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Stock Trade Simulation Using an Average Based Trend Indicator with Heuristic Enhancements

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Abstract— **The spread of Covid-19 is making a serious impact on the world economy. As policies to maintain economic activities have been implemented in a timely manner, many stock markets have regained their stock prices to pre-Covid-19 pandemic levels. This paper describes results of statistical analyses of stock price fluctuations in the vicinity of the declaration of a state of emergency following the Covid-19 pandemic. Daily historical data concerning Dow Jones Industrial Average (DJIA), Nasdaq Composite Index (NASDAQ), France Stock Index (CAC), German Stock Index (DAX), Shanghai Composite Index (SSEC) and Nikkei Stock Average (Nikkei) are used for stock trade simulations. The results show that these stock prices plunged for approximately 20 days before the trading day that marked the lowest price, and increased for the following 25 days. Through the analyses of the results, a technical indicator defined by the difference between a stock price and the moving average is devised to predict stock price trend reversals. A stock trade simulator is developed using the devised indicator to examine the degree of stock price prediction. The simulator is enhanced by heuristics using candlestick patterns to avoid large losses. Experimental results using ten years of stock price data from nine world major stock markets show that the simulator achieved the success rate of up to 74% with trade fees for purchasing a stock. Meanwhile, the success rate remains within 25% for selling a stock, because a margin loan for borrowing a stock squeeze profits. Although the developed simulator has some limitations, it provides a tool for measuring profitability among stock markets and analyzing a stock trade opportunity that leads to a significant profit and/or loss.**

Keywords— Covid-19 pandemic; Technical analysis; Global market comparison; Candlestick chart pattern, APAD.

I. INTRODUCTION

This research paper is based on the previously reported contribution on analyses of the impact of Covid-19 pandemic on global stock prices [1]. More than two years have passed since the first Covid-19 pandemic was confirmed. But the spread of coronavirus is still continuing and the number of daily corona cases remains high. The spread of Covid-19 is forecasted to have a significant adverse impact on the global economy. While the global real Gross Domestic Product (GDP) grew by 2.9 percent in 2019, it was projected at –4.9 percent in 2020 grew [2]. The Covid-19 pandemic had a more negative impact on activity in the first half of 2020 than anticipated. Global growth was projected at 6% in 2021, moderating to 4.4% in 2022. While the vaccine is expected to be effective for economic recovery, there are concerns about the impact of the zero-tolerance Covid-19 policy in China [3].

World stock markets experienced a large crash in the first quarter of 2020. Concerns about a further plunge of stock prices prevailed over global markets. However, due to the economic policies of each country, stock prices of world markets have turned from falling to rising in Mar. 2020. Because it is rare for the major world stock price indexes to fall all at once and then recover, we expect to deepen our understanding of stock price movements and to find an indicator for signaling stock price trend reversals by analyzing stock price fluctuations regarding the declaration of a state of emergency on Covid-19 pandemic.

It can be easily inferred that there is a difference in the degree of collapse and recovery reflecting the situation in each country. What is missing is a comparison of the stock price fluctuations of world markets from a statistical point of view. This study discusses a comparison of representative stock indexes of the U.S., European, and Asian markets [4]. Specifically, we focus on Dow Jones Industrial Average (DJIA), Nasdaq Composite Index (NASDAQ), France Stock Index (CAC), German Stock Index (DAX), Shanghai Composite Index (SSEC), and Nikkei Stock Average (Nikkei). Daily historical data are used for the research.

Dimson et al. [5] recommend investing in the U.S. markets rather than emerging ones because of the growth rate of stock prices and the stability of the investment environment. Reference [6] compares profitability of the U.S. and Asian markets by simulations that find buy-timing using a candlestick pattern model consisting of six parameters. The results of the simulation shows that the profitability of the U.S. markets outperforms other markets. However, these studies were carried out before the spread of the Covid-19 coronavirus.

Ngwakwe [7] estimates how Covid-19 pandemics affected world stock indexes, i.e., Euronext 100, SSEC, DJIA, and S&P500. The results of analyses show that SSEC has resilience to Covid-19 pandemic with profit in stock values during the first fifty days into the pandemic, while the other indexes experience adverse impact from the Covid-19 pandemic with a significant loss at that time period. All stock indexes experience a higher variability or fluctuation of stock market prices.

Verma et al. [8] statistically analyze the impact of the Covid-19 outbreak on global economic development. The indicators used in the analyses include S&P500 stock index, crude oil, gold, and 20-year treasury bond. They find that S&P500 stock index experiences high uncertainty from Feb. 2019 to Apr. 2020, i.e., the latest month of their research.

Buszko et al. [9] deal with the problem of stability of stock prices during the Covid-19 pandemic. The K-means and the Ward clustering methods are applied to the Warsaw Stock Exchange (WSE), which is one of the most important markets in the Central and Eastern European countries (CEE). The paper proposes several indicators describing the stability of stock price fluctuations, and concludes that the indicators defined in terms of profitability, volume, and volatility leads to much better results than other indicators.

This paper has two purposes. One is to analyze stock price fluctuations of approximately 245 trading days, or approximately one year, before and after the declaration of Covid-19 pandemic, and statistically compare degrees of impact on the world markets [1]. Through the analysis, we have devised an indicator for signaling a change of the direction of a price trend. The other purpose of this paper is to give definition of the devised indicator, and to discuss its prediction accuracy in terms of profits with experimental results using major global stock market's daily price data.

Obthong et al. [10] review studies on machine learning techniques and algorithms employed to improve the accuracy of stock price prediction. Of the ten studies compared, four show that prediction accuracies range from 54.41% to 90.19%. Islam et al. [11] show a comparative study for stock price prediction using three different methods, namely autoregressive integrated moving average (ARIMA), artificial neural network (ANN), and geometric Brownian motion. Empirical results using S&P500 index show that the conventional statistical model ARIMA and the Brownian motion model provide better approximation than the ANN model for next-day stock price prediction.

Stock trading consists of selling and buying pairs, and profits are fixed. What is lacking in these studies is experimental evaluations in terms of profits. Since an important objective of stock investment is to make a profit, a profit-focused evaluation is inevitable for the sake of traders. We come up with the idea of developing a simulator that implements both sell and buy timing, and performing experiments using global stock market data to examine the effectiveness of the simulator.

The findings of this research are as follows:

I. The extent of the stock market plunge and recovery at the time of the pandemic declaration is examined using daily stock data of the six major markets. All markets show uptrend reversals in stock prices within four business days, i.e., Mar. 18 to 23, 2020.
II. The stock price best recovered in NASDAQ, followed by Nikkei and DJIA. Stock price recoveries in European markets lag behind that of U.S. and Asian markets.
III. It is found that the trajectory of 25-day average of difference between a stock price and the 5-day average reverses on the lowest price day. We propose an indicator to predict trend reversal named APAD, an acronym for "Average of Price and 5-day Average Difference." We developed stock trading simulators that use the APAD indicator to find trade opportunities and to measure the degree of profit.
IV. The simulator is enhanced by heuristics using candlestick chart patterns. A series of enhancements improves the success rate of simulated stock trades by approximately 8.5% in a long position. The results of experiments on ten years of stock price data from nine major markets in the world show that the simulators achieve the success rate of up to 74% with trade fees in a long position, while the success rate stays within 25% in a short position because a margin for borrowing a stock squeeze profits.

The remainder of the paper is organized as follows. Section II gives the background of the candlestick chart and introduces indicators that characterize stock price fluctuations. Section III shows the extent of stock price plunges and recoveries regarding the Covid-19 pandemic declaration. Section IV statistically examines the indicators for characterizing stock price fluctuations. Section V deals with the development of the stock trade simulator using a devised indicator named APAD, and the enhancement of the simulator using candlestick pattern heuristics. Section VI concludes the paper with our plans for future work.

II. CANDLESTICK CHART AND PRAMETERS

This section introduces formations of a candlestick chart. The candlestick attributes to be analyzed are identified.

A. Formation of Candlestick

As depicted in Figure 1, a daily candlestick is formed with the market's opening, high, low, and closing prices of a specific trading day [12][13]. The candlestick has a wide part, which is called *real body* representing the range between the opening and closing prices of the day of trading, as shown in Figure 1. The color of the *real body* represents whether the opening price or the closing price is higher. If the price rises, a hollow body is drawn suggesting *bullish* or buying pressure. Otherwise, a filled body is drawn suggesting *bearish* or selling pressure.

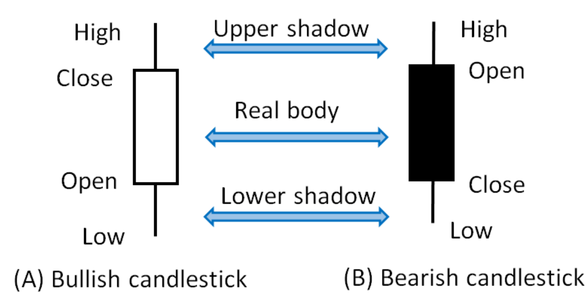

Figure 1. Candlestick formation.

The thin lines above and below the body, which are named *shadows*, represent the range of prices traded in a day. The high is marked by the top of the upper shadow and the low by the bottom of the lower shadow.

B. Candlestick Chart and Parameters

A candlestick chart is a graph in which candlesticks are arranged in order of market dates. It is used as a tool to get information on whether the current price is higher or lower than the historical stock price movements, and what kind of price movements have been made in a certain period of time. Moving averages form a line graph by connecting the average of closing prices over a certain period of time. The line graph is useful to decide whether stock prices are in a rising or falling trend by considering the relative position between the current stock price and the moving average. As for periods of time to compute averages, each country uses its own periods. For example, the short-term average is often calculated for 5 days, the medium-term average is for 25 days, and the long-term average is for 75 days in Japan.

Figure 2 illustrates indicators including the averages that formalize a candlestick chart. In accordance with the candlestick chart notation, the following six attributes or indicators are used for analysis.

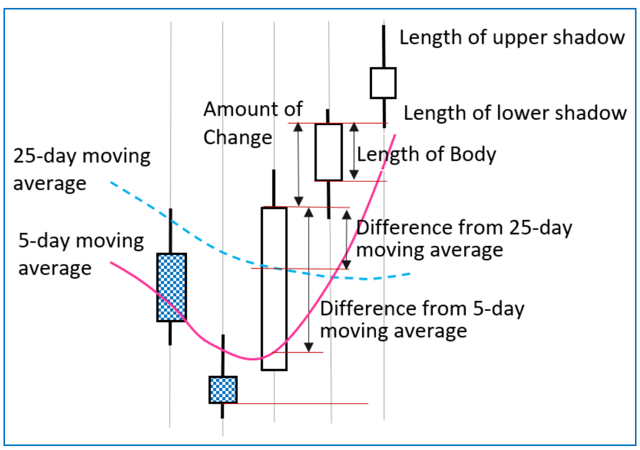

Figure 2. Candlestick chart and its parameters.

