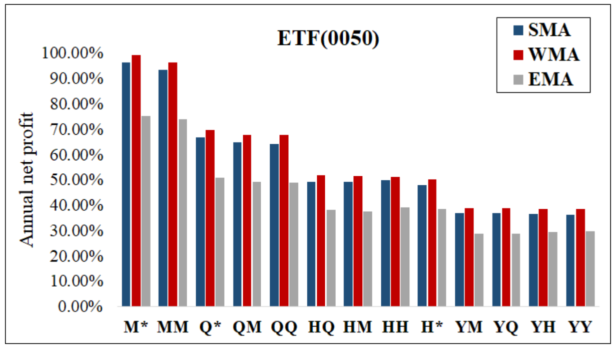


FIGURE 11. Performance of the proposed method for 0050.

The experimental results are shown in Figures 18-19 that indicate our trading strategies have promising results in the U.S. stock markets as well [68]. That is, no matter whether the correlation coefficients between them are greatly positive, negative, or have very weak correlation, as WMA can enhance the weight of recent data to effectively represent recent trends, using WMA is actually more profitable. In contrast, SMA gives the same weight to different closing prices, while EMA rapidly and excessively decreases the weight of past data. In addition, all nine targets both in U.S. and Taiwan show that the M* and MM sliding window yield more stable profits in the experiments, which recommends them to investors.

E. COMPARISON OF THE PROPOSED METHOD AND THE TRADITIONAL METHOD IN THE TESTING PERIOD

This experiment uses the sliding windows with the top five performances in training periods: M*, MM, QM, Q*, and QQ. Then, we compare the performance during the testing period with that of the traditional method. The traditional method selects the best strategy from among eight traditional strategies: SMA (5, 20), SMA (5, 60), SMA (10, 20), SMA

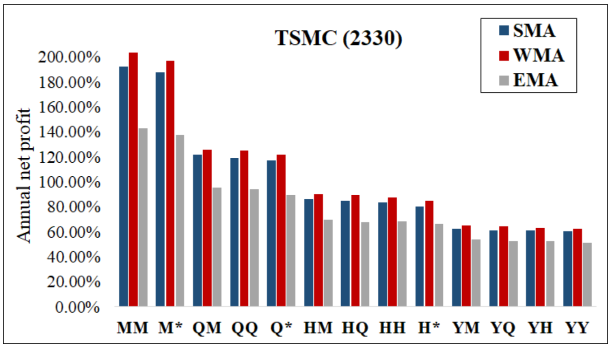


FIGURE 12. Performance of the proposed method for 2330.

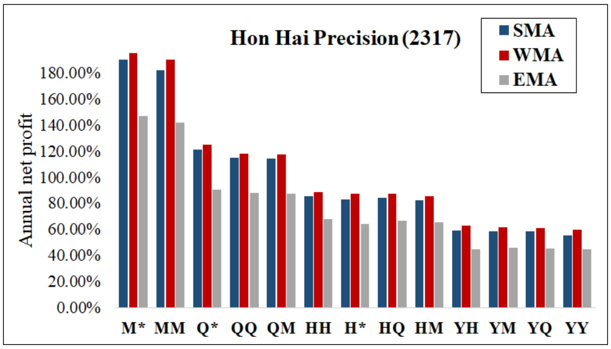


FIGURE 13. Performance of the proposed method for 2317.

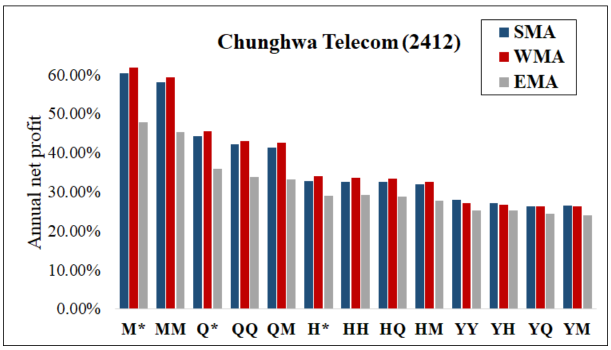


FIGURE 14. Performance of the proposed method for 2412.

