Statistical Analysis of Stock Profits to Evaluate Performance of Markets

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***Abstract*— Candlestick charting is one of the most popular techniques used to predict short-term stock price trends. Despite popularity, there is still no consistent conclusion for the predictability of the technique mainly due to qualitative description of candlestick patterns. This paper proposes a retrieval model with six parameters that allows us to define both candlestick patterns and price zones where the patterns occur. Because criteria that trigger exit from a market largely affect profits and losses, we propose three market exit criteria. Simulations to estimate profits are performed using five global markets with approximately the same parameters for the retrieval model and the market exit criteria. The results of simulations indicate that the proposed method leads to trades with around 85% of successful stock trades in the case of a typical uptrend candlestick pattern. Five global markets are also analyzed and compared to show graphically the profitability of the markets based on simulated profits.**

Keywords*— *Stock price prediction; Technical analysis; Candlestick charts; Market exit criteria; Profit simulation; Global market comparison.

I. INTRODUCTION

Forecasting a direction of future stock prices attracts the attention of not only financial investors but also researchers in computer science. The common motivation is to predict the future direction of prices for successful stock trade and developing computer system to support a trader. While many researches on stock price prediction focus on a specific market, some researches deal with multiple stock markets to seek global investment opportunities.

Dimson et al. [1] discuss performances of global markets including emerging and developed ones. Though emerging markets have grown to a significant size up to 2007, developed markets, notably US markets, have outpaced the growth in emerging markets in the 21st century because of global financial crisis. Ahmad et al. [2] measure the impact of volatility in six emerging stock markets of Asia. The results of statistical analyses show volatility is significantly related to return in each market.

What is missing in the research of Dimson et al. [1] is the lack of algorithmic and statistical analyses for objective comparison among global markets in terms of profits from a trader's point of view. They discuss performances of global markets from an economic point of view without mentioning results of statistical analyses. They suggest that US stock markets are more profitable than others and that is the same conclusion to which we arrived in this paper. Meanwhile, Ahmad et al. [2] examine volatilities among Asian stock markets to find out a causal relation between volatility and stock returns. While their research uses statistical analyses, it fails to include developed markets.

The purpose of this resarch is to compare profitability of emerging and developed markets based on algorithmic and statistical analyses. We develop a simulator program in Java that implements a retrieval model to find opportunities for buying stocks, and algorithms to trigger selling stocks to lead to profitable trade. The experimental results are statistically analyzed to examine the extent of relationship among measured variables. Simulated profits are displayed in bar graphs to easily compare the global stock markets under discussion.

The contributions of this paper are as follows:

I. Proposal of a model using six parameters to retrieve candlestick patterns that are both similar in price patterns and price level, i.e., price high and/or low zone in which they occur.
II. Proposal of three novel algorithms to trigger selling stocks to fix profit in case of a long market position.
III. Evaluation of performances of the proposed model and the algorithms to trigger selling stocks through simulations in terms of profit.

The remainder of the paper is organized as follows. Section II recapitulates some related work. Section III gives backgrounds of the candlestick charting. Section IV proposes a model for retrieving similar candlestick charts and the triggering algorithms. Section V presents experimental results on a strong uptrend pattern using five markets' data in US and Asia stock markets. Section VI concludes the paper with our plans for future work.

II. RELATED WORK

There have been a growing number of studies on predicting future movements of stock markets. In this section, we review previous studies on performances of global markets and predictabilities of candlestick patterns.

A. Studies on Performances of Global Markets

Dimson et al. [1] discuss performances of markets in emerging and developed countries from an economic perspective. They find that emerging markets achieved a higher return of 11.7% per year than a developed markets' return of 10.5% from 1950 to 2019. However, because of the global financial crisis, the average return of US stocks is 10.6%, while that of the world stocks excluding US ones is

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5.3% in the 21st century. They conclude that investors should be modest to invest in emerging markets because exchange rate movements are largely affected by inflation in emerging countries in addition to questionable capabilities to maintain a fair market.

Ahmad et al. [2] statistically examine six emerging Asian stock markets with respect to stock returns and volatility. The markets include KSE100 (Pakistan), Nikkei 225 (Japan), KOSPI (South Korea), Hang Seng (Hong Kong), SSE (China), and BSE (India). The results show that KOSPI has the highest average annual return of 12.67%, followed by BSE with 11.61%.