(1) Amount of stock price change (the difference between a stock's closing price on a trading day and its closing price on the previous trading day)
(2) Length of candlestick body
(3) Length of upper shadow
(4) Length of lower shadow
(5) Difference between the stock price of a trading day and the 5-day moving average
(6) Difference between the stock price of a trading day and the 25-day moving average

III. STOCK PRICE PLUNGE AND RECOVERY REGARDING COVID-19 PANDEMIC

This section describes the process of data analysis to follow how this research is performed. Stock price fluctuations of the six markets are compared with the ratio of the stock price to the lowest stock price to measure impacts of Covid-19 on each market.

A. Data Analysis Process

Figure 3 overviews the data analysis process in this research that consists of the following operations.

(1) Downloading daily historical data from a Web site,
(2) Calculating the six attributes mentioned in Section II,
(3) Extracting price data around the lowest price during Covid-19 pandemic,
(4) Calculating the average and standard deviation of the six attributes.

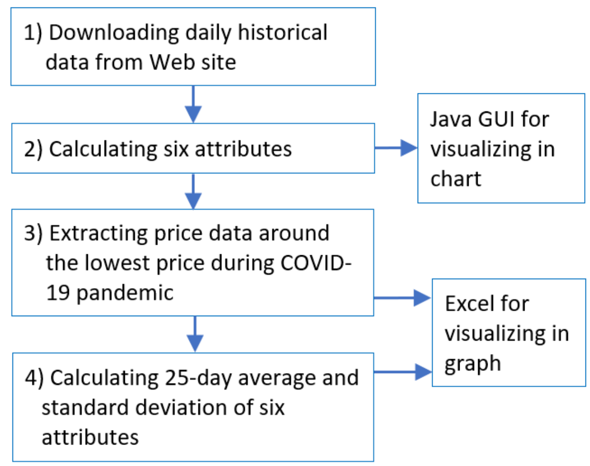

Figure 3. Overviews of data analysis process.

Among the sites that provide global stock data, the Web site [4] provides daily stock data for more than 10 years in more than 40 markets. All data used in the research are downloaded manually from the site.

Because the daily stock data only consist of close, open, high, low prices, and volume of stock trading, Java programs are developed for performing operations 2) to 4), and visualizing the candlestick chart. Excel is used for visualizing data of 3) and 4) in graphs.

B. Comparison of Stock Price Fluctuations

In order to understand overall structures of stock price fluctuations, we compare the stock price ratios to the lowest price that was recorded in Mar. 2020. Let *CPr[n]* be the closing price of a trading day n, and *CPrMin* be the lowest closing price recorded in Mar. 2020. The price ratio *PrRatio[n]* is calculated by the following formula;

$$PrRatio[n] = (CPr[n] - CPrMin) * 100 / CPrMin \quad (1)$$

Figure 4 is a graph of the price ratio of the six markets' stock prices to the lowest ones for 490 days, or approximately two years before and after the lowest. The lowest prices were recorded on one of the four business days from Mar. 18 to 23, 2020. Although the date of the lowest price slightly varies from market to market, stock prices continued to rise after hitting the lowest price in all markets.

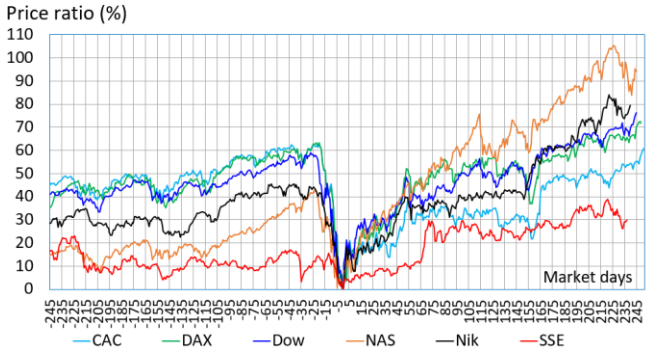

Figure 4. Ratio of stock index compared to the lowest price.

Table I summarizes the stock price profiles compared to the lowest price. The lowest prices have been recorded from Mar. 18 to Mar. 23 in the six markets under comparison. Since Mar. 22, 2020 is Sunday, they show that the stock trends reversed from downtrend to uptrend in just 4 trading days in the six markets. The degree of plunge is 63.34% in DAX (Germany), followed by 62.76% in CAC (France), and 58.95% in DJIA (US), as shown in the column "Highest price before Covid-19 pandemic." The lowest decline was of 22.95% in SSEC (China).

TABLE I. SUMMARY OF STOCK PRICE INDICATORS COMPARED TO THE LOWEST PRICE

	Day of lowest price	Highest price before Covid-19 pandemic (%)	Highest price after Covid-19 pandemic (%)	Recovery (%)
CAC40(France)	Mar. 18	62.76	61.03	-1.73
DAX(Germany)	Mar. 18	63.34	72.59	9.25
DowJones(U.S.)	Mar. 23	58.95	76.3	17.35
NASDAQ(U.S.)	Mar. 23	43.09	105.45	62.36
Nikkei(Japan)	Mar. 19	45.49	84.06	38.57
SSEC(China)	Mar. 23	22.95	38.94	15.99

A matter worthy of note is the degree of recovery from the lowest price. NASDAQ achieves the finest recovery of 62.36% rise as the highest price ratio after the Covid-19 pandemic is 105.45%, and the highest one before the pandemic is 43.09%. Following NASDAQ, Nikkei (Japan) comes back by 38.57% rise. The slowest recovery is recorded –1.73% in CAC, followed by 9.25% in DAX. From the stock price movements of the two markets, it can be inferred that the impact of the Covid-19 pandemic in Europe is larger than the other regions.

IV. COMPARISON OF INDICATORS REGARDING STOCK PRICE FLUCTUATIONS

This section presents the results of comparisons of the six indicators introduced in Section II with respect to the average and standard deviation in statistics. In order to compute the meaningful standard deviation, we calculate the average and standard deviation of the past 25 days [14] including the reference trading day. This period is commonly used for the calculation of the six attributes of a candlestick.

A. Amount of Stock Price Change

Figure 5 shows a graph of the 25-day moving averages and standard deviations of price changes of each stock market. As seen at the center part of Figure 5, the averages (in solid lines) of stock price changes plummet during approximately 20 days before the lowest trading day, i.e., around Feb. 20, 2020 in the five markets excluding SSEC. Stock price averages rally for approximately 25 days after the bottom, i.e., around Apr. 24, 2020.

The standard deviations (in dashed lines) over this period, also increase in the range of 3.5 to 6 times of those of the other period reflecting the high volatility of price movements.

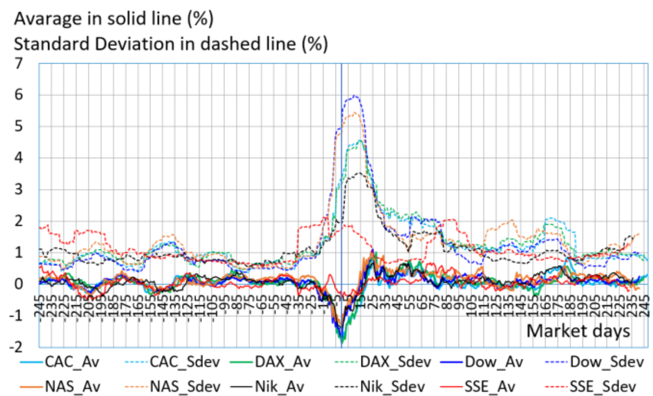

Figure 5. Average and standard deviation of price change.

Taking a closer look at the standard deviations, DJIA reaches the maximum of 6.00%, followed by NASDAQ of 5.47%, CAC of 4.56%, DAX of 4.54%, Nikkei of 3.53%, and SSEC of 2.14%, which is considered to reflect the strength of the impact on each market. The standard deviations of each market have roughly doubled after the lowest price, i.e., the right part, compared to those before the lowest price, i.e., the left part, which suggests that unstable trading has continued for roughly 180 days after the lowest price day.

B. Length of Candlestick Body

Figure 6 shows the 25-day averages and standard deviations of the candlestick body lengths of the six stock markets. Figure 6 shows that the averages of SSEC are positive (plus) during the plunge period (–20 to 0), which means stock prices increase on average within a market day. The 25-day average of candlestick body lengths in NASDAQ is almost zero level during the plunge period. NASDAQ has consistently positive average during the period of stock price recovery (0 to 25), which means that the stock price continued to rise during trading hours. The four other markets experience remarkable negative averages, e.g., –1.39% in CAC, –1.15% in DAX, –0.967% in Nikkei, and –0.83% in DJIA at the lowest, suggesting that colored candlesticks are prominent.

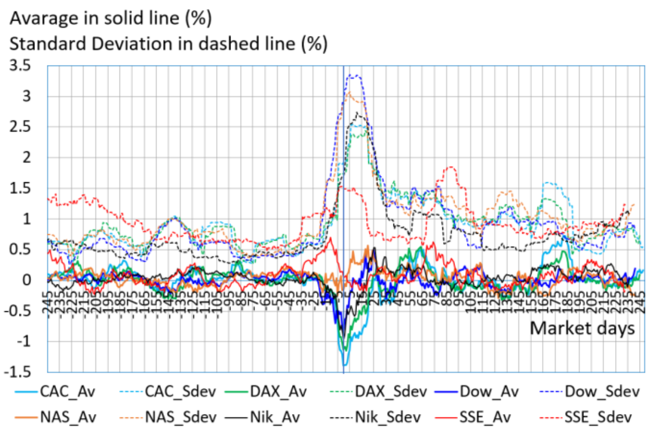

Figure 6. Average and standard deviation of candlestick body length.

The largest standard deviation of 3.36% is marked in DJIA, followed by 3.07% in NASDAQ, 2.73% in Nikkei, 2.54% in CAC, 2.44% in DAX, and 1.85% in SSEC. Trends of the average and standard deviation of SSEC are notably different from the other markets.

C. Length of Upper and Lower Shadows

Figures 7 and 8 illustrate the 25-day averages and standard deviations of the lengths of the upper and lower shadows. The two figures look similar, revealing that the lengths of upper shadows are apparently correlated with those of the lower shadows.

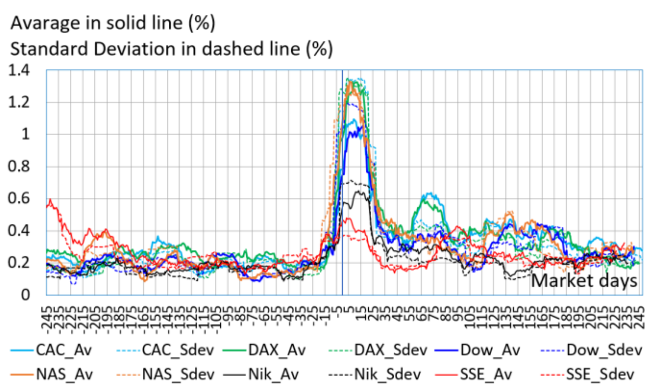

Figure 7. Average and standard deviation of upper shadow length.