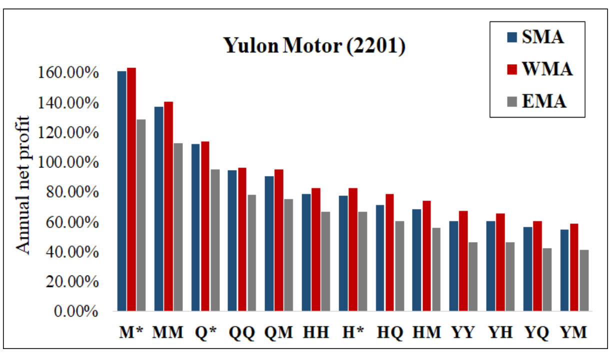


FIGURE 15. Performance of the proposed method for 2201.

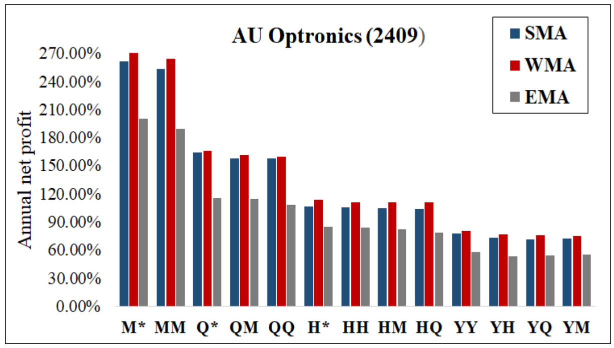


FIGURE 16. Performance of the proposed method for 2409.

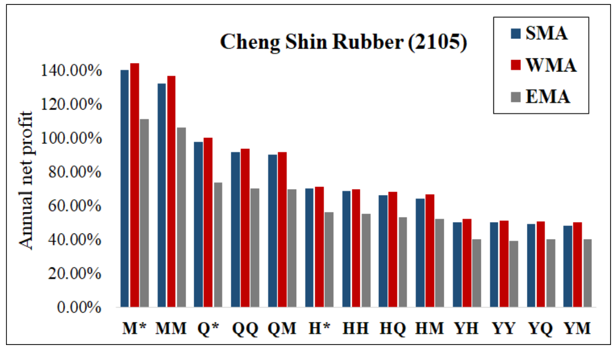


FIGURE 17. Performance of the proposed method for 2105.

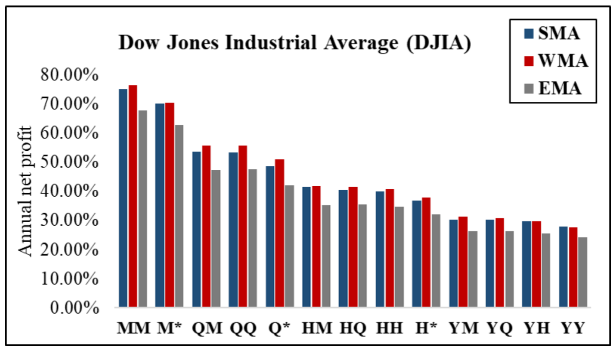


FIGURE 18. Performance of the proposed method for Dow Jones.

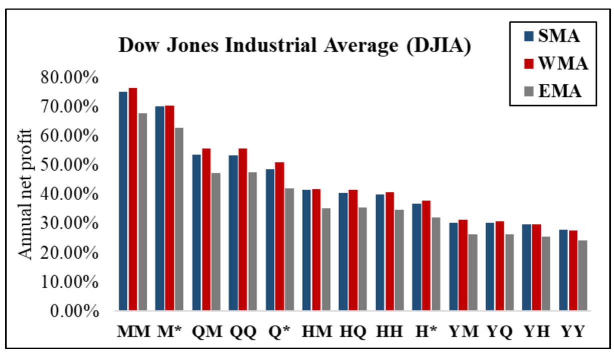


FIGURE 19. Performance of the proposed method for NASDAQ.