B. Studies on candlestick patterns

The researches in [4]-[13] are on usefulness of candlestick patterns in technical analysis [3]. Most researches focus on one market. Some researches use stock data of multiple markets, but their aims are to confirm their estimated profits.

1) Studies disapproving of candlestick patterns

As for the candlestick pattern method in technical analysis [3], several studies [4]-[6] conclude that it is useless based on the experiments using the stock exchange markets' data in the US, Japan and Thailand.

Horton [4] studies the profitability of 4 pairs of three-day candlestick patterns on 349 stocks that are representing major industry groups. The main conclusion of his study is that these candlestick patterns create no value for trading individual stocks.

Marshall et al. [5] find that under fixed holding period of 10 days, candlestick charting strategies are unprofitable for Dow Jones Industrial's components from 1992 to 2002. They also confirm that candlestick strategies generate no profit in Japanese markets from 1975 to 2004.

Based on experiments using stock data in the Stock Exchange of Thailand, Tharavanij et al. [6] conclude that any candlestick patterns cannot reliably predict market directions even with filtering by well-known stochastic oscillators [3].

2) Studies approving of candlestick patterns

Other studies conclude that applying certain candlestick patterns is profitable at least for short-term trading [7]-[13].

Caginalp et al. [7] study and favorably evaluate the predictive power of eight three-day reversal candlestick patterns on the S&P 500 index from 1992 to 1996. They propose to define candlestick patterns as a set of inequalities using opening, high, low, and closing prices. These inequalities are taken over in later studies.

Goo et al. [8] define 26 candlestick patterns using modified version of inequalities that are proposed by Caginalp et al. [7]. They examine these patterns using stock data of Taiwan markets, and conclude that the candlestick trading strategies are valuable for traders.

Chootong et al. [9] propose a trading strategy combining price movement patterns, candlestick chart patterns, and trading indicators. A neural network is employed to determine buy and sell signals. Experimental results using stock data in the Stock Exchange of Thailand show that the proposed strategy generally outperforms the use of traditional trading methods based on indicators.

One of the obstacles of candlestick charting is the highly subjective nature of candlestick pattern [3] since the candlestick patterns are defined using words and illustrations. Tsai et al. [10] propose an image processing technique to analyze the similarities of the candlestick charts. Their experimental results using Dow Jones Industrial Average index show that visual matching of candlestick charts is useful for predicting short-term stock movements.

Zhu et al. [11] examine the effectiveness of five different candlestick reversal patterns in predicting short-term stock movements. They use Chinese exchanges' data from 1999 to 2008 in the experiments. The results of statistical analyses suggest that the candlestick patterns perform well in predicting price trends.

Jamaloodeen et al. [12] statistically analyze the predictive power of two popular Japanese candlestick patterns, i.e., Shooting Star and Hammer patterns. They use over six decades of historical daily data of the S&P 500 index. Their findings include the two patterns are highly reliable when using high price for the Shooting Star and low price for the Hammer.

Udagawa [13] proposes a dynamic programing method to skip small and noisy candlesticks to improve predictability of candlestick charting. Experimental results show that the proposed method is effective in predicting both an uptrend and a downtrend.

The researches in [4]-[13] are dedicated to discuss effectiveness of candlestick patterns to spot a good opportunity for successful stock trading. On the other hand, this research aims to objectively compare profitability of emerging and developed markets using algorithms and statistical analyses. The proposed method implements a retrieval model that uniquely considers price zones in which candlestick patterns occur. In addition, the proposed method realizes algorithms that tell us when to sell stocks to fix profits, which allows us to estimate precise profits in stock trading, and to compare global markets in an objective manner.

III. CANDLESTICK CHART AND PATTERNS

This section introduces the formation of a candlestick. A series of candlesticks forms a candlestick pattern. Samples of well-known candlestick chart patterns that are believed to be useful for a successful investment are depicted. Criticism of candlestick patterns for predicting stock price movements are also mentioned.

A. Formation of Candlestick

A daily candlestick line is formed with the market's opening, high, low, and closing prices of a specific trading day [3]. The candlestick has a wide part, which is called *real body* representing the range between the opening and closing prices of that day's 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.