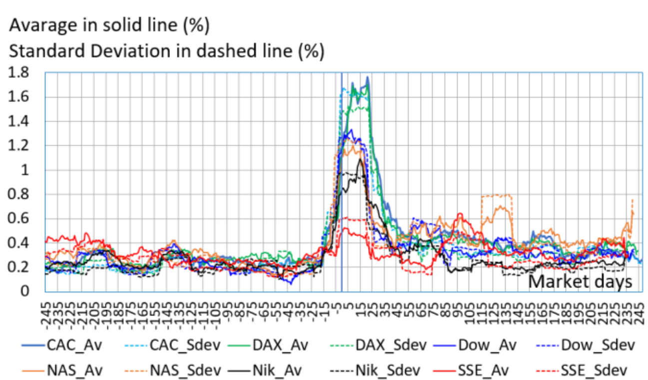

Figure 8. Average and standard deviation of lower shadow length.

In the five markets excluding SSEC, the averages and standard deviations of the upper and lower shadows increase sharply during the period from approximately 10 days before the lowest price to approximately next 25 days.

Notably in the European markets of DAX and CAC, both the averages and standard deviations have surged about six times after the lowest price compared to these before the lowest price for the upper shadows, and about eight times for the lower ones. Those surges mean that rough price movements occur during the period.

On the other hand, the Asian market is relatively stable. In SSEC, the averages and standard deviations are doubled after the lowest price than before for the upper shadows, and are tripled for the lower ones. Nikkei marks about three times higher for the upper shadows, and about five times higher for the lower ones.

Figure 9 is a scatter plot of the lengths of upper and lower shadows in the Nikkei market. It illustrates that there is a strong correlation between the lengths of the upper and lower shadows.

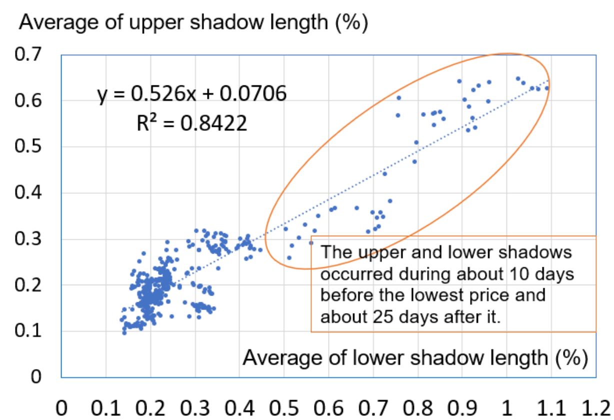

Figure 9. Scatter plot of upper and lower shadow length of Nikkei.

The points surrounded by an ellipse correspond to the shadows that occur in the period between approximately 10 days before and approximately 25 days after the lowest price. These points occupy a different portion of Figure 9 from the rest of the points. R-squared (R^2) in statistics is 0.8422, which indicates that 84.22% of the upper shadow length can be explained by the lower shadow length, and vice versa.

D. Difference Between Stock Price and 5-day Average

Figure 10 shows the 25-day averages and standard deviations of the "difference between a stock price and 5-day moving average" for the six markets. The 25-day averages of the difference sharply decrease about 20 days before the lowest price, and sharply increase until 25 days after the bottom.

The standard deviation increased more than fourfold in the five markets except SSEC, during the period from about 20 days before the lowest price to 25 days after the lowest price. High standard deviation around 2% continues in all markets nearly 80 days after the day recorded the lowest price.

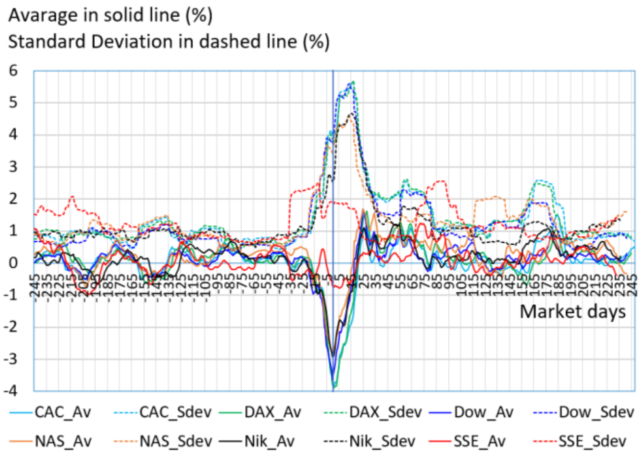

Figure 10. 25-day average and standard deviation of "difference between stock price and 5-day average."

In the five markets excluding SSEC, the day when the 25-day average of the "difference between a stock price and 5-day moving average" reverses the trend from downward to upward roughly coincides with a day when the stock price bottoms out. As for the standard deviations, they remain high in the five markets except SSEC for the 20 days following the lowest day.

We investigate how the period for calculating the average of the "difference between a stock price and 5-day moving average" relates to the timing of the stock price reversal. Figure 11 shows the *P*-day average of the "difference between the 5-day average and the stock price" in NASDAQ, where *P* is 8, 12, 18, 25, 30, and 35. When *P* is 12, 25, 30, and 35, the date when this average is at its minimum coincides with the date when the stock price is at its lowest. When *P* is 8 and 18, the *P*-day average begins to rise two days before the lowest price.

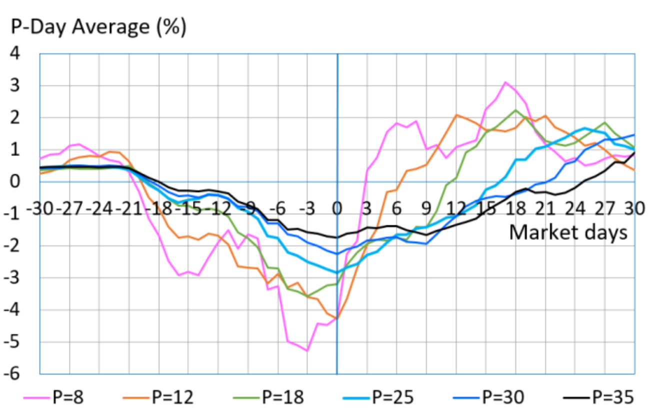

Figure 11. P-day average of "difference between stock price and 5-day average" in NASDAQ.

Figure 12 shows the results using Nikkei 225 stock data. When *P* is 12 and 18, the minimum value of the *P*-day average coincide with the day when the stock price reached its lowest price. On the other hand, when *P* is 25, 30, or 35, this average reached its minimum value on the next day when the stock price reached its lowest value.

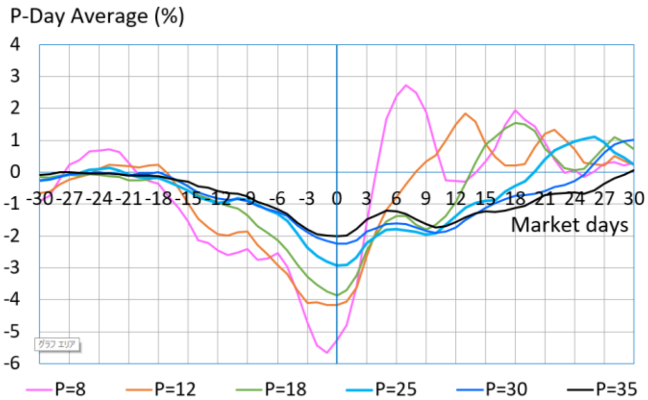

Figure 12. P-day average of "difference between stock price and 5-day average" in Nikkei.

Although there are slight differences from stock market to market, this average can be used to predict a stock price reversal with an error of less than one day if *P* is greater than 25. This is an important finding and detailed analyses are discussed in Section V.

E. Difference Between Stock Price and 25-day Average

Figure 13 shows the 25-day averages and standard deviations of the "difference between a stock price and 25-day moving average" for the six markets. This indicator shows a minimum value 4 to 14 days after the lowest stock price in the six markets, which indicates that this indicator is too slow to predict a stock trend reversal.

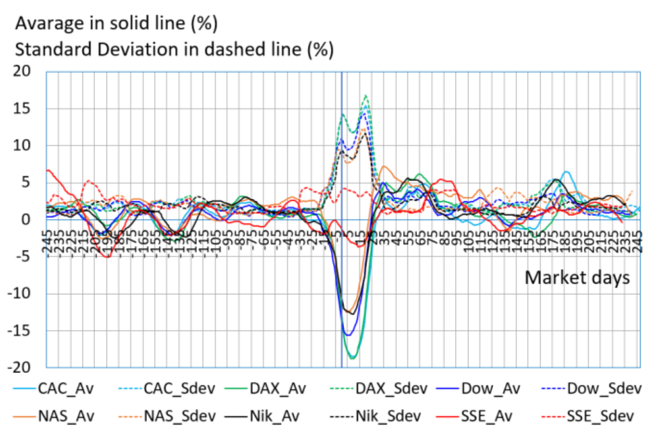

Figure 13. 25-day average and standard deviation of "difference between stock price and 25-day average."

Again, in the five markets excluding SSEC, the averages and standard deviations fluctuate largely during a period between approximately 20 days before the day of the lowest price and the following 25 days.

The standard deviation increased more than fivefold in the five markets except SSEC. Standard deviation close to

4% continues in all markets nearly 80 days after the lowest price day.

V. Developing Stock Trading Simulator

In this section, we propose a new trend reversal indicator based on the analysis described in Section IV. The definition of the indicator, and the configuration of stock trading simulators using the indicator are described. Stock trading simulation are performed using nine markets around the world for ten years. The results of the simulation are analyzed in terms of profits.

A. Trend Reversal Indicator APAD

As mentioned in Section IV-D, the 25-day average of "difference between a stock price and 5-day moving average" starts to rise just after the day when the lowest price is recorded. Based on the results of the analysis, we propose a trend reversal indicator named APAD, i.e., an acronym for "*P*-day Average of stock Price and *N*-day Average Difference." Generally, APAD is defined using two parameters, *P* and *N*. *P* and *N* are arbitrary periods of market day.

