Innovative Candlestick Technical Trading Strategies Using Genetic Algorithms

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Abstract

The issue of whether the candlestick analysis method is profitable has been extensively discussed in academia in recent years, and the related studies have all been published in influential journals. Early studies regarding candlestick analysis methods focused on the six types of two-day solid candlestick patterns. Although the studies can be viewed as a milestone in the literature, the hit ratios for the proposed buy signals were only slightly higher than 50%. In this paper, we use genetic algorithms to evolve the candlestick technical trading strategies, which can effectively reduce the complexity of the information processing and enables us to consider factors that may affect the price trend more comprehensively. We incorporate the "rolling forward method" and split the data into a training period, a validation period, and a testing period to prevent the overfitting problem. To the best of our knowledge, we are the first to combine genetic algorithms with the candlestick analysis method to create innovative trading strategies.

Keywords: Candlestick Analysis Method, Genetic Algorithms, Artificial Intelligence,Technical Analysis

JEL Classifications: G11, C63

1. Motivation

Many studies have verified the importance of utilizing technical analysis for investors. Lebaron *et al.* (1999), which has had considerably far-reaching effects on the study of artificial intelligence in economics and finance, simulated the inefficient market proposed in the empirical literature. They found that in an inefficient market, it was quite obvious that the winning investors used technical rules. Coincidentally, Joshi *et al.* (2000) also showed that incorporating technical analysis rules into personal investment rules was a winning strategy

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(dominant strategy) through a multiperson prisoner's dilemma game.

The candlestick analysis method is a method for carrying out technical analysis by utilizing a few days of candlestick patterns. Originating from Japan in the 18th century, this method was used in the early days for determining the futures price of rice. In recent years, it has gradually gained the attention of academia, and relevant research has been published in high-impact journals. For example: Caginalp and Laurent (1998); Fock *et al.* (2005); Marshall *et al.* (2006); Goo *et al.* (2007); Marshall *et al.* (2008); Horton (2009); Shiu and Lu (2011); Lu *et al.* (2012); Lu and Shiu (2012); Lu and Chen (2013); Lu (2014); Zhu *et al.* (2016); Chen *et al.* (2016); Lu and Shiu (2016); Lu *et al.* (2016); and Lu (2018).

Caginalp and Laurent (1998) were the earliest to carry out an empirical study in connection with the candlestick analysis method. They used a three-day candlestick pattern to define eight patterns as stock price reversal signals and tested whether these reversal signals were effective by applying them to the S&P 500 components from 1992 to 1996. They found that the candlestick analysis method indeed had predictive value. Subsequently, the predictive value of candlestick analysis has triggered heated discussions in empirical academic research. There are many documents that support the predictive value and profitability of the candlestick analysis method (Goo *et al.*, 2007; Shiu and Lu, 2011; Lu *et al.*, 2012; Lu and Shiu, 2012; Lu and Chen, 2013; Lu, 2014; Zhu *et al.*, 2016; Chen *et al.*, 2016; Lu and Shiu, 2016; Lu *et al.*, 2016; Lu, 2018), but there are also many documents that hold the opposite view (Fock *et al.*, 2005; Marshall *et al.*, 2006; Marshall *et al.*, 2008; Horton, 2009). Scholars have also combined candlestick charting with deep learning techniques to forecast stock market movements. (Kamo and Dagli, 2009; Martiny, 2012; Ahmadi *et al.*, 2016; Ahmadi *et al.*, 2018; Hu *et al.*, 2018; Fengqian and Chao, 2020; Ananthi and Vijayakumar, 2021; Hung and Chen, 2021). However, there are known limitations in deep learning techniques that hinder their implementation in practice. A major drawback is that deep learning techniques require massive datasets to tune parameters for better performance.

Lu and Shiu (2012) pointed out that past studies focused on the six types of two-day solid candlestick patterns proposed by Nison (1991). They used a four-digit numbers approach, which ranks the orders of the first day opening price, the first day closing price, the second day opening price, and the second day closing price. For example, the pattern depicted by 1234 is that the first day opening price ranking, the first day closing price ranking, the second day opening price ranking, and the second day closing price ranking are 1, 2, 3, and 4, respectively. They also listed all patterns for a two-day solid candlestick, which totaled 24 types. They used the data of the Taiwan 50 Index component stocks for the period from 2 January 2002 to 31 December 2009 to test the average rates of return and the proportion of positive rates of return, the "hit-ratio" they called, for buying and holding for 1 day, 5 days and 10 days after these 24 types of patterns appeared. They found that the 1324 candlestick pattern appearing in the uptrend was a buy signal. If one bought the next day at the opening price and held for 5 days or 10 days, the average rates of return were all significantly positive. Moreover, the 1234 candlestick pattern appearing in the downtrend was a buy signal. If one bought the next day at the opening price and held for 5 days or 10 days, the average rates of return were all also significantly positive. In this manner, 1324 could be regarded as the continuation signal, and 1234 could be regarded as the reversal signal. In particular, the candlestick pattern portions in these two types of buy signals were not any of the six types of two-day solid candlestick patterns proposed by Nison (1991).

Lu and Shiu (2012) can be viewed as a milestone that started to comprehensively research the reliability of a two-day candlestick pattern as a buy signal. However, Lu and Shiu (2012) did not split the data into training, validation and testing periods, which cannot prevent the problem of overfitting. Changes in the data source or the interval might affect the significance of profitability. We incorporate the “rolling forward method” and split the data into a training period, a validation period and a testing period to prevent the overfitting problem. In addition, the hit-ratios for the buy signals proposed by Lu and Shiu (2012) were only slightly higher than 50%. In fact, in technical analysis, whether stock prices can steadily remain above the season average, trading volume, volume-price structure and so on are all very important factors in predicting future trends. The buy conditions are consequently further enhanced in the present paper. The uptrend and the downtrend are considered, and the aforementioned factors that affect the effectiveness of the signal are considered overall as buy conditions to find a more reliable buy signal. The amount of information processing designed in this way is extremely large, but the complexity of the information processing is effectively reduced through the use of genetic algorithms (GAs) in the present paper.

In the present paper, artificial intelligence methods are used for the first time in a series of studies on the candlestick analysis method. In the past, when the candlestick analysis method was looking for an effective buy signal, it took a great deal of effort to process the addition of one more condition. Genetic algorithms overcome this limitation. For genetic algorithms, adding one more condition only requires adding one more bit to the string, which takes little effort. Therefore, it is believed that the innovative introduction of artificial intelligence methods to the candlestick analysis method in the present paper will be a large step forward for this series of studies. We found that the proposed innovative candlestick technical trading strategies using GAs can beat the buy signals, as proposed by Lu and Shiu (2012).

The remainder of this paper is organized as follows. Section 2 introduces the research design. The questions of interest are then addressed, with the experimental designs given in Section 3. The empirical results are presented and discussed in Section 4, followed by the concluding remarks in Section 5.