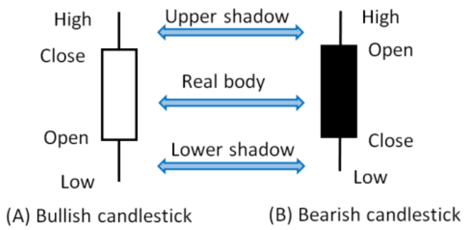

Figure 1. Candlestick formation

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. *Samples of Candlestick Patterns*

Dozens of candlestick patterns are identified and become popular among worldwide stock traders [3]. These patterns have colorful names like *morning star*, *evening star*, *three white soldiers*, and *three crows*.

Figure 2 shows the *morning star* pattern which is considered as a major reversal signal when it appears in a price low zone or at a bottom. It consists of three candles, i.e., one short-bodied candle (filled or hollow) between a preceding long filled candle and a succeeding long hollow one. The pattern shows that the selling pressure that was there the day before is now subsiding. The third hollow candle overlaps with the body of the filled candle suggests a start of a bullish reversal. The larger the filled and hollow candles, and the higher the hollow candle moves, the larger the potential reversal. The opposite version of the *morning star* pattern is known as the *evening star* pattern which is a reversal signal when it appears in a price high zone or at the end of an uptrend.

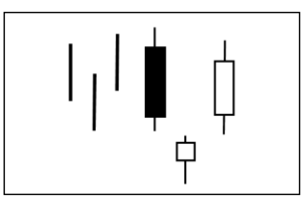

Figure 2. *Morning star* pattern

Figure 3 shows the *three white soldiers* pattern which is interpreted as a strong indication of a bullish market reversal when it appears in a price low zone.

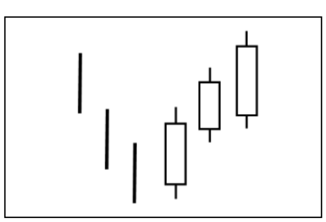

Figure 3. *Three white soldiers* pattern

It consists of three long hollow candles that close progressively higher on each subsequent trading day. Each candle opens higher than the previous opening price and closes near the high price of the day, showing a steady advance of buying pressure.

C. *Criticism of Candlestick Patterns*

The major criticism of the candlestick chart patterns is that the patterns are qualitatively described with words, such as "long/short candlesticks," "higher/lower trading," "strong/weak signal," supported by some illustrations [3]. Without modeling the candlestick patterns in a way that a computer can process and perform experiments comprehensively, arguments on the effectiveness of chart patterns would not come to an end.

In addition, some candlestick chart patterns yield a different, even opposite, forecast depending on whether they appear in price high and/or low zones. Formulating a suitable mathematical formulation of trend is still an open issue.

It deems that because of the lack of the strict definition of the candlestick chart patterns, mixed results are obtained in the studies on candlestick patterns. Negative conclusions to the predictability of candlesticks are reported [4]-[6], while positive evidences are provided for several candlestick chart patterns in experiments using U.S., Brazil and Asian stock markets [7]-[13].

IV. PROPOSED MODEL FOR RETRIEVING CANDLESTICK PATTERNS

This section describes a model that allows us to retrieve similar to both candlestick patterns and price zones where the patterns occur. Three criteria that cope with moderate and sudden stock price changes are proposed to find opportunities for selling stocks.

A. *Retrieval Model of Candlestick Patterns*

After trial and error, we propose a model for retrieving similar candlestick charts that take into account where the stock price occurs in price zones in addition to a price change and a length of candlestick body. Figure 4 illustrates the model that consists of the six parameters as follows:

(1) Change of prices w.r.t previous closing price,
(2) Length of candlestick body,
(3) Difference between stock price and 5-day moving average,
(4) Difference between stock price and 25-day moving average,
(5) Slope of 5-day moving average,
(6) Slope of 25-day moving average.