Let *CPr[D]* be the closing price of a trading day *D*, and *CPr[1]* represent the most recent trading day as defined in (1). Let *PAD (D, N)* represent a ratio of the difference between the closing price and the *N*-day average of a market day *D* to the closing price as defined by the following formula:

$$PAD\,(D, N) = \{CPr[D] - \frac{1}{N}\sum_{k=D}^{k=D+(N-1)} CPr[k]\,\} * 100\,/\,CPr[D] \qquad (2)$$

APAD (D, N, P) is defined as the *P*-day average of *PAD (D, N)* as follows:

$$APAD\,(D, N, P) = \frac{1}{P}\sum_{j=D}^{j=D+(P-1)} PAD(j, N) \qquad (3)$$

Based on examination of Figure 10 through 12, *N* and *P* is set to five for calculating the fast APAD. *P* is set to twenty-five for the slow APAD as defined by the following formulas:

Fast APAD: *APAD (D, 5, 5)* (4)

Slow APAD: *APAD (D, 5, 25)* (5)

Since the APAD is a percentage price oscillator (PPO) [12] that calculates a difference relative to a closing price, the APAD can be applied to compare the world's major stock markets.

Figure 14 illustrates the candlestick chart for 30 days before and after Mar. 18, 2020 in the DAX market. The top three-quarters of this figure are used to draw candlesticks and the rest is used to draw the APDAs.

The vertical lines in magenta color, usually centered, indicating the day of interest. Candlestick charts are displayed with 5-day and 25-day averages, in accordance with Japanese stock market conventions. APADs are shown in the lower one-quarter of Figure 14. The magenta line shows the fast *APAD (D, 5, 5)*, and the blue line shows the slow *APAD (D, 5, 25)*.

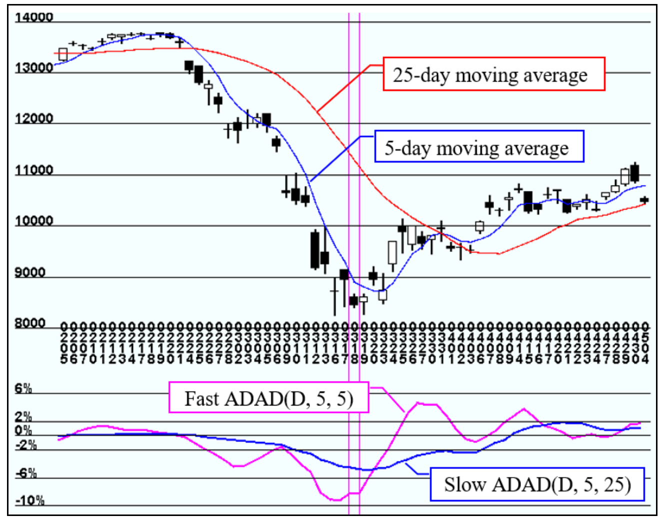

Figure 14. Candlestick chart for 30 days before and after Mar. 18, 2020 in DAX market.

The proposed two APAD lines go across up on Mar. 20, i.e., the two days after the lowest price is recorded. The two lines do not crossover on Mar. 5, which means to predict that stock prices will continue to fall. In other words, a short-term recovery from Feb. 28 to Mar. 5 is a "*dead cat bounce*," i.e., a temporary recovery of stock prices during a prolonged decline period.

The two lines also do not crossover during the decline from Mar. 27 to April 3, which suggests that Apr. 3 is a "*buying on the dips*" type of opportunity since the slopes of the fast and slow APAD lines increase on Apr. 3. The magenta line crosses down through the blue line on Apr. 17. However, the slope of the slow APAD is positive on Apr. 17, which indicates that the uptrend of the stock price is continuing in the medium term of 25 days. During periods when the slope of the slow APAD is positive, no action should be taken for a down trend.

Similar results have been obtained in the other markets. Regarding recovery from the plunge caused by Covid-19 pandemic, it is confirmed that the fast and slow APAD lines forecast short-term trends properly.

B. System Configuration for Stock Trading Simulator

Figure 15 shows the configuration of stock trading simulators developed in this study. The CSV files storing the stock prices are manually downloaded from the global Web site [4]. *Read_CSV_Data* is a Java program that converts the CSV file into an *in-memory data store*. The data store provides all the data needed for analyses, including the price change, the body length of a candlestick, the moving average of stock prices, and the APADs, etc.

A Java program named *T2L* (Trade Tracker for a Long position) is a simulator that tracks buying opportunities using APADs, and virtually performs stock trade in a long position. Meanwhile, a program named *T2S* (Trade Tracker for a Short position) is a simulator for a trade in a short position. *T2L* and *T2S* are independent programs, each generating a log file for further analysis using a spread sheet tool including Excel. A program named *GUICC* (GUI for Candlestick Chart) is a tool for drawing candlesticks, the moving averages and the APADs, etc. and is used to draw candlestick charts, e.g., Figure 14.

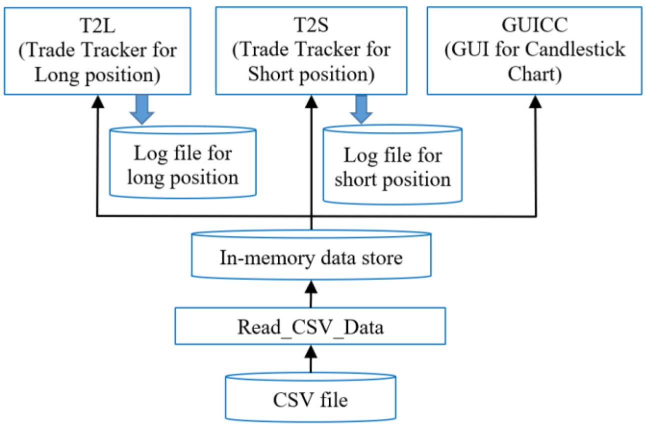

Figure 15. Configuration of developed stock trading simulator.

In the downloaded CSV file, the most recent stock prices are stored at the beginning of the file. *Read_CSV_Data* reads data from the beginning of the CSV file and stores the data in an internal array while maintaining the order. For example, the opening price stored in the CSV file is stored in an array named *Open[]* with the *double* data type. *Open[1]* memorizes the opening price of the most recent trading day. Since the NASDAQ market trades approximately 254 days per year, the opening price of the NASDAQ market ten years ago is stored in the vicinity of *Open[2540]*. An array named *Mday[]* with the *int* data type is used for storing market dates in integer, e.g., 20220430 to indicate Apr. 30, 2022.

Figure 16 shows the basic structure of the developed simulator. The stock market to be analyzed corresponds to the name of the CSV file, e.g., *NASDAQ.csv* for NASDAQ composite index. *Read_CSV_Data* method reads the data from the specified CSV file. A method named *FindIndex* is a method that takes a market date as an argument and converts it to an index of an internal array.

```
public class Stock_Trading_Simulator {
    public static void main(String[] args) {
        String filename= "c:/temp/NASDAQ.csv";
        Read_CSV_Data( filename );
        int IndexFrom= FindIndex( 20120501 );
        int IndexTo= FindIndex( 20220430 );
        T2L( IndexFrom, IndexTo);
        T2S( IndexFrom, IndexTo);
    }
}
```

Figure 16. Basic structure of developed simulator.

In this study, the start and end dates of the simulation are May 1, 2012 and Apr. 30, 2022, respectively. The variables *IndexFrom* and *IndexTo* store the indices of the internal array corresponding to the dates. These two variables are used as arguments of the *T2L* and *T2S* methods that perform simulations.

C. Tracking Buy Opportunities using APAD

1) Overall Algorithm for Buying Simulation

Figure 17 shows the overall algorithm for the buying simulation. The *T2L* method has two parameters, i.e., *IndexFrom* and *IndexTo*. The parameter *IndexFrom* specifies the start date of a simulation. Strictly, the value of *IndexFrom* is the index value of arrays corresponding to the start date. Similarly, the parameter *IndexTo* specifies the end date of a simulation.

```
T2L ( int IndexFrom, int IndexTo ) {
    int flg= -1;      // to indicate state of finding buy-opportunity
    for ( j= IndexFrom; j>=IndexTo; j-- ) {
        /* Buy signal is detected */
        if ( flg < 0 & Buy_Signal_B ) {
            traded_p = ((Open[j] + Close[j]) / 2) ;
            holding_day_cnt= 0;
            flg= 1;       // to indicate buy-stock state
        /* Sell signal is detected in long position */
        } else if ( flg > 0 & Sale_Signal_B ) {
            diff = ((Open[j] + Close[j]) / 2) - traded_p - buying_cost;
            profit= profit + diff;        // Total profit
            flg= -1;      // to indicate state of finding buy-oppotunity
        }
        holding_day_cnt++;
    }
}
```

Figure 17. Overall simulation algorithm in long position.

When *flg* < *0* & *Buy_Signal_B* is *True*, the process of trading in a long position is started:

- Set the variable *traded_p*, which indicates the trading price of the stock, to the average of the opening and closing prices.
- Set the variable *holding_day_cnt*, which presents the number of days to hold a stock, to 0.
- Set the variable *flg* to 1 for indicating a trade in a long position.

Buy_Signal_B is a conditional expression that signals the start of a buy, and is defined using the APADs and candlestick patterns. The details are described in the following subsections.

When *flg* > *0* & *Sale_Signal_B* is *True*, the trade is closed.

- Set the profit of the trade to the variable *diff* using the expression: *diff = ((Open[j] + Close[j]) / 2) – traded_p – buying_cost.*
- Set the cumulative profit to the variable *profit* using the substitution expression *profit= profit + diff.*
- Set the variable *flg* to –1 to indicate the state for tracking buy opportunities.

Sale_Signal_B are conditional expressions that suggests the end of a buying stock. The details are discussed in the following subsection. *Buying_cost* is a fee of cash trade, and is defined in the following Subsection *4)*.

2) Criteria for buying stock in long position

As observed in Section V-A, the good timing to buy stock is occurred when the slope of the fast APAD is positive or when the fast APAD crosses the slow APAD above it.

Let *APAD_F[j]* be the fast APAD of a trading day *j*, and *APAD_S[j]* be the slow APAD. The larger the value of variable *j*, the more it represents the past, so *j+1* indicates stock data of one market day earlier.

The *Buy_Signal_B* is defined as follows:

$$Buy\_Signal\_B = (b1 \mid (b2 \,\&\, b3)) \,\&\, b4; \quad (6)$$

$$b1 = APAD\_F[j] - APAD\_F[j+1] > 0; \quad (7)$$

$$b2 = APAD\_F[j+1] - APAD\_S[j+1] < 0; \quad (8)$$

$$b3 = APAD\_F[j] - APAD\_S[j] > 0; \quad (9)$$

The Boolean variable *b1* shows that the slope of the fast APAD is positive. *B2* and *b3* mean that the fast APAD goes across up the slow APAD.

To improve the success rate in stock price simulation, it is necessary to reflect the characteristics of stock price fluctuations on the day of stock trading. Let *Pchg[j]* be the ratio of price increase, and *Pbody[j]* be the ratio of candlestick length to the closing price in percentages, respectively. The formula *b4* including parameter values of 0.15 and 0.40 is determined by a parameter tuning through experiments using the NASDAQ stock data.

$$b4 = Pchg[j] > 0.15 \,\&\, Pbody[j] > 0.40; \quad (10)$$

The Boolean variable *b4* means that the stock price rises on the day. The Boolean expression (6) must be *True* to begin the simulation in a long position.