2. Research design

2.1 Processing of time series data

Overfitting is an issue that must be addressed in all data modeling techniques. In the process of optimizing the trading rules, genetic algorithms tend to find the rule for generating the best profitability in the training period but such a rule may contain some noise that does not exist in the entire time series data. To find the optimal rule for the entire dataset, the data were split into training, validation, and testing periods to prevent this problem in previous studies (e.g., Allen and Karjalainen, 1999; Yu *et al.*, 2004) and are thus divided into these three types of periods in the present paper.

The “rolling forward method” was proposed by Pesaran and Timmermann (1995), and Wang (2000) reiterated its importance. Subsequently, most of the studies that have used artificial intelligence methods to find reliable buy signals or investment strategies have used the “rolling forward method” (e.g., Yu *et al.*, 2004). Therefore, the present paper uses the “rolling forward method”.

Because the FTSE TWSE Taiwan 50 Index was established in 2003, the 2003 to 2019 data of the Taiwan 50 Index component stocks are used in the present paper. According to the principle of the “rolling forward method,” the time series data are split into two sequences. Most of the existing studies in which the best rule was searched for by artificial intelligence methods, such as Chen *et al.* (2008), Chung and Shin (2018), Yu *et al.* (2004), Yang at el. (2011), and so on, set the training period to be longest. Following Yu *et al.* (2004), we further set the validation period and the testing period to be equally long. As a result, we obtained the length of the training period, validation period, and testing period of each sequence to be 5, 4 and 4 years, respectively. The training period, validation period, and testing period of each sequence are shown in Figure 1:

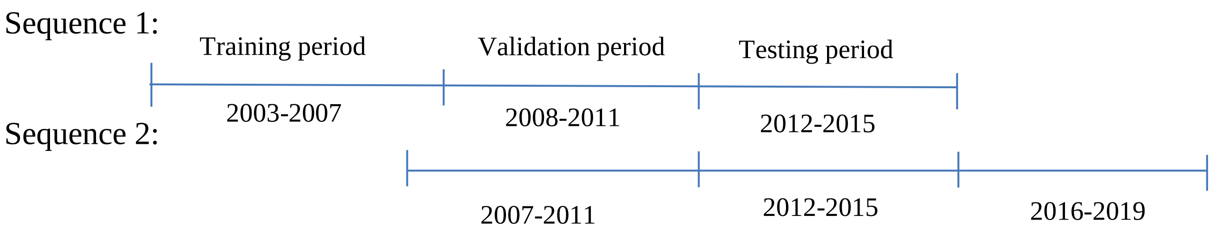

Figure 1: Training, validation and testing periods for 2 time sequences.

2.2 Design of genetic algorithms (GAs) for the best buy signal

2.2.1 Designing and generating the string representations of the buy signal

The two-day solid candlestick pattern proposed by Lu and Shiu (2012) was added as a condition of the buy signal in the present paper. Since the use of genetic algorithms requires that the species to be evolved be coded as a string, the representation of Lu and Shiu (2012) is used first to encode the two-day candlestick pattern as the first four bits of the market condition for the buy signal. Thus, the first four bits of the string are numbers. Next, in the consideration of the market conditions that may affect the effectiveness of the buy signal after the first four bits, such as bits 5 to 10 in Table 1, the bits may be 0, 1, or #, which is randomly generated by the program. A 0 bit means that the market condition defined by the bit cannot appear, 1 means that the market condition defined by the bit should appear, and # means that it does not matter whether the market condition defined by the bit appears.

Table 1: String design for the buy signal

bit	Market conditions
1	The ranking for the opening price of the first candlestick
2	The ranking for the closing price of the first candlestick
3	The ranking for the opening price of the second candlestick
4	The ranking for the closing price of the second candlestick
5	Progressive increase in the closing price five-day moving average (MA(5)) seven days before the two-day candlestick pattern appears: the uptrend of Lu and Shiu (2012)
6	Progressive decrease in the closing price MA(5) seven days before the two-day candlestick pattern appears: the downtrend of Lu and Shiu (2012)
7	The closing price of the second candlestick is above the MA(period), and the value of the period is revised according to the market situation
8	The trading volume MA(5) is greater than the trading volume MA(20) for 10 days before the consecutive two-day candlestick
9	The trading volume of the second candlestick is greater than J% of the trading volume MA(20), and the value of J is revised according to the market conditions
10	Volume contraction appears seven days before the two-day candlestick pattern appears: progressive decrease in the trading volume MA(5)

The reasons for designing bits 5 to 10 are explained as follows: The fifth and sixth bits are used to distinguish between the buy signal in the uptrend and the buy signal in the downtrend and cannot both be 1 at the same time. [1] The seventh bit is used to define whether the last price of the buy signal needs to be higher than the MA (period), in which the period is the number of trading days. The moving average over a certain period, denoted by MA(period), refers to the mean of the closing prices of the period. For example, closing price MA (5) on day *t* is defined as follows:

$$\text{MA}(5)=\frac{C(t-4)+C(t-3)+C(t-2)+C(t-1)+C(t)}{5}, \tag{1}$$

where C(t) is the closing price on day t.

Since a month has approximately 20 trading days, the curve connecting the daily MA (20) is referred to as the month average. A quarter has approximately 60 trading days. Thus, the curve connecting the daily MA (60) is referred to as the season average. In technical analysis, the season average is an important bullish or bearish turning point. Stock prices above the season average represent a bull market, and those falling below the season average represent turning from bullish to bearish. Since the characteristics of the rise and fall of stock prices differ in bullish and bearish markets, the judgment of whether the market is bullish or bearish beforehand is one of the factors that may affect the effectiveness of the signal. The purpose of the eighth and ninth bits is to utilize the trading volume moving average to judge the strength of the buying interest. The eighth bit is used to judge whether the buy signal is in line with a trend of volume increase 10 days before the two-day candlestick pattern appears. Generally, the short-term trading volume moving average being higher than the long-term trading volume moving average indicates the continuous enhancement of the buying interest. The ninth bit is used to judge whether a certain trading volume is still maintained in the last two days of the buy signal, and the value of J is adjusted according to the number of days held. Generally, the smaller the number of days held is, the greater the risk. Therefore, the value of J should be greater to prevent a reversal of the market conditions after the stock is bought. In technical analysis, it is generally believed that the market outlook is optimistic when prices rise on increasing volume or prices fall on decreasing volume. Conversely, prices rising on decreasing volume or prices falling on increasing volume are referred to as volume-price deviation, and the market outlook is not optimistic. Therefore, the volume-price trend in a period of time is also a factor that may affect the effectiveness of the signal. The 10th bit is used to judge whether there is a trend of volume contraction in the buy signal in the seven days before the candlestick pattern appears. It is generally believed that the signal for a bottoming and reversal of stock prices is volume shrinkage, which represents the trading volume shrinkage caused by the unwilling-to-sell mentality at these low prices, whereas in an uptrend of the stock prices, it is

[1] Lu and Shiu (2012) used progressive increase (progressive decrease) in the consecutive seven-day MA(5) to define the uptrend (downtrend). Therefore, MA(5) is the preset value.

inadvisable for the trading volume to shrink, and only when prices rise on increasing volume does the trend gather strength to the upside.