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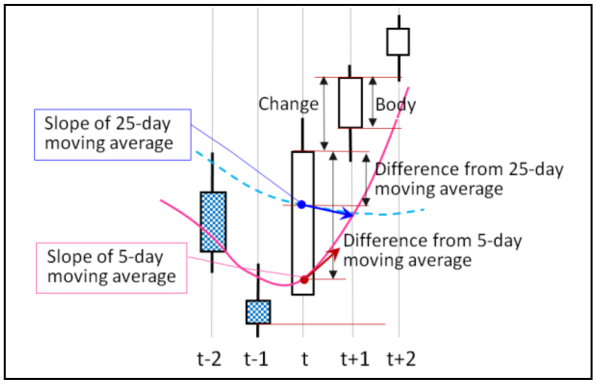

Figure 4. Candlestick pattern retrieval model

While most researches of candlestick patterns use a series of inequalities or technical indicators to identify stock price trends, i.e., an uptrend or a downtrend or a sideway (flat), the proposed model is unique in a sense that it uses two moving averages and their slopes. 5-day and 25-day moving averages are used since they are widely used in Japan. The moving averages are significant to identify the price zone where the candlestick pattern occurs. The slopes of the averages are also important to identify their trends.

Retrieval of similar candlestick charts in this research takes the following steps:

(1) Specify a reference day, i.e., typically a day of trend reversal, such as the last day of the *morning star* pattern in Figure 2.

(2) Define tolerances of the six parameters with respect to the reference day.

(3) Retrieve candidate candlesticks that satisfy all conditions C_1 to C_6.

C_1: if a difference between a closing price change of the reference day and that of a candidate day is within the change tolerance (*change_tol*), then C_1 is true.

C_2: if a difference between a body length of the reference day and that of a candidate day is within the body tolerance (*body_tol*), then C_2 is true.

C_3: if a difference between a closing price and a 5-day moving average of the reference day and that of a candidate day is within the tolerance (*av5diff_tol*), then C_3 is true.

C_4: if a difference between a closing price and a 25-day moving average of the reference day and that of a candidate day is within the tolerance (*av25diff_tol*), then C_4 is true.

C_5: if a slope of a 5-day moving average of the reference day and that of a candidate day is within the given tolerance (*slope5_tol*), then C_5 is true.

C_6: if a slope of a 25-day moving average of the reference day and that of a candidate day is within the given tolerance (*slope25_tol*), then C_6 is true.

(4) Check the conditions below on the two days following the reference day, i.e., ones labeled *t+1* and *t+2* in Figure 4.

F_1: if the change of the reference day and that of the day labeled *t+1*, i.e. the day after the reference day, are in the same direction.

F_2: if the change of the reference day and that of the day labeled *t+2*, are in the same direction.

Retrieval conditions of F_1 and F_2 are empirically derived. Setting values of six parameters are statistically determined to retrieve a suitable set of similar charts in order to analyze expected profits as described in Section V.

B. *Finding selling opportunities*

A set of similar candlesticks is retrieved by specifying a reference date and tolerances concerning six parameters shown in Figure 4. In the rest of the paper, we deal with patterns of uptrend in a long market position.

Traders will make a profit by a “buy low and sell high” strategy in uptrend. Candlestick patterns can suggest us when a specified trend begins, but do not cope with when a reverse of the trend begins. So, we need criteria or algorithms that tell us when to sell back stocks to fix profits and/or losses of a stock trading. One is the use of reversal candlestick patterns indicating downtrends. However, considering that candlestick patterns are derived from experience, use of the reversal patterns to trigger selling stocks seems incomplete and unprofitable due to dynamic nature of stock price movements.

In this study, we examine an approach using algorithm. Specifically, we decide an opportunity of selling stocks using the following three criteria:

(1) Sum of the negative change prices (*SumNC*) criterion: The value of *SumNC* is calculated by summing change prices in percentage that moved downward from the previous market day thorough a holding period. If The value exceeds a specified value then selling stocks is triggered.

(2) Sum of the negative differences from 5-day average (*SumND5av*) criterion:
The value of *SumND5av* is calculated by summing negative differences between a 5-day average and stock price thorough a holding period. Selling stocks is triggered when the value exceeds a specified limit.

(3) Plunge detection criterion:
This criterion intends to cope with quick price decline. When the stock price falls below the 5-day average then the range of price movements over the past 5 days (*PM5day*) is calculated. If the range is broader than a certain multiple of the standard deviation of price changes, the price fall is judged as a plunge and selling stocks is triggered.

V. EXPERIMENTAL RESULTS

After outlining processes of experiments, statistical analyses of profits using Dow Jones Industrial Average, NASDAQ Composite index, Shanghai Composite index, Hang Seng index, and Nikkei Stock Average are discussed to evaluate performance of each market.