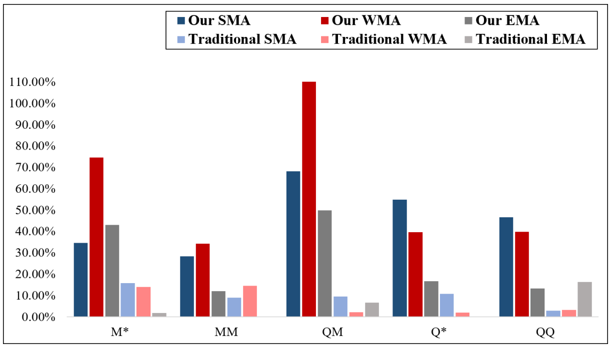


FIGURE 20. Results of the proposed method and the traditional method for the testing period.

TABLE 3. The t-test results of the average profits between the proposed method and the traditional method.

Null Hypothesis (H_0)	p value	Result
$\mu_{Proposed\ SMA} \leq \mu_{Traditional\ SMA}$	0.001039	Reject H_0
$\mu_{Proposed\ WMA} \leq \mu_{Traditional\ WMA}$	0.016074	Reject H_0
$\mu_{Proposed\ EMA} \leq \mu_{Traditional\ EMA}$	0.029142	Reject H_0

(10, 60), SMA (20, 120), SMA (20, 240), SMA (60, 120), and SMA (60, 240). It selects the strategy with the highest profit during the training period and applies it to the testing period. The experimental results are shown in Figure 20. They show that our method outperforms the traditional method for these periods. In the periods, M*, MM and QM, the WMA performs better than the SMA and the EMA, which is consistent with the performance during the training period. Furthermore, the results show that the size of the sliding window should not be too long because the 2-phase sliding window can help identify the current situation. A short testing period can frequently lead to an immediate reaction to trading decisions. Additionally, statistical testing is applied to examine whether the proposed method has better performance than the traditional MA. Table 3 demonstrates the t-test results of the testing comparison. The p value in Table 3 is less than 0.05; therefore, the null hypothesis is rejected. It means that the proposed intelligent method has significant improvement from the traditional MA. In summary, the experimental results show that the proposed trading system has significant improvement and is profitable in both U.S. and Taiwan's stock markets.

VI. CONCLUSION

Technical indicators can help investors decide when to buy or sell stocks. The MA is the most important and widely used indicator because it directly reflects fluctuations in the stock market. Traditional methods usually use the MA with a small number of parameters and many restrictions, which undervalue its potential. In this study, the automated trading system based on the MA removes all restrictions on the traditional MA and significantly reduces the shortcoming of its lagging nature to show its promising potential. Then, the study proposes a novel algorithm to optimize the trading strategy—the GQTS algorithm, which is better able to intensify its search than the QTS algorithm. Furthermore, a state-of-the-art mechanism, the 2-phase sliding window, is proposed to consider more investment situations, find better times to buy and sell stocks, and dynamically change the strategy used in dealing with changeable stock markets. The experiments show that our method, which extends the limit of the MA, can beat U.S. and Taiwan's stock market, and outperform traditional approaches. It also reveals that some buying and selling strategies are better able to identify trading points than others, and that trading signals are generated when any two MAs cross. Moreover, a sliding window size of M* yields the best performance; this is the sliding window size we recommend to investors because the shorter testing period in the 2-phase sliding window can help identify the current situation and allow investors to respond immediately to trading decisions. M* also indicates that the Taiwan stock market has the phenomenon of being subject to economic cycles. In addition, the WMA can yield a more stable return than the SMA or the EMA. In summary, the proposed method shows promising results both in developed and emerging stock markets.

In the future work, we aim to optimize the parameters of different technical indicators, since there are still some well-known technical indicators, such as KD and RSI, that have not been applied in the proposed model. Then, using the best combination of optimized indicators to compose the best trading strategies and test the performance in the different stock markets.

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