2.2.2 Design of the uptrend and downtrend pools

The uptrend pool refers to the group of buy signals with an uptrend before the two-day candlestick pattern; it is the pool where the best rule is initially generated and evolved. The downtrend pool refers to the group of buy signals with a downtrend before the two-day candlestick pattern; it is the pool where the best rule is initially generated and evolves.

Owing to the proposal of Lu and Shiu (2012), candlestick patterns that do not combine with an uptrend or downtrend are all useless signals. Therefore, a pool is generated called the uptrend pool, in which the strings are all restricted to the fifth bit being 1, and another pool is generated called the downtrend pool, in which the strings are all restricted to the sixth bit being 1. The buy signal strings of the uptrend pool and the downtrend pool are slightly different due to the different market situations. The buy signal strings used in the uptrend pool are the 1st to the 9th bits, and the buy signal strings used in the downtrend pool are the 1st to the 7th and the 10th bits.

In practice, in connection with the two pools, the program generates M strings for each by way of the following. First, N four-bit strings are generated for each of the 24 types of two-day solid candlestick patterns. In connection with these 24*N (equal to M) strings, the corresponding 5th to 10th bits are then given, and their bit values are all randomly generated by the program. For example, the strategy represented by the string 132410110X that appears in the uptrend pool is the two-day candlestick pattern of 1324 that appears, which meets the market conditions defined by the seventh and eighth bits, and the market conditions defined by the ninth bit do not appear, meaning one should buy at the opening price on the next day and hold for H day(s).[2] In the downtrend pool, the strategy represented by string 1243010XX1 is a buying strategy in which the candlestick pattern of 1243 appears, the market conditions defined by the 10th bit are in accord, and the market conditions defined by the 7th bit do not appear.[3]

2.2.3 Methods for using the training period, validation period, and testing period (same for the uptrend and downtrend pools)

Following practices in the literature, such as those of Allen and Karjalainen (1999) and Yu *et al.* (2004), the methods for using the training period, validation period, and testing period are as follows:

First step. The buy signal with the highest fitness (defined in Section 2.2.4) in terms of the

[2] The 10th bit is X because the 10th bit is not considered in the uptrend pool.
[3] The eighth and ninth bits are X because the eighth and ninth bits are not considered in the downtrend pool.

training period data in the initial randomly generated string population is found. This buy signal is referred to as the initial "best rule". Additionally, the fitness of this string in the data of the training period and the validation period is calculated.

Second step. A new generation of string populations is generated through the operators of genetic algorithms. (The operation of these operators and the process for generating the next generation are explained in the next section)

Third step. The buy signal with the highest fitness in terms of the data of the training period in the next generation of the string population is found, and the fitness of this string in the data of the training period and the validation period is calculated.

Fourth step. If the fitness of this string in the data of the training period and validation period is better than the previous "best rule," then this string becomes the new "best rule".

Fifth step. The second through fourth steps are repeated until the maximum number of generations (G) is reached or the "best rule" has not changed after I generations.

Sixth step. The "best rule" is applied to the testing period to obtain data, such as the rate of return and the hit-ratio.

2.2.4 Fitness calculation (same for the uptrend and downtrend pools)

A string represents a buy signal. In other words, when the market conditions corresponding to the string appear (if it is the t-th day), the stock is bought at the next-day opening price, held for H days, and sold at the closing price on the H-th day. Then, the rate of return is defined as follows:

$$\frac{P_{t+H}^{closing} - P_{t+1}^{opening}}{P_{t+1}^{opening}} \quad , \tag{2}$$

where $P_{t+1}^{opening}$ is the buying price. This parameter is represented hereinafter by P_b. $P_{t+H}^{closing}$ is the selling price. It is represented hereinafter by P_s.

The fitness of a certain string is calculated as follows.

1. First, the average rate of return for the string, that is, the average of the rate of return for each buy, is calculated. If this string is recommended as a buy for a total of K times in the data period, then the average rate of return is

$$AR = \left(\sum_{k=1}^{K} \frac{P_{s,k} - P_{b,k}}{P_{b,k}}\right) / K \quad , \tag{3}$$

where $P_{b,k}$ is the buying price at the k-th instance and $P_{s,k}$ is the selling price at the k-th instance.

2. If the average rate of return for the string is positive, then the fitness is increased

according to the frequency of hits for the string, in addition to the average rate of return. The calculation method is as follows:

$$fitness = AR \times [1 + (frequency\ of\ hits \times l\%)] , \tag{4}$$

where $l\%$ is the ratio of the increased fitness. We know from the aforementioned equation that the entire fitness contains two parts.

The first part is the average rate of return (AR). The second part is $AR \times frequency\ of\ hits \times l\%$, and when the average rate of return is higher and the frequency of hits is greater, the overall fitness is higher.

The reasons for using this calculation are as follows: The average rate of return reflects the profitability of the string, which is of course important. Moreover, the addition of fitness in the design according to the frequency of hits for the string means that strings that obtain the same *AR* are weighted by their frequency of hits instead of assigning the same fitness to strings with the same average rate of return. If the same average rate of return is achieved but one of the strings does not have a high frequency of hits, it is very possible that its average rate of return is only due to a certain instance, or a few instances, of particularly high rates of return. Although such a rule can achieve the same high average rate of return in the training period and the validation period, the model might not perform well in the testing period because it is unusual for the same special high-return market conditions to appear. Therefore, the addition of fitness due to the frequency of hits allows the fitness of such strings to be lower than that of strings that are frequently hit, which is equivalent to preventing the overfitting problem to a certain extent.

3. If the average rate of return of the string is negative, then the fitness is the average rate of return, and no fitness is added according to the frequency of hits.

2.2.5 Generating a new string population with genetic algorithms (same for the uptrend and downtrend pools)

First, the operators of the genetic algorithms are introduced. The three most common operators in genetic algorithms (selection, crossover, and mutation) are designed as follows in the present paper:

1. Selection: Tournament selection is used in the present paper. That is, two strings are randomly picked from the previous generation, their fitness is compared, and the string with higher fitness is selected as the parent. If two parents are needed for crossover, then two strings are randomly picked from the previous generation again, and the string with higher fitness is selected as the second parent.

2. Crossover: A random breaking point is selected, where the breaking point must be after the first four bits. The first four bits in the present paper are special, and the entire set of bits

represents a type of information. Consequently, a set of the first four bits cannot be separated. The breaking points of the parents are consistent. The offspring generation has a 50% probability of taking information from the first parent before the breaking point and taking information from the second parent after the breaking point and a 50% probability of the opposite.

3. Mutation: The first four bits are treated as a set, and each following bit has a probability of mutation at a particular mutation rate (the exogenous parameter is P_m. The design can be given exogenously). When the set of the first four bits is determined to mutate, the new set is randomly drawn as a substitute from the 24 types of two-day candlestick patterns, with an equal probability for each type of pattern (uniform distribution). When each following bit is determined to mutate, the probabilities in Table 2 are applied. For example, the square in the lower right corner means that the probability of changing from # to # is 1/3.

