

The Application of Trend Following Strategies in Stock Market Trading

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Abstract— Trend-following (TF) strategies use fixed trading mechanism in order to take advantages from the long-term market moves without regards to the past price performance. In contrast with most prediction tools that stemmed from soft-computing such as neural networks to predict a future trend, TF just rides on the current trend pattern to decide on buying or selling. While TF is widely applied in currency markets with a good track record for major currency pairs [1], it is doubtful that if TF can be applied in stock market. In this paper a new TF model that features both strategies of evaluating the trend by static and adaptive rules, is created from simulations and later verified on Hong Kong Hang Seng future indices. The model assesses trend profitability from the statistical features of the return distribution of the asset under consideration. The results and examples facilitate some insights on the merits of using the trend following model.

Keywords—Trend-following, Stock Market, Trading Algorithm

I. INTRODUCTION

Trend following is a simplistic trading strategy that tries to take advantage of long-term moves that seem to play out in various markets. A trend following system aims to work on the market trend mechanism and take benefit from both sides of the market being able to gain profits from the ups and downs of the stock market. Traders who use this approach can use current market price calculation, moving averages and channel breakouts to determine the general direction of the market and to generate trade signals. Traders who opt for trend following strategy do not aim to forecast or predict markets; they simply jump on the trend and ride it.

Basically there are two approaches for gaining insights of the markets in trading. Fundamental analysis is one of them and also the most commonly used approach in studying the markets. This analysis considers many external factors that are supposed to affect the supply and demand of a particular market. Sources from which the information can be obtained for fundamental analysis may include government policies, domestic and foreign events, political and economic news, and cooperates' annual reports. By carefully examining the supply and demand factors, or "fundamentals" for a particular market, it is believed to possibly predict changes in market conditions. These changes are then supposedly related to the fluctuation of the price of the market. It was however argued that nobody can be absolutely certain about the accuracy of the market information. Market trends change upon a flux of news that come by every day is too complex to be accurately analyzed [2]. The bubble burst of dot-com stocks by the hype of "new digital economy" is one

classical example of failure. Furious debates still continue on the efficacy of fundamental analysis, so are other analysis.

The second popular approach into market forecasting is called technical analysis that works in opposite principle of the fundamental analysis. The underlying philosophy for this approach is that the market prices well reflect all known factors at all times. So the price is already a solid performance indicator as a result of the supply and demand for that particular market. Therefore technical analysis evaluates solely on the market prices themselves rather than on any fundamental factor else outside the market. Traders who are solely armed with technical analysis suppose that a careful analysis of daily price movement as well as a long term trend is all that is required to predict a price trend for their trading.

II. TECHNICAL ANALYSIS

For decades traders were hoping to have some reliable decision making tools that would assist them in market forecasting. Many such tools are available both as commercial products and research prototypes. Predicting market trends is a hot area in the academic research community using methods of soft computing. Some popular choices are Genetic Algorithms [3], Support Vector Machines [4], and Artificial Neural Networks [5, 6]. They are used to analyse past financial data ranging from ten to twenty years to attempt to divine the market direction. Many research papers in the literature claim that they yield significant results of "indicators" and they offer pretty good accuracy. Still, the question of whether technical analysis works has been a topic of contention for over three decades. Can past prices forecast future performance?

On the other hand, there is an alternative type of technical analysis that neither predicts nor forecasts. This kind is entirely based on price. Instead of striving to predict a market direction, this strategy is to react to the market's movements whenever they occur; hence the name Trend Following (TF). TF responds meticulously to what has recently happened and what is currently happening, rather than anticipating what will happen. TF is solely based on some statistically trading rules. In [7], a simulator has attempted to program TF into trading agents which base on linear regression of direct market trends. The obvious challenge for generating profits in this strategy is how to define such rules. The rules are usually derived from the traders' judgments and are subjective in nature. A main contribution of this paper is to define and program these rules into an automated trading simulator.

III. PRINCIPLES OF TREND FOLLOWING METHODS

Some principles of trend following methods are reviewed here [8]. In the later section we proposed a logical way of setting the rules. The success of Trend Following strategies obviously depend on certain underlying assumptions. The first assumption is the regular occurrence of price trends that are resulted from a variety of factors. The trends go up and down all the time in markets. Market prices are the objective data as they are the ultimate indicators reflected from the factors. The price movements are enough for making decisions in trading, and little anything else according to TF strategies. Individual price histories and charts can just be used as primary data for TF trading program to operate.