3) Criteria for selling stock in long position

The accuracy of predicting a stock decline is generally less accurate than the accuracy of predicting its price increase [15]. Because of the difficulty of the prediction, we must rely on heuristics. The Boolean condition *Sale_Signal _B* in Figure 17 consists of several Boolean expressions that are derived by experiments using APAD and candlestick attributes. Specifically, *Sale_Signal_B* is defined as follows:

$$Sale\_Signal\_B = b11 \,\&\, ((b12 \,\&\, b13 \,\&\, b14 \,\&\, b15) \mid b16); \quad (11)$$

Let *Avg5[j]* be the 5-day average of stock price of a trading day *j*. The Boolean variable *b11* is defined by the following expression, which indicates that the difference between the stock price and the 5-day moving average is less than 2%, which means that the stock price is close to the 5-day average.

$$b11 = (Close[j] - Avg5[j]) * 100 / Close[j] < 2.0; \quad (12)$$

The variables *b12*, *b13*, and *b14* are conditions regarding APAD. The variable *b12* is defined by the following expression, which indicates that the slope of the fast APAD for the previous day of the stock trade is positive.

$$b12 = (APAD\_F[j+1] - APAD\_F[j+2]) > 0.0; \quad (13)$$

The variable *b13* is defined by the following expression, which indicates that the slope of the fast APAD on the trading day is negative.

$$b13 = (APAD\_F[j] - APAD\_F[j+1]) < 0.0; \quad (14)$$

The variable *b14* specifies the slope of the slow APAD is negative, which indicates that stock prices are falling in the medium term of 25 days.

$$b14 = (APAD\_S[j] - APAD\_S[j+1]) < 0.0; \quad (15)$$

The variables *b15* and *b16* are conditions related to stock price fluctuations on the day of stock trading. The variable *b15* is defined by the following formula, which specifies that the ratio of candlestick length to the closing price on the day is less than 0.3%, suggesting a bearish candlestick. The value of 0.3% is determined thorough experiments.

$$b15 = Pbody[j] < 0.3; \quad (16)$$

The variable *b16* is calculated by the following formula, which indicates that if the stock price on the day is 0.2% lower than the traded price, the stock should be sell back.

$$b16 = ((Open[j] + Close[j]) / 2 - traded\_p) * 100 / traded\_p < -0.2; \quad (17)$$

B16 represents the degree of tolerance for loss. The tolerance values closer to zero gives better results in terms of profit, which suggests that traders in practice should be rigorous in losses.

4) Calculating fee of cash trade

Purchasing shares comes with trading fees. The stock trading with the lowest fee is offered by an online trading in a long position. A trading in a long position is initiated with the purchase of a stock in anticipation that its value will rise over time. The trading fees vary across brokers and an amount of a stock trade. Table II summarizes trading fees of some popular Japanese online brokers. This study assumes the trading fee is 0.1% of the traded stock price due to the fact that the fee is applicable to the trade with an amount between 1M JPY (≒ US$7,500) and 3M JPY (≒ US$22,500).

TABLE II. TYPICAL TRADING FEES OF JAPANESE ONLINE BROKERS

	～ ¥1M	¥1M ～ ¥3M	¥3M ～ ¥5M
SBI	0	0	¥2,576
Rakuten	0	¥3,300	¥5,500
Manex	¥550	¥2,750	¥5,500

The following formula is used to calculate the fee in this study.

$$buying\_cost = traded\_p * 0.001; \quad (18)$$

The *T2L* method performs simulations with and without fees in a long position.

5) Experimental results using NASDAQ historical data

Experiments using NASDAQ daily data are performed to confirm the profit characteristics of trading with the APADs. The period of the experiment is ten years, strictly between May. 1, 2012 and Apr. 30, 2022. Table III shows a sample of logging data in a long position. The log data include pairs of stock buy and sale dates, profits generated on each stock trade. Cumulative profit can be calculated by summing profits and can be used for drawing the cumulative profit graph shown later. Pairs of holding days of a stock and profits are used to draw scatter plots.

TABLE III. SAMPLE OF STOCK TRADE LOG DATA.

No.	Buy Date	Sale Date	Buy Price	Holding days	Profit	Net profit	Fee
...	...	...	...	...	...	...	...
225	20200302	20200305	8809.7	3	-45.3	-54.1	8.8
226	20200313	20200316	7742.6	1	-594	-601.7	7.7
227	20200317	20200318	7119.7	1	-173.7	-180.8	7.1
228	20200319	20200320	7073.6	1	-9.8	-16.8	7.1
229	20200324	20200501	7307	27	1336.1	1328.8	7.3
230	20200508	20200512	9089.1	2	24.8	15.7	9.1
231	20200518	20200526	9206	5	214.7	205.5	9.2
232	20200529	20200611	9436.1	9	205.9	196.4	9.4
233	20200622	20200623	10001	1	130.1	120.1	10
234	20200630	20200709	9967	6	588.7	578.7	10
...	...	...	...	...	...	...	...

Table IV shows the total profits for the combination of parameters *P* and *N* of APADs using NSADAQ daily stock price data. The largest profit of US$20,940.8 is recorded when *N* is 3 and *P* is greater than or equal to 12. The second largest profit of US$20,641.4 is recorded when *N* is 5 and *P* is greater than or equal to 15. It is worth noting that profits are greater when *N* is an odd number than when it is an even number.

TABLE IV. SIMULATED PROFITS REGARDING APAD PARAMETERS P AND N

P \ N	2	3	4	5	6
3	18,704.2	N/A	N/A	N/A	N/A
4	19,373.9	19,367.9	N/A	N/A	N/A
5	19,435.9	21,105.9	19,268.4	N/A	N/A
6	19,533.5	20,799.2	19,440.3	19,834.5	N/A
7	19,704.4	20,663.6	19,945.3	20,347.9	14,676.8
8	19,588.9	20,924.4	19,891.5	20,599.3	15,687.1
9	19,586.5	20,924.4	19,810.2	20,616.5	15,468.8
10	19,541.6	20,916.8	19,779.0	20,611.4	15,340.1
12	19,588.9	20,940.8	19,925.7	20,604.2	15,497.1
15	19,588.9	20,940.8	19,925.7	20,641.4	15,518.6
20	19,661.3	20,940.8	19,925.7	20,641.4	15,518.6
25	19,588.9	20,940.8	19,925.7	20,641.4	15,518.6
30	19,588.9	20,940.8	19,925.7	20,641.4	15,518.6

Table V shows the number of trades for the combination of parameters *P* and *N*. In general, the number of trades decreases as the parameter *N* increases, which means that values of APAD *(D, N, P)* are less sensitive to individual stock price fluctuations. For the parameter *P* being greater than or equal to 15, the number of trades is 355 when parameter *N* is 3, and 276 when parameter *N* is 5. The number of trades is 22.2% lower for parameter *N* of 5 than for parameter *N* of 3. This indicates that a value of 5 for the parameter *N* is more suitable than a value of 3 in terms of the number of trades, although slightly less profitable. In the following experiments, the value of the parameter *N* is set to 5 and the value of the parameter *P* is set to 25, which is consistent with the usage of moving average practice in Japan.

TABLE V. TRADE COUNTS REGARDING APAD PARAMETERS P AND N

P \ N	2	3	4	5	6
3	433	N/A	N/A	N/A	N/A
4	416	377	N/A	N/A	N/A
5	415	358	307	N/A	N/A
6	414	358	297	290	N/A
7	414	358	294	282	260
8	413	356	293	279	250
9	414	356	294	278	247
10	414	356	293	277	246
12	413	355	292	277	244
15	413	355	292	276	243
20	413	355	292	276	243
25	413	355	292	276	243
30	413	355	292	276	243

Figure 18 depicts the cumulative profits and the cumulative fees. The simulator generates profits in all periods since cumulated profits exceed cumulated fees. As the graph shows, the simulated profit can be divided into three periods according to the degree of profit. The first period is from the beginning of the simulation to the day of the lowest price, indicated by the arrow ⇧, i.e., approximately Mar. 23, 2020. The simulator makes an average profit of about $43.87 per trade including fees.

The second period is from the date of the lowest price to the date about a year later, indicated by the arrow ⇩. The simulator earns an average profit of $257 per trade including fees. The last period is from the last day of the second period to April 30, 2022, i.e., the last day of the simulation. The simulator generates an average profit of about $157 per trade including fees.

The average profit in the second period is noticeably larger than those in the other periods, which suggests an impact of monetary policy. Trades in the vicinity marked by the arrow ⇧ result in a loss of approximately US$900, which motivates us to improve the simulator.

Linear regression formulas with the R-squared are added near the line graphs. R^2 is a statistical measure of how closely the data are fitted to the regression line. All R^2s are greater than 0.9351, which indicates that the developed simulator makes profits in proportion to the number of trades throughout the simulation period.

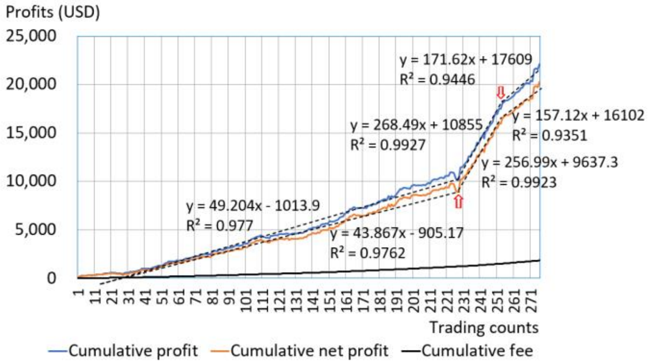

Figure 18. Cumulative profit and cumulative fee in long position.

Figure 19 is a scatter plot of all trades in a long position with the fee using the NASDAQ historical stock data. The lower left point in Figure 19 corresponds to the trade with the largest loss, meanwhile the top right dot shows the most profitable trade.

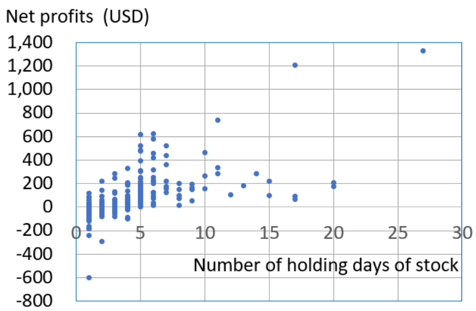

Figure 19. Scatter plot of trades in long position with fees.

Figure 20 is a candlestick chart that coincidentally contains the most profitable trade and the most lossy one. The most lossy trade begins on Mar. 13, 2020 indicated by vertical lines in orange color. The most profitable one starts on Mar. 24, 2020 indicated by vertical lines in magenta color.

Figure 20. Candlestick chart including profitable and lossy trades.