Table 2: Mutation probability table

$0 \xrightarrow{p:0} 0$	$0 \xrightarrow{p:1/3} 1$	$0 \xrightarrow{p:2/3} \#$
$1 \xrightarrow{p:1/3} 0$	$1 \xrightarrow{p:0} 1$	$1 \xrightarrow{p:2/3} \#$
$\# \xrightarrow{p:1/3} 0$	$\# \xrightarrow{p:1/3} 1$	$\# \xrightarrow{p:1/3} \#$

The process for generating a new string population is explained as follows: (see also Figure 2)

First step. First, the string with the highest fitness from the previous generation is added to the new generation. (This process is referred to as elite retention in genetic algorithms.) In this way, only *M*-1 strings are required to generate.

Second step. There is a crossover rate (the exogenous parameter is P_c. The design can be given exogenously) for the probability that crossover will be carried out, and there is a $1-P_c$ probability that mutation will occur. In the present paper, according to the conventions in the literature on artificial intelligence economics, P_c=0.7. The actual practice is to randomly take a number *S* from 0 to 1. If *S*<0.7, then the crossover is used to generate the offspring generation. Otherwise, the offspring generation is generated by way of mutation.

Third step. Crossover or mutation is carried out to generate one offspring generation.

Fourth step. The second step and third step are repeated until *M* strings are generated, and then the new string population is generated completely.

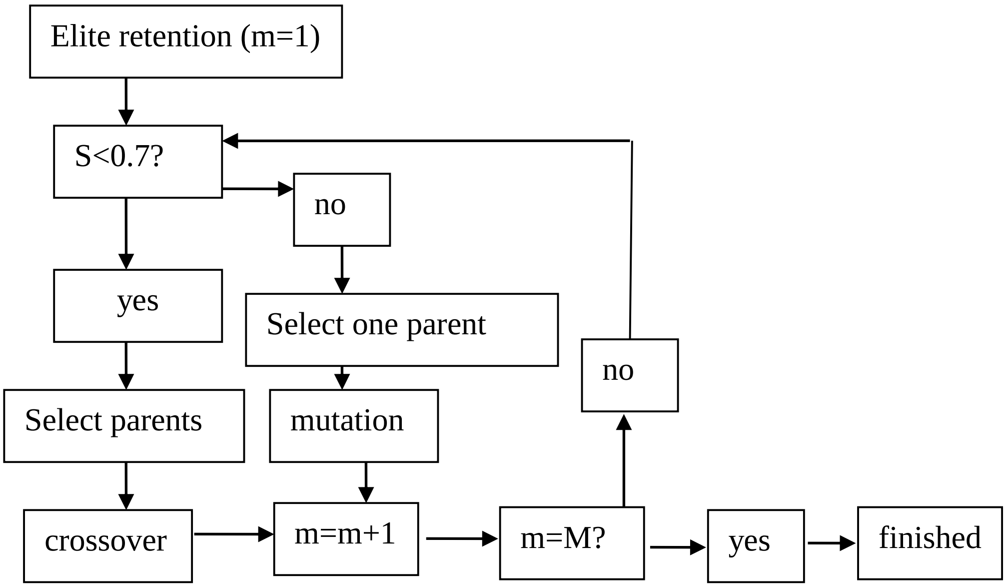

Figure 2: Flowchart for generating a new string population

3. Experimental design

Lu and Shiu (2012) mentioned that for the two-day candlestick pattern of 1324 that appears in the uptrend, if one buys the next day at the opening price and holds for 5 days or 10 days, the average rates of return are all significantly positive. Moreover, for the two-day candlestick pattern of 1234 that appears in the downtrend, if one buys the next day at the opening price and holds for 5 days or 10 days, the average rates of return are all also significantly positive. However, the data were not split in the paper, which indicates the problem of overfitting is not prevented. In addition, some important factors in technical analysis, such as whether stock prices can steadily remain above the season average, trading volume, and volume-price structure, were not considered. For these reasons, an improved method is developed in the present paper to find a more reliable buy signal.

To compare this method with the method of Lu and Shiu (2012), experiments are carried out for holding the stocks for 5 days and for 10 days. To be in line with the large-sample rule, each type of experiment was carried out more than 30 times to facilitate statistical analysis. The parameters for the market conditions of the strings used in the experiment are indicated in Table 1. The value of the "period" for the seventh bit is set to 60 in the uptrend pool, mainly because the season average is an important bullish or bearish turning point. Stock prices that steadily stand above the season average are an important indicator to whether the increase can continue in the uptrend. Moreover, since the stocks in the present paper are held only for 5 days or 10 days, finding the buy signal in the downtrend pool is equivalent to grabbing a rebound. There is thus no need to wait until the trend reverses to an uptrend. Therefore, the value of the "period" is set to be comparatively short. In the five-day hold experiment, the value of the period is set to 20, mainly because the number of holding days is short and the risk is comparatively high.

Consequently, a rebound in the downtrend should be confirmed by a longer moving average line (month average). In the downtrend pool, in the 10-day hold experiment, the value of the period is set to 10, mainly because compared to those of the 5-day hold, the holding time of the 10-day hold is longer and the risk is slightly lower. Therefore, a rebound in the downtrend can be confirmed by a shorter moving average line (two-week line). In addition, with regard to the value of *J* for the ninth bit, generally speaking, since the lower the number of days held is, the greater the risk, the value of *J* should be larger to prevent a reversal of the market conditions after entering the market. Therefore, the value of *J* is set to 75 in a 5-day hold but 35 in a 10-day hold.

Regarding the common parameters, according to the conventions in the literature on artificial intelligence economics, this paper sets the mutation rate as (P_m)=0.03 and the crossover rate as (P_c)=0.7. Initially, *N* strings are randomly generated for each of the 24 types of two-day solid candlestick patterns. In the present paper, *N*=5 is set. Therefore, the total number of strings in each pool is *M*=24*5=120. In addition, the condition in which the genetic algorithms terminate the repeated evolution of the string population to find the best buy signal is as follows: The best buy signal has not changed in 50 consecutive generations (*I*=50), or the evolution has already reached 150 generations (*G*=150). The experimental parameters are listed in Table 3 below.

Table 3: Experimental parameters

Mutation rate (P_m)=0.03	Fitness increment ratio (l) $= 5$
Crossover rate (P_c)=0.7	Number of days in holding the stock (*H*) =5 or 10
Number of strings (*M*)=120	Maximum number of generations (*G*)=150
Frequency of experiment=150	Maximum number of generations where the “best rule” does not change (*I*)=50

4. Empirical results

In connection with the number of days that the stocks are held, 5 days and 10 days, 150 experiments are carried out in the present study. In every experiment, the method in the present study finds the best rule, and an average rate of return is obtained by averaging the rates of return for several buys in the testing period. Since the average rate of return for every experiment may differ, we can further obtain the mean and standard deviation of the average rate of return for these 150 experiments.