Secondly, the success assumes that TF trading systems can possibly harvest profit from these trends. As believed by some experts, the basic trading strategy that all trend followers try to systematize is to ‘cut losses’ and ‘let profits run.’ This basic premise is that the most profit is gained when a trader is synchronized to an enduring trend. To do this, traders need to adopt a strict discipline that minimizes behavioral bias (i.e., intuitive or “gut” feel). It does not anticipate a trend beginning or end, and acts when the trend changes.

Based on this premise, a Performance Probability Score (PPS) model [8] was proposed as a classic approach to trend following. PPS incorporates analysis of relative valuation and relative price performance to produce risk and reward expectations for individual stocks. The core of the model is a binary separation of whether long-term relative price performance is positive or negative. Price performance is used as a key indicator derived from the price trend over a reasonable length of time. Trend following is doing the same. The basic rule of PPS is to stay with a positive or negative rating until a definable change has occurred. In other words, PPS does not anticipate changes in trends.

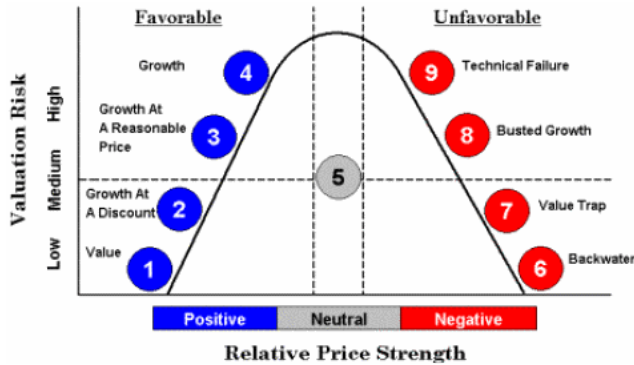


Figure 1. Division of relative price strength along the price trend. (Source: Legg Mason)

IV. OUR PROPOSED MODEL

Based on the concept of the PPS model, our model attempts to reap profits from the difference of the initial market price and the market volatility. Changes in price mean opportunities that may lead to a gradual reduction or

increase of the initial trade. Conversely, certain adverse price movements may lead to an exit for the whole trade.

When there is a turn detected in contrary to the trend, the system will have to decide whether to signal a pre-programmed exit or wait until the turn establishes itself as a trend in the opposite direction. If the situation favours an exit as reasoned by the rules, the system will re-enter when the trend re-establishes. In order to have the TF trading system automated, we need the following elements to be considered.

Trade Management: Some rules are implemented over the decision of how much to trade over the course of the trend. This includes decision of how much to trade at each time, and how much money to risk in each trade. In order to minimize risk, for example, the trading size is reduced during periods of higher market volatility or losing periods. The trade is managed to let the profit runs when market is good, and holds back during bad times to preserve capital until more positive price trends reappear.

Market Price: The market price should be the sole input data to the system. Although there could be information derived from the market price history, as a general rule other indicators estimating where price will go next should be disregarded. In order to run the TF system in real-time, likewise must be for the availability of the latest market price. Price and time are pivotal at all times.

Rules: The main rules are simply to maximize profits and cut losses. The rules operate systematically and objectively without consideration of any analysis of fundamental supply or demand factors. The rules automate the trading by making decisions on when to enter the market, for how long to stay in a trade for profit, and when to exit the trade if it becomes unprofitable.

We proposed a new model that is derived from PPS but with more accurate and more adaptive detection of the change(s) that trigger a buy or sell action. Hence some rules must be formulated for determining when to enter or exit a position in the market based on two important signals. The two signals that are directly derived from the market price trend tell us when to enter a market, and when to exit a market. These two signals are two fundamental variables in defining the rules of the trading model.

A. Static P & Q Rules

Trading rules are the underlying mechanism of a TF system. In our model, the rules mainly depend on two variables, namely P and Q . P is defined to be the amount of the trend in the upward direction that triggers a position to be opened. Literally P stands for a proposition for signaling it is time to enter the market since certain significant progress of market growth is observed. Q is the amount of opposite trend after a pivotal turn that will cause an opened position to close. Q can simply be considered as a signal to quit the trade from the market in order to prevent any deep loss.

Let T denotes the market trend which is a continuous curve made up of $Price(t)$ in the function of time t . For example in the following diagram, it will open a long position when the current $Price$ at point t over the trend T advances over P ; and it will close out the position when the trend T declines deeper than Q .