The trade on Mar. 13, 2020 is put into action because (7) and (10) are *True*. Since the stock price drops significantly the next day, (17) is set to *True*, and the simulator swiftly buys back the stock, however, resulting in the worst loss of US$601.60.

The trade on Mar. 24, 2020 is performed because conditions (7), (8), and (9) are *True*. After that, the simulator continues to hold on the stock as the price keep exceeding the buying price. Since the fast APAD falls below the slow APAD on May 1, 2020, the Boolean conditions (12), (13), (14), (15), and (16) are set to *True*. The simulator sells back the stock, and bringing the best profit of US$1,328.80. Meanwhile, the simulator refrains from trading on Apr. 22, 2020 because (15) is *False*, i.e., the slow APAD is positive.

D. Enhancing decision of buying opportunities

1) Enhancement to avoid lossy trade

Stock prices sometimes move in anomalous ways for a day or so, often causing a loss-making trade. Candlestick-based trade decision processes are augmented to help the simulator avoid trades with large losses in a practical way.

Figure 21 shows an enhanced algorithm for simulating in a long position. The condition *CandlePattern_Avoid_Buy* is added after the condition of *Buy_Signal_B*. *CandlePattern _Avoid_Buy* consists of several candlestick patterns that signal for avoiding a buy of a stock. All patterns must be *False* for a trade in a long position to be started. Typical patterns of *CandlePattern_Avoid_Buy* are described below.

```
T2L_CP ( int IndexFrom, int IndexTo ) {
    int flg= -1;     // to indicate state of finding buy-opportunity
    for ( j= IndexFrom;  j>=IndexTo; j-- ) {
        /*  Buy signal is detected */
        if ( flg < 0  & Buy_Signal_B ) {
            if ( ! CandlePattern_Avoid_Buy ){
                traded_p = ((Open[j] + Close[j]) / 2) ;
                holding_day_cnt= 0;
                flg= 1;       // to indicate buy-stock state
            }
        /*  Sell signal is detected in long position */
        } else if ( flg > 0 & Sale_Signal_B ) {
            diff = ((Open[j] + Close[j]) / 2) - traded_p - buying_cost;
            profit= profit + diff;          //  Total profit
            flg= -1;      // to indicate state of finding buy-oppotunity
        }
        holding_day_cnt++;
    }
}
```

Figure 21. Overall simulation algorithm enhanced by candlestick pattern in long position.

As observed in Figure 20, the slope of the fast APAD becomes positive on Mar. 13, 2020. However, the stock purchase on this day results in unsuccessful. According to the candlestick charting, the price fluctuation on this day corresponds to the *falling window candlestick pattern*, which predicts stock prices continue to fall [13]. Let *Pgap[j]* be the ratio of the gap to the closing price of the trading day in percentage. This pattern is implemented by the disjunction of the two Boolean conditions below:

cb1= Pbody[j+1] < 0.3 & Pgap[j] > 0.58; (19)

cb2= Pgap[j] > 2.0; (20)

The Boolean variable *cb1* is calculated by the previous day's candle being less than 0.3% suggesting downtrend, and the gap on the stock trading days being more than 0.58%. This is a weak upward stock price movement accompanied by a gap in a downtrend, meaning that the stock price movements are difficult to predict. The variable *cb2* is set to *True* when a gap is greater than 2.0%, which is a rare large gap, and shows signs of avoiding a stock trade. The values of 0.58, 0.3 and 2.0 are experimentally determined through trial and error using the NASDAQ stock data.

Other pattern that should be avoided for buying a stock occurred on Mar. 17, 2020 as shown in Figure 20, indicated by vertical lines in cyan color. The opening and closing prices of a stock are nearly within the range of the prior day's opening and closing prices. This pattern is named the *bullish piercing pattern*, and is considered to be a weak reversal signal [13]. Since the slope of the fast APAD turns slightly positive on Mar. 17, 2020, it is necessary to implement a process that takes into account the *bullish piercing pattern* in order to avoid the trade on the day. The variable cb3 checks the pattern. Parameter values are heuristically determined thorough experiments using NASDAQ daily data. *Abs* means a function that calculates the absolute value of an argument.

*cb3= Abs((Open[j+1] – Close[j]) * 100 / Close[j]) < 0.2*
& Pbody[j+1] < –3.0 & Pbody[j] > 3.0 (21)

Figure 22 shows a gap-related pattern that is scarcely mentioned in the literature [12][13]. The pattern observed on May 3, 2019 in NASDAQ.

Figure 22. Sample of gap-related pattern.

The pattern consists of a three-days' bearish candlesticks followed by a bullish candlestick with a significant gap. This pattern is spotted by the following formula:

cb4= Pbody[j+3] <0 & Pbody[j+2] <0 & Pbody[j+1] < 0
& Pbody[j] > 0.75 & Pgap[j] > 0.5 (22)

The values of 0.75 and 0.5 are determined through experiments. The slope of the fast APAD turns positive on the day. So, without a decision using the candlestick pattern, the simulator buys stocks and incurs a loss of US$84.00 including trading fees. Several other candlestick patterns to avoid buying stocks are incorporated into the developed simulator.

2) Experimental results using NASDAQ historical data

Table VI compares the main characteristics of the simulators before and after the improvement. First of all, the number of trades decreases from 276 to 223.

TABLE VI. SUMMARY OF EXPERIMENTAL RESULT IN LONG POSITION

	APAD only		APAD with enhancement	
	Without fee	With fee	Without fee	With fee
Total no. of trades	276	276	223	223
No. of profitable trades	188	182	171	166
No. of lost trades	88	94	52	57
Sucess rate	68.12%	65.94%	76.68%	74.44%
Amount of profit (USD)	27,783.88	26,475.82	25,432.36	24,225.54
Amount of loss (USD)	-5,180.87	-5,834.40	-1,344.64	-1,701.45
Net profit (USD)	22,603.02	20,641.42	24,087.72	22,524.10
Most profitable trade (USD)	1,336.10	1,328.80	1,515.70	1,502.90
Most lossy trade (USD)	-594.00	-601.70	-206.50	-221.30

The success rate of trading in the study is defined by the following formula:

Success rate=
the number of profitable trades
/ the total number of trades (23)

The number of profitable trades indicates the number of trades with positive profit. The total number of trades is 276. Success rate of trades is 68.12% (= 188 / 276) without the trading fee, and is 65.94% (= 182 / 276) with the fee.

After the enhancement using candlesticks, the success rate increases from 65.94% to 74.44% (= 166 / 223) with the fee. Net profit increases from US$20,641.42 to US$22,524.10. It is noteworthy that the maximum loss is significantly reduced from US$–601.70 to US$–221.30 with the trade fee after the enhancement.

Figure 23 shows the cumulative profit and the cumulative trade fee. Comparison with Figure 18 shows that there is no noticeable drop in the graphs. All R^2s are greater than 0.9523, maintaining significant correlation between the cumulative profit and the number of trades.

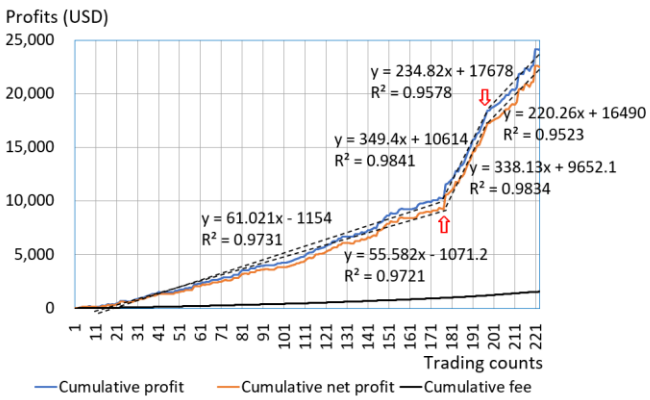

Figure 23. Cumulative profit and cumulative fee after enhancement.

Figure 24 shows a scatter plot of trades with the fee after enhancement. In comparison with Figure 19, it can be seen that the number of trades that resulted in a loss are decreased significantly, while the number of the profitable trads is roughly the same before and after the enhancement.

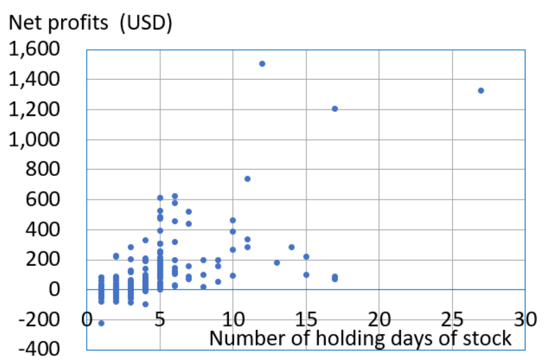

Figure 24. Scatter plot of trades with fees after enhancement using candlestick pattern.

Figure 25 shows a histogram of the number of holding days of a stock and the number of occurrences.

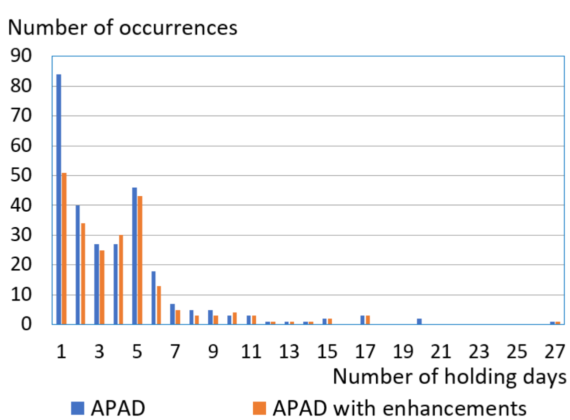

Figure 25. Histogram of the number of holding days in long position.

A trade within two days' stock holding period often results in a loss, because the stock price moves contrary to trader's expectations. Figure 25 indicates that the proposed enhancement using candlestick patterns has the effect of noticeably reducing the number of stock trades with one-holding day, i.e., from 84 to 51.

E. Tracking Sell Opportunities using APAD

1) Overall Algorithm for Selling Simulation

Figure 26. shows the overall algorithm for the selling simulation, or simulation in a short position. The *T2S* method has two parameters, i.e., *IndexFrom* and *IndexTo*. Strictly, the value of *IndexFrom* is the index value of arrays corresponding to the simulation start date. Similarly, the value of *IndexTo* specifies the end date of the simulation.

```
T2S ( int IndexFrom, int IndexTo ) {
    int flg= 1;      // to indicate state of finding short-sell-oppotunity
    for ( j= IndexFrom; j>=IndexTo; j-- ) {
        /*  Short-sell signal is detected */
        if ( flg > 0  & Sale_Signal_S ) {
            traded_p = ((Open[j] + Close[j]) / 2) ;
            holding_day_cnt= 0;
            flg= -1;       // to indicate short-sell-stock state
        /*  Buy signal is detected in short position  */
        } else if ( flg < 0 & Buy_Signal_S ) {
            diff = traded_p -  ((Open[j] + Close[j]) / 2)  - selling_cost;
            profit= profit + diff;         //  Total profit
            flg= 1;       // to indicate state of finding short-sell-oppotunity
        }
        holding_day_cnt++;
    }
}
```

Figure 26. Overall simulation algorithm in short position.