4.1 Experimental results of holding stocks for five days

The following presents the results of Sequence 1 and Sequence 2.

4.1.1 Experimental results of Sequence 1

A. Uptrend buy signal

(a) Average rate of return: By additionally averaging a total of 150 average rates of return for the testing period from the best uptrend buy signal found in every experiment, we obtain the value 0.0031510440274481574, which is higher than the average rate of return of -0.00822130839029948 in the testing period from the uptrend buy signal of Lu and Shiu (2012) (the two-day candlestick pattern 1324 appeared after the uptrend). In addition, the standard deviation for the average rate of return in the testing period from the best uptrend buy signals found in the 150 experiments is 0.0021962888958637805. The following verifies whether the average rate of return in the testing period for the best rule of the method in the present study is significantly better than the average rate of return in the testing period for the uptrend buy signal of Lu and Shiu (2012):

$$H_0: \mu \leq \mu_0.$$
$$H_1: \mu > \mu_0.$$

The Z value can be used for verification according to

$$Z=\frac{\bar{X}-\mu_0}{S/\sqrt{N}}\ , \tag{5}$$

where μ_0 =-0.008221308390299488, $\bar{X}$ =0.0031510440274481574, S=0.0021962888958637805 and N=150.

Therefore, Z=63.41711386659954>$Z_{0.001}$. Thus, the average rate of return for the best uptrend buy signal found in the present study is significantly better than the average rate of return for the uptrend buy signal of Lu and Shiu (2012).

(b) Hit-ratio: By additionally averaging the hit-ratios for the testing period from the best uptrend buy signals found in the 150 experiments, we obtain 0.5332138284250959, which is more than double the hit-ratio of 0.23809523809523808 in the testing period from the uptrend buy signal of Lu and Shiu (2012) (the two-day candlestick pattern 1324 appeared after the uptrend). In addition, the standard deviation for the hit-ratio in the testing period from the best uptrend buy signals found in the 150 experiments is 0.059198940194245604. Therefore, Z=61.05598829519971>$Z_{0.001}$. Thus, the hit-ratio for the best uptrend buy signal found in the present study is significantly better than the hit-ratio for the uptrend buy signal of Lu and Shiu (2012).

B. Downtrend buy signal

(a) Average rate of return: By additionally averaging a total of 150 average rates of return for the testing period from the best downtrend buy signal found in every experiment, we obtain 0.01435409545898438, which is higher than the average rate of return of 0.011271651111432 in the testing period from the downtrend buy signal of Lu and Shiu (2012) (the two-day candlestick pattern 1234 appeared after the downtrend). In addition, the standard deviation for the average rate of return in the testing period from the best downtrend buy signals found in the 150 experiments is 0.012213680405498964. Therefore, Z=3.0909666707138173>$Z_{0.001}$. Thus, the average rate of return for the best downtrend buy signal found by the method in the present study is significantly better than the average rate of return for the downtrend buy signal of Lu and Shiu (2012).

(b) Hit-ratio: By additionally averaging the hit-ratios for the testing period from the best downtrend buy signals found in the 150 experiments, we obtain 0.49, which is lower than the hit-ratio of 0.5447761194029851 in the testing period from the downtrend buy signal of Lu and Shiu (2012). In addition, the standard deviation for the hit-ratio in the testing period from the best downtrend buy signals found in the 150 experiments is 0.0969905090031444. Therefore, Z=-6.916838771447666<$Z_{0.001}$. Thus, the hit-ratio for the best rule found in the present study is worse than the hit-ratio for the downtrend buy signal of Lu and Shiu (2012). However, in terms of the average rate of return, the average rate of return for the best downtrend buy signal found by the method in the present study is significantly better than the average rate of return for the downtrend buy signal of Lu and Shiu (2012). Thus, although the hit-ratio is lower, a high return may be obtained once hit. Therefore, the rule found by the method in the present study is still more profitable than the downtrend buy signal of Lu and Shiu (2012).

4.1.2 Experiment results of Sequence 2

A. Uptrend buy signal

(a) Average rate of return: By additionally averaging a total of 150 average rates of return for the testing period from the best uptrend buy signal found in every experiment, we obtain 0.0049573869077778835, which is higher than the average rate of return of 0.0011896666358499 in the testing period from the uptrend buy signal of Lu and Shiu (2012) (the two-day candlestick pattern 1324 appeared after the uptrend). In addition, the standard deviation for the average rate of return in the testing period from the best uptrend buy signals found in the 150 experiments is 0.0033879446518100946. Therefore, Z=13.620340808745237>$Z_{0.001}$. Thus, the average rate of return for the best uptrend buy signal found in the present study is significantly better than the average rate of return for the uptrend buy signal of Lu and Shiu (2012).

(b) Hit-ratio: By additionally averaging the hit-ratios for the testing period from the best uptrend buy signals found in the 150 experiments, we obtain 0.5387140189132302, which is higher than the hit-ratio of 0.5 in the testing period from the uptrend buy signal of Lu and Shiu (2012). In addition, the standard deviation for the hit-ratio in the testing period from the best uptrend buy signals found in the 150 experiments is 0.03283384948144166. Therefore, Z=14.440827640918402>$Z_{0.001}$. Thus, the hit-ratio for the best uptrend buy signal found in the present study is significantly better than the hit-ratio for the uptrend buy signal of Lu and Shiu (2012).

B. Downtrend buy signal

(a) Average rate of return: By additionally averaging a total of 150 average rates of return for the testing period from the best downtrend buy signal found in every experiment, we obtain 0.009021072387695313, which is higher than the average rate of return of 0.00428437096732003 in the testing period from the downtrend buy signal of Lu and Shiu (2012) (the two-day candlestick pattern 1234 appeared after the downtrend). In addition, the standard deviation for the average rate of return in the testing period from the best downtrend buy signals found in the 150 experiments is 0.010330009065575107. Therefore, Z=5.615920310516115>$Z_{0.001}$. Thus, the average rate of return for the best downtrend buy signal found by the method in the present study is significantly better than the average rate of return for the downtrend buy signal of Lu and Shiu (2012).

(b) Hit-ratio: By additionally averaging the hit-ratios for the testing period from the best downtrend buy signals found in the 150 experiments, we obtain 0.7666666666666667, which is higher than the hit-ratio of 0.5828571428571429 in the testing period from the downtrend buy signal of Lu and Shiu (2012). In addition, the standard deviation for the hit-ratio in the testing period from the best downtrend buy signals found in the 150 experiments is 0.42436951523243627. Therefore, Z=5.3048054470958315>$Z_{0.001}$. Thus, the hit-ratio for the best downtrend buy signal found in the present study is significantly better than the hit-ratio for the downtrend buy signal of Lu and Shiu (2012).

The above experimental results of holding stocks for five days are organized in Table 4 and Table 5.