A. Data Conversion

The stock prices are converted to the ratio of closing prices. The conversion contributes to reduction of the effects of highness or lowness of the stock prices. The formula below is used for calculating the ratio of prices in a percentage.

$$R_i = (CP_i - CP_{i-1}) * 100 / CP_i \ (1 \leqq i \leqq n) \quad (1)$$

CP_i indicates the closing price of the i-th business date. CP_n means the closing price of the current date. R_n is the ratio of the difference between CP_n and CP_{n-1} to the closing price of the current date CP_n. The daily stock data from Nov. 25, 2009 to Dec. 24, 2019 are used in experiments on the research. The number of data is approximately 2,536 for each market.

B. Statistics of Candlestick Parameters

Table I summarizes statistics of six parameters concerning the proposed retrieval model of a candlestick pattern shown in Figure 4. The statistics of each parameter are calculated for all market days in the five markets. They provide basis of setting parameter values in this study.

TABLE I. SUMMARY OF STATISTICS OF SIX PARAMETERS

	Dow		NASDAQ		Nikkei 225		Shanghai		Hang Seng	
	Average	Deviation	Average	Deviation	Average	Deviation	Average	Deviation	Average	Deviation
Body length	0.0274	0.8433	0.0176	0.8670	−0.0082	0.9092	0.0981	1.2283	−0.0547	0.8024
Change	0.0435	0.8847	0.0623	1.0721	0.0454	1.2951	0.0053	1.3576	0.0149	1.1411
Difference of price and 5–day average	0.0720	0.9467	0.1005	1.1560	0.0583	1.4048	−0.0248	1.5335	0.0063	1.2700
Difference of price and 25–day average	0.4349	2.1902	0.5931	2.6560	0.3167	3.3890	−0.1672	4.1897	0.0357	3.1771
Slope of 5–day average	0.0390	0.3793	0.0548	0.4614	0.0359	0.5615	−0.0047	0.6275	0.0082	0.5167
Slope of 25–day average	0.0393	0.1496	0.0542	0.1821	0.0342	0.2370	−0.0042	0.2983	0.0085	0.2197

Averages of all six parameters are positive for Dow Jones and NASDAQ indicating that the two markets are on uptrends as a whole. Nikkei 225 and Hang Seng mark negative values for candlestick body length. In Shanghai, four parameters excluding candlestick body length and price change are negative values, suggesting that the market is less profitable than other markets.

C. Finding Profitable Trading Days for Each Market

Stock prices fluctuate depending not only on international but also domestic political and economic news. Therefore, the day suitable for buying stocks differs in each market. For a fair comparison of the markets, a preferred reference day for each market is determined by the following processes.

(1) For all market days, profit and/or loss of buying stock in a long position is calculated using a simulator.

(2) Sort market days by calculated profits, and select the day that generates the highest profit in 2019.

The following days are chosen as reference days.

・June 4, 2019: for DOW and NASDAC markets

・October 10, 2019: for Nikkei225 market

・January 4, 2019: for Hang Seng and Shanghai markets

Figure 5 shows the candlestick chart of Dow Jones index around June 4, 2019 coded by 0604.

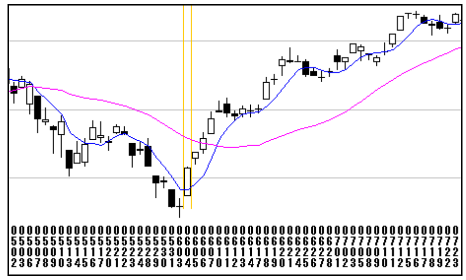

Figure 5. Candlestick chart of Dow Jones index around June 4, 2019

The day is the last day of a *morning star* pattern and the first day of a *three white soldiers* pattern. These patterns are known as strong uptrend patterns in the candlestick charting.

D. Experiments using Dow Jones Industrial Average

Experiments are performed using the GUI shown in Figure 6. Values of parameters used in the experiments are statistically determined.

First click on the *File* button to choose a CSV file containing a set of stock price data. The full path of the file is displayed. In Figure 6, a file named *Dow_ed.csv* is chosen.