When the Boolean condition $flg > 0$ & *Sale_Signal_S* is *True*, the process of trading in a short position is started:

- Set the variable *traded_p*, which indicates the trading price of the stock, to the average of the opening and closing prices.
- Set the variable *holding_day_cnt*, which represents the number of days to hold the traded stock, to 0.
- Set the variable *flg* to –1 to indicate the trade in a short position.

When $flg < 0$ & *Buy_Signal_S* is *True*, the trade is closed.

- Set the profit of the trade to the variable *diff* using the expression: $diff = traded\_p - ((Open[j] + Close[j]) / 2) - selling\_cost$.
- Set the cumulative profit to the variable profit using the substitution expression $profit = profit + diff$.
- Set the variable *flg* to 1 to indicate the state for tracking sell opportunities.

Sale_Signal_S and *Buy_Signal_S* are Boolean expressions that signals the start, and the end of the trade in a short position, respectively. The details are discussed in the following sections.

2) Criteria for selling stock in short position

In the following formulas, parameter values are experimentally determined using the NASDAQ stock data.

Let *CP_5avg[j]* be the difference between the closing price and the 5-day average of a trading day *j* in percentage. *CP_25avg[j]* is for the 25-day average that is defined in analogy with *CP_5avg[j]*. The *Sale_Signal_S* is defined as follows:

$$Sale\_Signal\_S = s1 \,\&\, s2 \,\&\, s3 \,\&\, s4 \,\&\, s5 \,\&\, (s6 \mid s7) \tag{24}$$

$$s1 = (Pbody[j] + Pchg[j] + CP\_5avg[j]) < -1.2; \tag{25}$$

$$s2 = (CP\_5avg[j] + CP\_25avg[j]) > -9.0; \tag{26}$$

$$s3 = CP\_5avg[j] < 2.0; \tag{27}$$

$$s4 = Pbody[j] < 0.6; \tag{28}$$

$$s5 = APAD\_F[j] > 0.2 \,\&\, APAD\_S[j] < 1.0; \tag{29}$$

$$s6 = (APAD\_F[j] - APAD\_F[j+1]) < 0; \tag{30}$$

$$s7 = (APAD\_S[j] - APAD\_S[j+1]) < 0; \tag{31}$$

The Boolean variable *s1* indicates the price notably falls on the trading day. The variable *s2* means that the stock price is within a certain range from the moving averages, i.e., the stock price is not in the bottom range. *S3* is *True* if the stock price is less than 2% of the 5-day average. *S4* represents that the ratio of the length of the body of a candlestick to the stock price is less than 0.6%, i.e., a slight price increase at most in a trading day.

The Boolean variables *s5*, *s6*, and *s7* are those concerning the APADs. *S5* is set to *True* if the fast APAD is greater than 0.2 and if the slow APAD is less than 1.0, which suggests a weak trend of price increase. The variables *s6* and *s7* are *True* if the slopes of the fast APAD and the slow APAD are negative, which indicates a downtrend.

3) Criteria for buying stock in short position

The timing to buy the traded stock back in a short position, i.e., *Buy_Signal_S* in Figure 26, is defined as follows:

$$Buy\_Signal\_S = (s11 \mid s12 \mid s13);$$

$$s11 = (trade\_p - (Open[j] + Close[j]) / 2) * 100 \,/\, trade\_p < -0.5; \tag{32}$$

$$s12 = Pchg[j+1] > 0.0 \,\&\, Pchg[j] > 0.0 \,\&\, Pbody[j] > 0.4; \tag{33}$$

$$s13 = Pchg[j] > 1.2 \,\&\, Pbody[j] > 0.8; \tag{34}$$

The Boolean variable *s11* is set to *True* if the current stock price is 0.5% higher than the traded value. The condition is essential to keep losses small. *S12* is set to *True* if the stock price rises for two consecutive days and the length of the candlestick on the trading day is greater than 0.4%. *S13* is set to *True* if the stock price is greater than 1.2% and the candlestick length is greater than 0.8%. The variable *s12* and *s13* are used to check whether the stock price for the day increase notably.

4) Calculating margin interest in short position

In a short selling trade, a trader must borrow a stock from an investment firm with a payment of margin interest. The leverage of trades is set to one in order to maintain the same conditions regarding the amount of the trades in long and short positions. Margin interest slightly vary across brokers. Typically, it consists of an annual interest rate and a fixed one. In this study, the margin interest is calculated using the following formula:

$$(\text{Stock price}) * (2.80\% / 365 * M + 1.15\%) \tag{35}$$

M is the total number of days for borrowing stocks. 1.15% indicates the fixed rate.

5) Experimental results using NASDAQ historical data

The line graphs in Figure 27 present the cumulative profit, net profit, and the margin interest calculated by (35) in a short position. The graph of profit in this figure can be approximated by three segmented lines. The first segment is the period from the beginning of the simulation to the 78th trade marked by X, which corresponds to Sep. 17, 2018. The second segment ranges from the 79th trade to the 114th trade marked by the arrow ⇩, which corresponds to Mar. 18, 2021, approximately one year after the date of the lowest price. The day of the lowest price marked by the arrow ⇧ is located roughly in the middle of the second segment. The third segment is the period from the 115th trade to the last trade, namely Apr. 25, 2022.

The minimum value of R-squared is 0.5534 that shows the degree of approximation is worse than a long position. This suggests that trades in a short position is less stable than those in a long position. The cumulated net profit is always negative because the margin calculated by (35) squeezes the profit generated by the simulator.

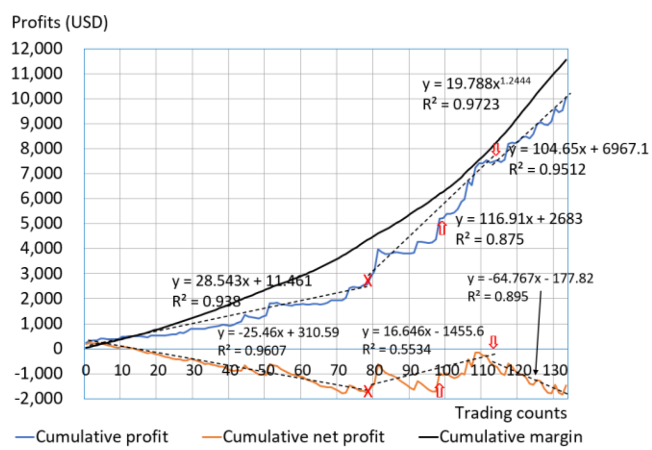

Figure 27. Cumulative profit, net profit, and margin interest in short position.

Figure 28 shows a scatter plot of simulated trades in a short position with the margin interest using the NASDAQ daily stock data. Significant losses are incurred in the trades in which the number of days to hold stock is one.

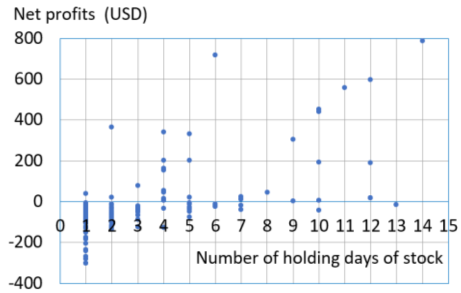

Figure 28. Scatter plot of trades in short position with margin interest.

The trade with the largest amounts of profit, which starts on Dec. 4, 2018 and ends on Dec. 26, 2018, is represented by the dot in the upper right corner of Figure 28. Figure 29 shows the candlestick chart of this lucrative trade.

Figure 29. Candlestick chart including successful trades.

The decision to buy the stock back based on the slope of the fast APAD and candlestick patterns is working profitably in this trade. It is noteworthy that Dec. 12, 2018, marked by the two dashed vertical lines, is not a day to buy the stock back although the slope of the fast APAD turns to positive. The variable *s13* defined by (34) is *False*, because the length of the candlestick body on Dec. 12, 2018 is –0.4%.

F. Improving decision of selling opportunities

1) Improvement to avoid lossy trade

Similar to the simulation in a long position, the simulation of short selling can be improved using candlestick patterns. Figure 30 shows an overall algorithm enhanced by candlestick pattern. The condition *CandlePattern_Avoid_Sale* is added after checking the *Sale_Signal_S*. *CandlePattern_Avoid_Sale* consists of several candlestick patterns that signal for avoiding a short sale of a stock. All patterns must be *False* for a trade in a short position to be performed.

```
T2S_CD ( int IndexFrom, int IndexTo ) {
    int flg= 1;       // to indicate state of finding short-sell-oppotunity
    for ( j= IndexFrom; j>=IndexTo; j-- ) {
        /*  Short-sell signal is detected */
        if ( flg > 0  & Sale_Signal_S ) {
            if ( ! CandlePattern_Avoid_Sale ){
                traded_p = ((Open[j] + Close[j]) / 2) ;
                holding_day_cnt= 0;
                flg= -1;      // to indicate short-sell-stock state
            }
        /*  Buy signal is detected in short position  */
        } else if ( flg < 0 & Buy_Signal_S ) {
            diff = traded_p -  ((Open[j] + Close[j]) / 2)  - selling_cost;
            profit= profit + diff;        //  Total profit
            flg= 1;       // to indicate state of finding short-sell-oppotunity
        }
        holding_day_cnt++;
    }
}
```

Figure 30. Overall simulation algorithm improved by candlestick pattern in short position.

Figure 31 shows a temporary-drop pattern that occurs after about a week of stock price rally, which is scarcely mentioned in the literature [12][13]. The pattern observed on Nov. 10, 2020 when the slope of the fast APAD changes the direction from up to down. This pattern is also observed on May 21, 2020, Jan. 3, 2019, Feb. 23, 2016, etc. Since this is a temporary decline, short selling on this day lead to losses.

Figure 31. Temporary-drop pattern after strong rally.

The following Boolean condition *cs1* is implemented in our simulator to avoid short selling on a temporary-drop after noticeable stock price rally. Unfortunately, because the condition involves more than six candlesticks, it is difficult be defined by a Boolean expression, and it needs to be processed by a program.

cs1= (Prices rise more than four days in the past six days) & (The amount of drop on the day is less than half of the cumulative increase in the past six days) (36)

The *Doji* candlestick [12][13], which has the opening price and the closing prices are equal or almost the same, is a sign of indecision. Our simulator is also implemented to refrain from a selling stock on the *Doji* candlestick. In addition, several other candlestick patterns to avoid a lossy buying stock trade are enhanced to the simulator.