Table 4: Performance of the average rate of return for each sequence in the 150 experiments for this method

	Sequence 1 uptrend buy signal	Sequence 1 downtrend buy signal	Sequence 2 uptrend buy signal	Sequence 2 downtrend buy signal
Mean	0.00315104402744815	0.01435409545898430	0.00495738690777788	0.00902107238769531
Standard deviation	0.00219628889586378	0.01221368040549890	0.00338794465181009	0.01033000906557510
Lu and Shiu (2012)	-0.00822130839029948	0.01127165111143200	0.00118966663584990	0.00428437096732003
Z value	63.4171138665995	3.09096667071381	13.6203408087452	5.61592031051611
P value	(<0.001)***	(<0.001)***	(<0.001)***	(<0.001)***

Table 5: Performance of the hit-ratio for each sequence in the 150 experiments for this method

	Sequence 1 uptrend buy signal	Sequence 1 downtrend buy signal	Sequence 2 uptrend buy signal	Sequence 2 downtrend buy signal
Mean	0.5332138284250959	0.49	0.5387140189132302	0.7666666666666667
Standard deviation	0.059198940194245604	0.0969905090031444	0.03283384948144166	0.42436951523243627
Lu and Shiu (2012)	0.23809523809523808	0.5447761194029851	0.5	0.5828571428571429
Z value	61.05598829519971	-6.916838771447666	14.440827640918402	5.3048054470958315
P value	(<0.001)***	(<0.001)***	(<0.001)***	(<0.001)***

4.2 Experimental results of holding stocks for 10 days

The following presents the results of Sequence 1 and Sequence 2.

4.2.1 Experimental results of Sequence 1

A. Uptrend buy signal

(a) Average rate of return: By additionally averaging a total of 150 average rates of return for the testing period from the best uptrend buy signal found in every experiment, we obtain 0.01417205614921375, which is higher than the average rate of return of -0.0163501557849702 in the testing period from the uptrend buy signal of Lu and Shiu (2012) (the two-day candlestick pattern 1324 appeared after the uptrend). In addition, the standard deviation for the average rate of return in the testing period from the best uptrend buy signals found in the 150 experiments is 0.0034589081367725383. Therefore, Z=108.07434326602132>$Z_{0.001}$. Thus, the average rate of return for the best uptrend buy signal found in the present study is significantly better than the average rate of return for the uptrend buy signal of Lu and Shiu (2012).

(b) Hit-ratio: By additionally averaging the hit-ratios for the testing period from the best uptrend buy signals found in the 150 experiments, we obtain 0.6876923076923078, which is much higher than the hit-ratio of 0.19047619047619047 in the testing period from the uptrend buy signal of Lu and Shiu (2012) (the two-day candlestick pattern 1324 appeared after the uptrend). In addition, the standard deviation for the hit-ratio in the testing period from the best uptrend buy signals found in the 150 experiments is 0.056526686371919495. Therefore, Z=107.73015873015875>$Z_{0.001}$. Thus, the hit-ratio for the best uptrend buy signal found in the present study is significantly better than the hit-ratio for the uptrend buy signal of Lu and Shiu (2012).

B. Downtrend buy signal

(a) Average rate of return: By additionally averaging a total of 150 average rates of return for the testing period from the best downtrend buy signal found in every experiment, we obtain 0.025143797132703982, which is higher than the average rate of return of 0.0103446690004263 in the testing period from the downtrend buy signal of Lu and Shiu (2012) (the two-day candlestick pattern 1234 appeared after the downtrend). In addition, the standard deviation for the average rate of return in the testing period from the best downtrend buy signals found in the 150 experiments is 0.0035546778534533445. Therefore, Z=50.98958901005788>$Z_{0.001}$. Thus, the average rate of return for the best downtrend buy signal found by the method in the present study is significantly better than the average rate of return for the downtrend buy signal of Lu and Shiu (2012).

(b) Hit-ratio: By additionally averaging the hit-ratios for the testing period from the best downtrend buy signals found in the 150 experiments, we obtain 0.6666666666666665, which is higher than the hit-ratio of 0.5634328358208955 in the testing period from the downtrend buy signal of Lu and Shiu (2012). In addition, the standard deviation for the hit-ratio in the testing period from the best downtrend buy signals found in the 150 experiments is 0.00000000000000011139. Therefore, Z=11350237472057520.0>$Z_{0.001}$. Thus, the hit-ratio for the best downtrend buy signal found in the present study is significantly better than the hit-ratio for the downtrend buy signal of Lu and Shiu (2012).

4.2.2 Experimental results of Sequence 2

A. Uptrend buy signal

(a) Average rate of return: By additionally averaging a total of 150 average rates of return for the testing period from the best uptrend buy signal found in every experiment, we obtain 0.009182128524062794, which is higher than the average rate of return of 0.00104489045984605 in the testing period from the uptrend buy signal of Lu and Shiu (2012) (the two-day candlestick pattern 1324 appeared after the uptrend). In addition, the standard deviation for the average rate of return in the testing period from the best uptrend buy signals found in the 150 experiments is 0.016076292195379243. Therefore, Z=6.199215879707876>$Z_{0.001}$. Thus, the average rate of return for the best uptrend buy signal found in the present study is significantly better than the average rate of return for the uptrend buy signal of Lu and Shiu (2012).

(b) Hit-ratio: By additionally averaging the hit-ratios for the testing period from the best uptrend buy signals found in the 150 experiments, we obtain 0.6532348619066776, which is higher than the hit-ratio of 0.43137254901960786 in the testing period from the uptrend buy signal of Lu and Shiu (2012). In addition, the standard deviation for the hit-ratio in the testing period from the best uptrend buy signals found in the 150 experiments is 0.2351132013423154. Therefore, Z=11.557187274562876>$Z_{0.001}$. Thus, the hit-ratio for the best uptrend buy signal found in the present study is significantly better than the hit-ratio for the uptrend buy signal of

Lu and Shiu (2012).

B. Downtrend buy signal

(a) Average rate of return: By additionally averaging a total of 150 average rates of return for the testing period from the best downtrend buy signal found in every experiment, we obtain 0.013209228515625, which is higher than the average rate of return of 0.00971726826259068 in the testing period from the downtrend buy signal of Lu and Shiu (2012) (the two-day candlestick pattern 1234 appeared after the downtrend). In addition, the standard deviation for the average rate of return in the testing period from the best downtrend buy signals found in the 150 experiments is 0.010045884636459695. Therefore, Z=4.257226282974962>$Z_{0.001}$. Thus, the average rate of return for the best downtrend buy signal found by the method in the present study is significantly better than the average rate of return for the downtrend buy signal of Lu and Shiu (2012).

(b) Hit-ratio: By additionally averaging the hit-ratios for the testing period from the best downtrend buy signals found in the 150 experiments, we obtain 0.9466666666666667, which is higher than the hit-ratio of 0.6457142857142857 in the testing period from the downtrend buy signal of Lu and Shiu (2012). In addition, the standard deviation for the hit-ratio in the testing period from the best downtrend buy signals found in the 150 experiments is 0.22545008425851168. Therefore, Z=16.349068412051416>$Z_{0.001}$. Thus, the hit-ratio for the best downtrend buy signal found in the present study is significantly better than the hit-ratio for the downtrend buy signal of Lu and Shiu (2012).