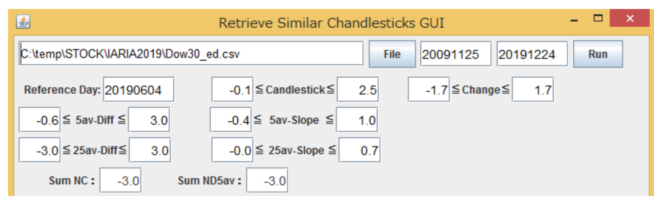

Figure 6. GUI for candlestick pattern retrieval model

The two text boxes in top right corner show periods of market days, i.e., 20091125 to 20191224. The text box labeled *Reference Day* specifies a reference market day that has a typical candlestick pattern for an uptrend reversal.

The two text boxes labeled *Candlestick* specify the tolerances of the length of the candlestick of a reference market day.

The two text boxes labeled *5av-Diff* mean the tolerances of the difference between the stock price and that of a 5-day average in percentage. The text boxes labeled *Change*, *25av-Diff*, *5av-Slope*, and *25av-Slope* are defined analogously.

The two text boxes labeled *SumNC* and *SumND5av* specify parameters to trigger selling stocks. The value of *PM5day*, which does not appear in Figure 6, is calculated by the following formula:

$$PM5day = 1 - (SumND5av / 5) \quad (2)$$

The formula is derived from experience so that the days of holding a stock is almost comparable to those of *SumNC* and *SumND5av*.

TABLE II. ESTIMATED PROFITS ON JUNE 4, 2019 AS REFERENCE MARKET DAY

MDay	x	y	z	SumNC			SumND5av			PM5day		
				Date to sell	Holding Days	Profit	Date to sell	Holding Days	Profit	Date to sell	Holding Days	Profit
20100216	1.680	0.394	0.812	20100331	31	5.605	20100427	49	6.885	20100427	49	6.885
20100707	2.819	1.205	0.582	20100721	10	1.077	20100720	9	2.147	20100716	7	0.843
20100901	2.544	0.493	1.239	20100930	20	4.980	20101109	48	10.098	20100923	15	3.788
20101118	1.575	0.200	-0.223	20101130	7	-1.556	20110111	36	4.357	20101123	3	-1.295
20101201	2.269	0.947	0.173	20110128	40	4.956	20110223	56	7.348	20110222	55	8.224
20110321	1.501	-0.149	0.561	20110418	20	1.386	20110504	31	5.600	20110418	20	1.386
20111006	1.676	-0.182	2.973	20111019	9	3.466	20111101	18	4.944	20111017	7	2.512
20120713	1.621	-0.390	0.616	20120731	12	1.840	20120725	8	-0.776	20120720	5	0.366
20121119	1.650	-0.058	0.378	20121219	21	3.537	20121226	25	2.501	20121127	5	0.653
20131010	2.183	0.734	0.421	20131107	20	3.082	20131205	39	4.547	20131205	39	4.547
20141017	1.633	0.118	1.312	20141210	37	6.868	20141211	38	7.228	20141210	37	6.868
20141218	2.427	0.150	0.869	20150105	10	-1.541	20150105	10	-1.541	20150105	10	-1.541
20150203	1.759	0.038	1.199	20150306	22	1.112	20150309	23	1.890	20150209	4	0.364
20150930	1.468	-0.078	1.231	20151109	28	8.592	20151112	31	6.997	20151021	15	5.331
20161107	2.076	0.401	1.402	20170109	42	8.589	20170119	49	7.810	20170130	56	9.020
20180214	1.027	1.233	0.075	20180228	9	0.601	20180301	10	-1.078	20180220	3	0.299
20180504	1.389	0.391	0.012	20180529	16	0.442	20180531	18	0.678	20180515	7	1.824
20190604	2.065	0.819	0.709	20190725	36	6.943	20190729	38	7.239	20190717	30	7.230
				Average=	**21.667**	**3.332**	**Average=**	**29.778**	**4.271**	**Average=**	**20.389**	**3.183**

E. Experiments on Profit Estimation

Table II shows an experimental result that is performed on June 4, 2019 as the reference day whose candlesticks are shown Figure 5. Because the length of the candlestick body on the day is 1.5036%, the length of candlestick body is restricted between 1.4036% (= 1.5036 − 0.1) and 3.5036% (= 1.5036 + 2.5). The value of *SumNC* and *SumND5av* are set to −3%. Accordingly, the value of *PM5day* is 1.6% (= 1 – (–3/5)).