2) *Experimental results using NASDAQ historical data*

Table VII summarizes the main characteristics of the simulators before and after the improvements in a short position. The number of trades decreases from 134 to 107, while the success rate increases from 67.91% to 71.03% without the margin interest, and from 24.63% to 25.23% with the margin interest. While profits decline slightly from US$3,503.68 to US$3,340.08, losses reduce notably from US$–4,984.35 to US$–3,270.74 with the margin interest.

TABLE VII. Summary of experimental results in short position

	APAD only		APAD with enhancements	
	Without margin	With margin	Without margin	With margin
Total no. of trades	134	134	107	107
No. of profitable trades	91	33	76	27
No. of lost trades	43	101	31	80
Sucess rate	67.91%	24.63%	71.03%	25.23%
Amount of profit (USD)	11,580.85	3,503.68	9,893.46	3,340.08
Amount of loss (USD)	-1,508.59	-4,984.35	-868.65	-3,270.74
Net profit (USD)	10,072.26	-1,480.68	9,024.81	69.34
Most profitable trade (USD)	877.10	785.50	877.10	785.50
Most lossy trade (USD)	-172.00	-300.30	-98.70	-280.30

Figure 32 shows line graphs of the cumulative profit, net profit, and margin interest in a short position after the improvement using candlesticks. The graph of cumulated profit in Figure 32 can be approximated by three segmented lines. The trade dates separating the three segments are the same as in Figure 27. The improvement boosts the net profit. However, the cumulative profits remain negative for most of the period.

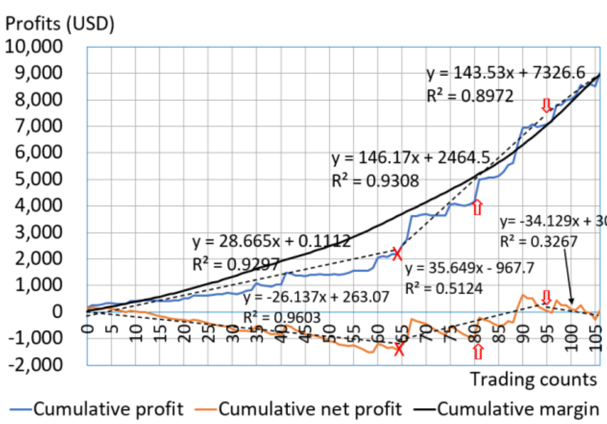

Figure 32. Cumulative profits and margin interest after improvement in short position.

Figure 33 shows a scatter plot of simulated trades with the margin interest after the improvement. Improvements have reduced the number of non-profitable trades, but not sufficient. There are a lot of loss-making trades of which stock holdings are one to seven days.

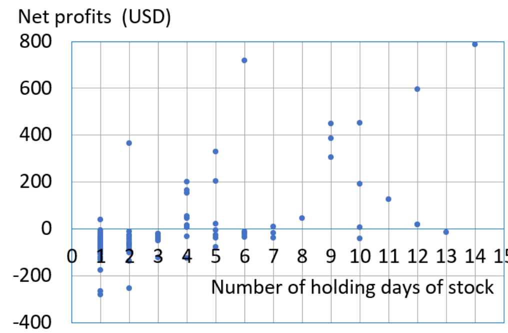

Figure 33. Scatter plot of trades with margin interest after improvement in short position.

Figure 34 shows a histogram of the number of holding days of a stock and the number of occurrences.

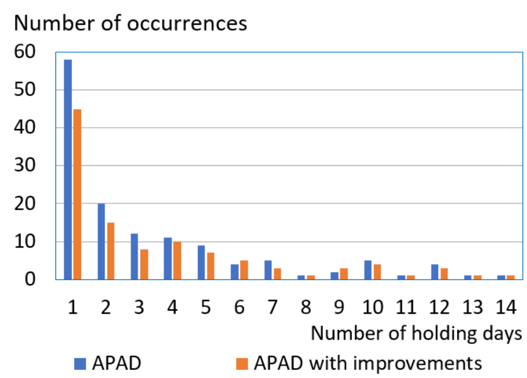

Figure 34. Histogram of the number of holding days in short position.

Similar to the histogram of a long position shown in Figure 25, the proposed improvement using candlestick patterns leads to a reduction in the number of lossy-making trades with a one-day holding period, i.e., from 58 to 45.

G. *Experiments using stock data of major stock markets*

Stock trade simulations are performed over the ten years' stock data using the nine markets, i.e., NASDAQ and Dow Jones Industrial Average (U.S.), Bovespa (Brazil), CAC (France), DAX (Germany), Nikkei 225 (Japan), S&P ASX (Australia), Sensex (India), and SSEC (China).

Table VIII shows the success rates for each market in both long and short positions, and with and without the fee or margin interest. Because this simulator is customized for the NASDAQ market, NASDAQ achieves the highest success rate of 74.44% with the fee in a long position. As for a short position, the Bovespa market has the highest success rate of 34.44% with the margin interest, followed by NASDAQ's success rate of 25.23%.

Table VIII. Success rates for each market in long and short positions

	Long Position		Short Position	
	Without fee	With fee	Without margin	With margin
NASDAQ	76.68%	74.44%	71.03%	25.23%
DJIA	68.80%	65.25%	66.67%	22.55%
Bovespa	68.75%	63.60%	79.47%	34.44%
CAC	61.57%	55.69%	57.94%	21.50%
DAX	61.99%	60.18%	62.50%	20.83%
Nikkei_225	61.19%	59.70%	42.73%	21.82%
S&P ASX	69.09%	66.18%	80.99%	20.66%
Sensex	77.51%	74.16%	67.91%	22.39%
SSEC	65.74%	63.75%	75.00%	22.12%

Figure 35 shows the line graphs of the cumulative profits with the fee for each market in a long position. Since stock prices in each market have risen significantly over the ten-year period of the simulation, the ratio of the profits, i.e., the Y-axis in Figure 35, is calculated by dividing the amount of profit by the average stock price of the market.

In NASDAQ, for example, the 25-day average price at the beginning of the simulation, i.e., May 1, 2012, is US$3,031.64. The 25-day average price at the end of the simulation, i.e., Apr. 30, 2022, is US$13,394.16. The average stock price of NASDAQ is US$8,212.90 by calculating the average of these two prices. The maximum ratio of the amount of profit to the average stock price is 275.5% as shown in Figure 35.

All graphs in Figure 35 show an upward trend. Cumulative profit in NASDAQ become larger with increasing slope after Covid-19 pandemic. Cumulative profit in SSEC rapidly increases in the period from the 63rd to the 95th trades, which correspond to Oct. 28, 2014 and Mar. 30, 2016, respectively. The other graphs are roughly linear. This indicates that the proposed simulator constantly generates profits in the nine markets over the ten-year simulation period.

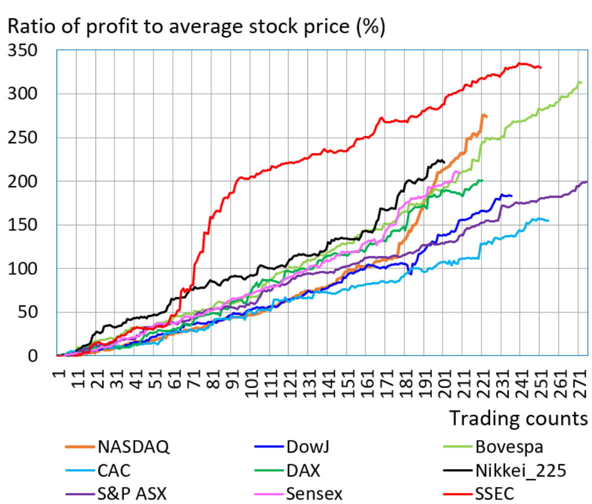

Figure 35. Line graph of profit for each market in long position.

Figure 36 shows the line graphs of the profits with the margin interest for each market in a short position. As the Bovespa's success rate of 34.44% suggests, Bovespa apparently achieves higher profits than NASDAQ. Other markets take losses.

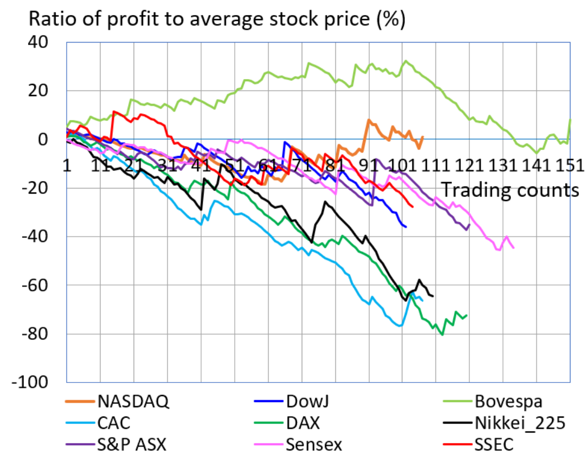

Figure 36. Line graph of profit for each market in short position.

The prediction accuracy of the developed simulator is still insufficient for a short position, as large portions of the graphs in Figure 36 are in the negative region.

VI. CONCLUSION AND FUTURE WORK

This paper describes the results of analyses of stock price fluctuations in European, U.S. and Asian markets with special focus on the effect of Covid-19 pandemic. In general, thanks to the timely implementation of monetary measures of each country, all stock prices under study have kept rising after the lowest price recorded in Mar. 2020.

Observed in the 490 business days, i.e., approximately two years, NASDAC see a 62.36% increase in its stock price compared to its highest price before the declaration of Covid-19 pandemic. CAC (France) decreased by –1.73%, followed by 9.25% increase in DAX (Germany). Analyses of the average and standard deviation of the six attributes of a candlestick chart reveal that CAC and DAX are deemed to experience a larger impact on stock prices than the other markets.

We propose a trend reversal indicator named APAD, an acronym for "Average of Price and 5-day Average Difference." The indicator is devised in the process of investigating how the difference between the stock price and 5-day average is related to the reversal of stock trends affected by Covid-19 pandemic.

Since the APAD is an indicator based on a 5-day average, the APAD can be difficult to deal with short-term fluctuations over one or two days. Candlestick chart patterns are used to compensate for this shortcoming. We developed a stock trading simulator that implements the APAD enhanced by heuristic candlestick chart patterns. Experiments using ten years of stock price data from nine major stock markets in the world were conducted, and analyzed the profit characteristics.

It is confirmed that the simulator achieved the success rate of up to 74.44% in NASDAQ including fees in a long position. However, as for in a short position, the success rate remains within 25.23% percent, because the approximately 1.15% margin interest to borrow stocks squeezes profits.

We are planning researches to improve the success rate and profitability of the developed simulator through the addition of candlestick patterns and the sophisticated use of the APADs. Further experiments using stock price data from various global markets and individual companies are planned to verify the functionality of the proposed simulators.

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