The above experimental results of holding stocks for 10 days are organized in Table 6 and Table 7.

Table 6: Performance of the average rate of return for each sequence in the 150 experiments for this method

	Sequence 1 uptrend buy signal	Sequence 1 downtrend buy signal	Sequence 2 uptrend buy signal	Sequence 2 downtrend buy signal
Mean	0.01417205614921375	0.025143797132703982	0.009182128524062794	0.013209228515625
Standard deviation	0.0034589081367725383	0.0035546778534533445	0.016076292195379243	0.010045884636459695
Lu and Shiu (2012)	-0.0163501557849702	0.0103446690004263	0.00104489045984605	0.00971726826259068
Z value	108.07434326602132	50.98958901005788	6.199215879707876	4.257226282974962
P value	(<0.001)***	(<0.001)***	(<0.001)***	(<0.001)***

Table 7: Performance of the hit-ratio for each sequence in the 150 experiments for this method

	Sequence 1 uptrend buy signal	Sequence 1 downtrend buy signal	Sequence 2 uptrend buy signal	Sequence 2 downtrend buy signal
Mean	0.6876923076923078	0.6666666666666665	0.6532348619066776	0.9466666666666667
Standard deviation	0.056526686371919495	0.00000000000000011139	0.2351132013423154	0.22545008425851168
Lu and Shiu (2012)	0.19047619047619047	0.5634328358208955	0.43137254901960786	0.6457142857142857
Z value	107.73015873015875	11350237472057520.0	11.557187274562876	16.349068412051416
P value	(<0.001)***	(<0.001)***	(<0.001)***	(<0.001)***

5. Conclusions

The issue of whether the candlestick analysis method is profitable has been extensively discussed in academia in recent years, and related studies have been published in influential journals. There are many studies that support the profitability of the candlestick analysis method, but there are also many studies that hold the opposite view.

Lu and Shiu (2012) used a four-digit numbers approach to underpin a study that comprehensively tested the reliability of the two-day candlestick pattern as a buy signal. They also confirmed that two types of new bullish candlestick patterns were profitable buy signals. However, the data were not split into training, validation and testing periods in the paper, which cannot prevent the problem of overfitting. Changes in the data source or the interval may affect the significance of profitability. As expected, the average rates of return for the buy signals found by the method in the present paper are all significantly better than the average rates of return for the buy signals proposed by Lu and Shiu (2012).

In addition to splitting the data into training, validation and testing periods in the present paper to prevent the problem of overfitting, the buy conditions are further strengthened. The uptrend and downtrend considered, as are the ability of stock prices to steadily remain above the season average, the trading volume, the volume-price structure and so on. Adding one factor for consideration in traditional methods require a higher calculation effort. Through genetic algorithms, adding one more condition only requires adding one bit to the string for the genetic algorithms, which takes minimal effort. Consequently, introducing genetic algorithms frees the research from limitations imposed by the tools.

There are several caveats to this study. First, our method uses the next-day opening price as the buying price, which may not be applicable in practice. Second, for the sake of simplicity in this study, we adopted two-day candlestick patterns as buy signals. We should emphasize that three-day and longer candlestick patterns as buy signals are also feasible, and we leave those scenarios to future work. Last, the FTSE TWSE Taiwan 50 Index is used in the present paper, which consists of the largest 50 companies by full market value in Taiwan. It is possible that candlestick patterns have different performances for smaller capitalized stocks, and we also leave this topic for future research.

An innovative dual-technology trading strategy that uses genetic algorithms to improve the candlestick analysis method is pioneered in the present study, and the average rates of return for the buy signals found by the method in the present paper are confirmed to be significantly better than the buy signals proposed in previous literature. We believe that the introduction of genetic algorithms is a significant step forward for research on the candlestick analysis method, and the method in the present paper will make notable contributions to the field of computation.

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References

Ahmadi, E., Abooie. M., Jasemi. M. & Mehrjardi. Y. Z. (2016). A nonlinear autoregressive model with exogenous variables neural network for stock market timing: The candlestick technical analysis. *International Journal of Engineering,* **29**, 1717-1725.

Ahmadi, E., Jasemi. M., Monplaisir. L., Nabavi. M. A., Mahmoodi. A. & Jam. P. A. (2018). New efficient hybrid candlestick technical analysis model for stock market timing on the basis of the Support Vector Machine and Heuristic Algorithms of Imperialist Competition and Genetic. *Expert Systems with Applications,* **94**, 21-31.

Allen, F., & Karjalainen. R. (1999). Using genetic algorithms to find technical trading rules. *Journal of Financial Economics,* **51**, 245-271.

Ananthi, M., & Vijayakumar. K. (2021). Stock market analysis using candlestick regression and market trend prediction (CKRM). *Journal of Ambient Intelligence and Humanized Computing,* **12**, 4819-4826.

Beveridge, S., & Oickle. C. (1997). Long Memory in the Canadian Stock Market. *Applied Financial Economics,* **7**, 667-672.

Chelley-Steeley, P. (2001). Mean Reversion in the Horizon Returns of UK Portfolios. *Journal of Business Finance and Accounting,* **28**, 107-126.

Chen, S., Bao. S., & Zhou. Y. (2016). The predictive power of Japanese candlestick charting in Chinese stock market. *Physica A: Statistical Mechanics and its Applications,* **457**, 148-165.

Chen, S. H., Kuo, T. W., & Hoi. K. M. (2008). Genetic programming and financial trading: how much about" what we know". In Zopounidis C., M. Doumpos, and P. M. Pardalos (eds.), Handbook of financial engineering, Springer, Boston, MA, 99-154.

Caginalp, G., & Laurent. H. (1998). The Predictive Power of Price Patterns. *Applied Mathematical Finance,* **5**, 181-205.

Chung, H., & Shin K.-s. (2018). Genetic Algorithm-Optimized Long Short-Term Memory Network for Stock Market Prediction. *Sustainability,* **10,** 3765.

Chaudhuri, K., & Wu. Y. (2003). Random walk versus breaking trend in stock prices: evidence from emerging markets. *Journal of Banking and Finance,* **27**, 575–592.

Eldridge, M. R., Bernhardt. C. & Mulvey. I. (1993). Evidence of Chaos in the S&P 500 Cash Index. *Advances in Futures and Options Research,* **6**, 179–192.

Fengqian, D., & Chao. L. (2020). An adaptive financial trading system using deep reinforcement learning with candlestick decomposing features. *IEEE Access,* **8**, 63666-63678.

Fock, J. H., Klein C., & Zwergel. B. (2005). Performance of Candlestick Analysis on Intraday Futures Data. *Journal of Derivatives,* **13**, 28-40.

Fama, E. F., & French. K. R. (1986). Common Factors in the Serial Correlation of Stock Returns. Center for Research in Security Prices Working Paper.

Greene, M. T., & Fieltz. B. D. (1977). Long Term Dependence in Common Stock Returns. *Journal of Financial Economics,* **4**, 339–349.