The other parameters are carefully adjusted to retrieve approximately 18 sample days that is suitable sample sizes to be statistically analyzed. The *x* column in Table II shows price changes of the market day *MDay*. *y* and *z* columns show price changes of the next day and the day after next. The *Date to sell*, *Holding Days*, and *Profits* columns mean the date to sell back stocks, the number of days to keep stocks holding, and simulated profits, respectively. Averages of profits are 3.332%, 4.271%, and 3.183% for *SumNC*, *SumND5av*, and *PM5day*, respectively.

Success trade ratio is calculated by dividing the number of retrieved dates that yield profits by the number of retrieved dates. Table III summarizes profit averages and success trade ratios for each parameter to trigger selling stocks. The simulated trade profit average using parameter *SumND5av* marks high profit average of 4.271%, while shows low success trade ratio of 0.833. The trade profit averages using parameters *SumNC* and *PM5day* show the opposite, i.e., rather low profit average with high success trade ratio. Product of the profit average and success trade ratio seems to suggest potential profits.

TABLE III. AVERAGES OF PROFITS AND SUCCESS TRADE RATIO

	SumNC	SumND5av	PM5day
Profit average (%)	3.332	4.271	3.183
Success trade ratio (%)	0.889	0.833	0.889
Profit average * Success trade ratio (%)	2.962	3.559	2.830

Figure 7 shows a graph with a profit in the y-axis, and a value of parameters *SumNC*, *SumND5av* and *PM5day* in the x-axis. Generally, the profits increase as the values of parameters to trigger selling stocks increase. Profits peak at the value of 4% to 6% and seem to decline over 8%.

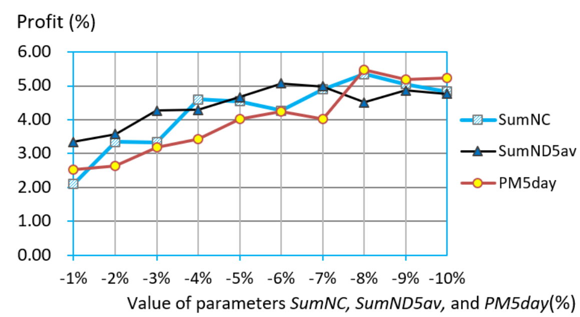

Figure 7. Graph showing exit value and profit

Figure 8 shows a graph with an average of stock holding days in the y-axis, and a value of parameters *SumNC*, *SumND5av* and *PM5day* in the x-axis. The averages in the y-axis increase approximately linearly as the values of parameters in the x-axis increase.

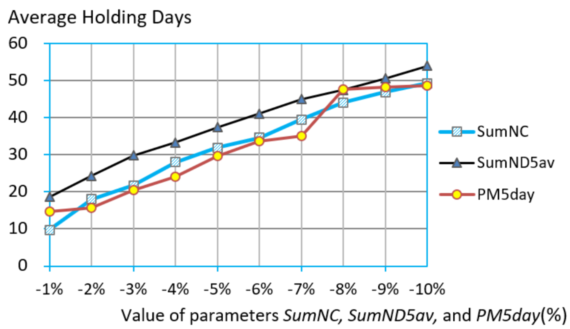

Figure 8. Graph showing exit value and average holding days

Table IV summarizes the result of the statistical analysis using Excel that is performed by specifying *Profit* as an independent variable and *Holding Days* as a dependent variable. *R Square* is 0.7647 suggests that 76.47% of *Profit* values can be explained by the variable of *Holding Days*. The last column of the table *ANOVA* shows the results of an overall *F* test. The value of *Significance F* is 0.000002074 (<0.05), which indicates that *Profit* are significantly related to *Holding Days*.

TABLE IV. RESULTS OF REGRESSION ANALYSIS

Summary Output

Regression Statistics	
Multiple R	0.8745
R Square	0.7647
Adjusted R Square	0.7500
Standard Error	1.7327
Observations	18

Analysis of Variance (ANOVA)

	df	SS	MS	F	Significance F
Regression	1	156.124	156.124	52.005	2.07407E-06
Residual	16	48.034	3.002		
Total	17	204.157			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-1.57202906	0.9073	-1.7326	0.1024	-3.4955	0.3514
Holding Days	0.19621534	0.0272	7.2114	0.0000	0.1385	0.2539

Figure 9 shows simulated profits in a bar graph for each retrieved day using *SumNC, SumND5av, and PM5day*.