Goo, Y., Chen. D.& Chang. Y. (2007). The Application of Japanese Candlestick Trading Strategies in Taiwan. *Investment Management and Financial Innovations,* **4**, 49-71.

Hsieh, D. A. (1991). Chaos and Nonlinear Dynamics: Application to Financial Markets. *Journal of Finance,* **46**, 1839–1877.

Horton, M. J. (2009). Stars, Crows, and Doji: The Use of Candlesticks in Stock Selection. *The Quarterly Review of Economics and Finance,* **49**, 283-294.

Hung, C. -C., & Chen. Y. -J. (2021). DPP: Deep predictor for price movement from candlestick charts. *PLoS ONE,* **16**, e0252404.

Hu, G., Hu. Y., Yang. K., Yu. Z., Sung. F., Zhang. Z, Xie. F., Liu. J., Robertson. N. M.,Hospedales. T.M. & Miemie. Q. (2018). Deep stock representation learning: From candlestick charts to investment decisions. In: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2706-2710.

Joshi, S., Parker. J.& Bedau. M. A. (2000). Technical Trading Creates a Prisoner's Dilemma: Results From an Agent-based Model. In Y. Abu-Mostafa, B. LeBaron, A. W. Lo & A. S. Weigend (Eds.), *Computational Finance* 99 (pp.465-479). MIT Press.

Kamo, T., & Dagli. C. (2009). Hybrid approach to the Japanese candlestick method for financial forecasting. *Expert Systems with Applications,* **36**, 5023-5030.

Lu, T.-H. (2014). The Profitability of Candlestick Charting in the Taiwan Stock Market. *Pacific-Basin Finance Journal,* **26**, 65-78.

Lu, T.-H. (2018). Can Profit Targets Improve the Profitability of Candlestick Charting. *International Journal of Revenue Management,* **10**, 216-226.

LeBaron, B., Arthur. W. B & Palmer. R. (1999). Time Series Properties of an Artificial Stock Market. *Journal of Economic Dynamics and Control,* **23**, 1487-1516.

Lu, T.-H. & Chen. J. (2013). Candlestick Charting in the European Stock Markets. *JASSA-The Finsia Journal of Applied Finance,* **2**, 20-25.

Lu, T.-H., Chen. Y.-C.& Hsu. Y.-C. (2015). Trend Definition or Holding Strategy: What Determines the Profitability of Candlestick Technical Trading Strategies? *Journal of Banking & Finance,* **61**, 172-183.

Lu, T.-H., Huang. Y.-L.& Chang. J.-R. (2016). Can Anomalies be Explained by Technical Analysis? Evidence from Candlestick Patterns. *Advances in Investment Analysis and Portfolio Management,* **7**, 65-83.

Lee, C.-C., Lee. J.-D.& Lee. C.-C. (2009). Stock prices and the efficient market hypothesis: Evidence from a panel stationary test with structural breaks. *Japan and the World Economy,* **22**, 49–58.

Lee, J. & Strazicich. M. C. (2003). Minimum LM unit root test with two structural breaks. *The Review of Economics and Statistics,* **85**, 1082–1089.

Lu, T.-H. & Shiu. Y.-M. (2012). Tests for Two-day Candlestick Patterns in the Emerging Equity Market of Taiwan. *Emerging Markets and Finance and Trade,* **48**, 41–57.

Lu, T.-H. & Shiu. Y.-M. (2016). Can One-day Candlestick Patterns be Profitable on the 30 Component Stocks of the DJIA? *Applied Economics,* **48**, 3345-3354.

Lu, T.-H., Shiu. Y.-M.& Liu. T.-C. (2012). Profitable Candlestick Trading Strategies-The Evidence from a New Perspective, *Review of Financial Economics,* **2**, 63–68.

Lo, A. W., & Mackinlay. A. C. (1988). Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test. *Review of Financial Studies,* **1**, 41-66.

Martiny, K. (2012). Unsupervised discovery of significant candlestick patterns for forecasting security price movements. In: Proceedings of the International Conference on Knowledge Discovery and Information Retrieval (KDIR-2012), 145-150.

Marshall, B. R., Young. M. R.& Rose. L. C. (2006). Candlestick Technical Trading Strategies: Can They Create Value for Investors? *Journal of Banking & Finance,* **30**, 2303-2323.

Marshall, B. R., Young. M. R. & Cahan. R. (2008). Are Candlestick Technical Trading Strategies Profitable in the Japanese Equity Market? *Review of Quantitative Finance & Accounting,* **31**, 191-207.

Nison, S. (1991). Japanese Candlestick Charting Techniques. New York: Institute of Finance.

Narayan, P. K. (2005). Are the Australian and New Zealand stock prices nonlinear with a unit root? *Applied Economics*, **37**, 2161–2166.

Narayan, P. K. (2006). The behaviour of US stock prices: evidence from a threshold autoregressive model. *Mathematics and Computers in Simulation,* **71**, 103–108.

Opong, K. K., & Sprevak. D. (2000). The Behaviour of the Irish ISEQ Index: Some New Empirical Tests. *Applied Financial Economics*, **10**, 693-700.

Poterba, J. M., & Summers. L. H. (1988). Mean Reversion in Stock Prices: Evidence and Implications. *Journal of Financial Economics,* **22**, 27-59.

Pesaran, M. H., &Timmermann. A. (1995). Predictability of stock returns: Robustness and economic significance. *Journal of Finance,* **50**, 1201-1228.

Qian, X. Y., Song. F. T., & Zhou. W. X. (2008). Nonlinear behaviour of the Chinese SSEC index with a unit root: evidence from threshold unit root tests. *Physica A: Statistical Mechanics and Its Applications,* **387**, 503-510.

Sewell, S. P., S. R. Stansell, I. Lee & M. S. Pan, (1993). Nonlinearities in Emerging Foreign Capital Markets. *Journal of Business Finance and Accounting,* **20**, 237–248.

Shiu, Y. -M., & Lu. T. -H. (2011). Pinpoint and Synergistic Trading Strategies of Candlesticks. *International Journal of Economics and Finance,* **3**, 234-244.

Wang, J. (2000). Trading and hedging in S&P 500 spot and futures markets using genetic programming. *The Journal of Futures Markets,* **20**, 911-942.

Yu, T., Chen, S. –H.& Kuo. T. –W. (2004). Discovering financial technical trading rules using genetic programming with lambda abstraction. In U. O'Reilly, T. Yu, R. Riolo, and B.

Worzel (eds.), Genetic Programming Theory and Practice II, Springer, 11-30.

Yang, Y., Mabu, S., Gu, Y., & Hirasawa. K. (2011). Multi-subroutines in Genetic Network Programming-Sarsa for trading rules on stock markets. SICE Annual Conference 2011, 167-172.

Zhu, M., Atri. S. & Yegen. E. (2016). Are candlestick trading strategies effective in certain stocks with distinct features? *Pacific-Basin Finance Journal*, **37**, 116-127.