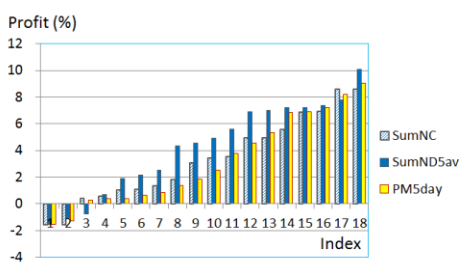

Figure 9. Calculated profits for each retrieved day (Dow Jones index)

As Figure 9 shows, the values of three parameters to trigger selling stocks produce comparable profits and/or losses. Strictly speaking, while *SumND5av* parameter yields better profits than those of the other two. *SumND5av* tends to generate larger losses while generates larger profits.

F. *Experiments on Asian Markets*

Experiments are performed using three Asian markets. The retrieval conditions are almost the same as those used in Dow Jones index, though in order to retrieve approximately 18 market days, values of parameters, such as *av5diff_tol*, *slope5_tol* etc., are adjusted within 0.5%.

Figure 10 shows simulated profits of Shanghai index. Five days out of 19 days result in losses. The maximum profit is estimated about 20%, which occurs on Oct. 28 2014. Other high returns of approximately 12% happen on Sept. 30, 2010 and Dec. 5, 2012. Excluding the three large profits, Shanghai market seems less profitable than Dow Jones market.

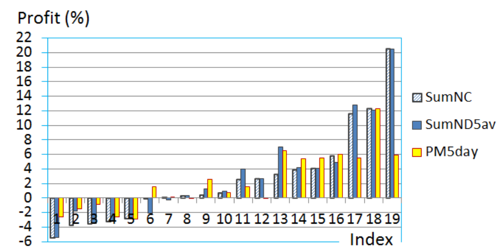

Figure 10. Calculated profits for each retrieved day (Shanghai index)

Figure 11 shows simulated profits of Hang Seng index. Four days out of 18 days result in losses. The maximum profit is estimated about 8%, which is less than that of Dow Jones index.

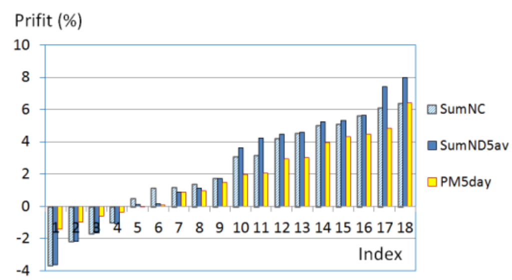

Figure 11. Calculated profits for each retrieved day (Hang Seng index)

Figure 12 shows simulated profits of Nikkei 225 index. Two days out of 18 days result in losses.

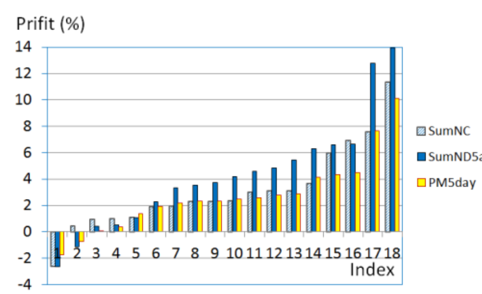

Figure 12. Calculated profits for each retrieved day (Nikkei 225 index)

Large profits of 14.0% and 12.9% occur on Sept. 11, 2017 and Nov. 15, 2012. Excluding the two profits, Nikkei 225 market seems comparable to Dow Jones market.

VI. CONCLUSION AND FUTURE WORK

This paper proposes a model for retrieving similar candlestick charts with six parameters. It deals with the 5-day and 25-day moving averages to identify their trends in addition to decide whether the price occurs in price high or low zones. Since successful stock trade is significantly depends on good timing of selling stocks, three criteria are proposed and the profits that they generate are simulated using developed and emerging markets in the US and Asia.

The experiments are performed on a pattern that suggests a strong uptrend according to the prediction based on candlestick pattern, i.e., the *morning star* pattern followed by the *three white soldiers* one. Daily stock data of two US markets and three Asian markets are used in the experiments. The results show that the pattern yields significant profits in all markets. As for profits in global markets, the experimental results generally support what is stated in the paper of Dimson et al. [1].

Future work may include experiments using other candlestick patterns to measure the profitability of the proposed method. Additional studies may be conducted to compare global markets to meet demands of finding the most profitable market.

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