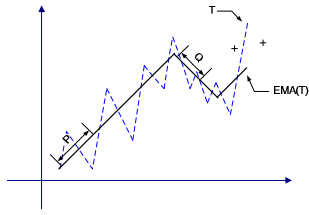


Figure 2. P and Q over the price trend T and $EMA(T)$

However in reality the market price trend doesn't go constantly on a straight line; it is much volatile that the line fluctuates up's and down's repeatedly. Therefore it is not possible (at least not practical) to apply the P & Q rules directly on the trend T because the frequent fluctuation will alarm off too many signals of trading actions. In order to compromise this fluctuation, an Exponential Moving Average (EMA) is adopted and upon which we applied the rules. EMA at the time of t is calculated as follow,

$$EMA(t) = \left(price(t) - EMA(t-1) \times \frac{2}{n+1} \right) + EMA(t-1)$$

where $price(t)$ is the current price at time t , n is the number of periods in minute for intra-day trading or days in inter-day trading, and t is any given market time. Using P & Q rules on EMA helps to smooth a fluctuating trend. The logic of the trading rule by using P & Q is shown in pseudo-code as follow.

Pseudo code of Static P & Q Rule

```
Repeat
  Compute  $EMA(T)$ 
  If no position opened
    If  $EMA(T) \geq P$ 
      If trend is going up
        Open a long position
      Else if trend is going down
        Open a short position
    Else if any position is opened
      If  $EMA(-T) \geq Q$ 
        Close position
  If end of market
    Close all opened position
Until market close
```

Our method as depicted in the pseudo code above, entails using a moving average, for a set of market price data, to determine when to enter the market and when to exit. Profits and losses were made along the way between buying and selling. The number of days n used to calculate the moving average is found by observing which value of n gave the best profit over a reasonable length of time.

In other TF systems, values for P and Q , or such similar parameters were either chosen arbitrarily or by subjective intuition of some experienced human traders. In some cases, the two parameters are represented by a single threshold whose value was calibrated intuitively. The threshold was used as a baseline to indicate appropriate timings of buying and selling. Those systems yielded certain results although not optimum. In our model, the value of P and Q are derived empirically from the historical market price data as it is

believed that market data is a reflection of the consequent trends and they are sufficient for references.

The values of P and Q , therefore can be either found by brute-force or heuristic methods based on the historical methods. In brute-force method, all combinations of P and Q values are tried exhaustively over a sample, and observed for the best performing pair as shown in Figures 3 and 4.

Alternatively, an artificial neural network can be trained by using historical dataset to estimate the most profitable set of P and Q values. For instance a pair of optimal P and Q values could be derived from a sample of Hang Seng index future contract used in an artificial neural network as in our experiment. A forward feed neural network with a hidden layer of 20 neurons was tested to give reasonable results. A 10% random sampling of dataset across ten years of records could be used as training set.

By the nature of neural network whose initial weights were set randomly and different samples were selectively used in the training phase, a range of P and Q values could be possibly obtained. Some post-processing was required to narrow the choices of P and Q values into a reasonable range. If any of the P and Q values gets too small, then there will be too many order executions. If the value is too large, for example 1000, there may be no order execution at all.



Figure 3. Ranges of P and Q values obtained from heuristic measures

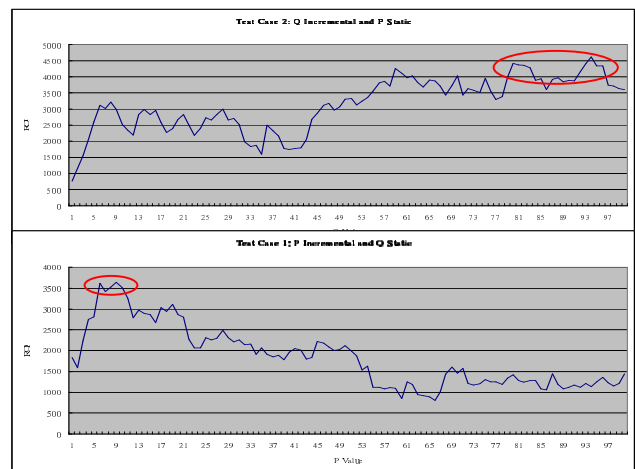


Figure 4. By holding the other value constant, it is possible to have multiple values of P and Q that generate good profits

B. Adaptive P & Q Rules

Previously, the values of P and Q are obtained from considering the combo values that give the best performance over a relative long period of time. It is intuitively observed that the lengths of P and Q that worked well in a particular section of a trend may not do the same in other situations. Hence the process of generating the P and Q values should be modified such that they would dynamically change to adapt to the real-time market trend.

In this adaptive operation, the amounts of progress and decline that govern the buying and selling are calculated in real-time at regular intervals along the market trend. Hence, P' and Q' are two new variables that are used in the trend following algorithm for the same purposes. They have basically the same meaning as P and Q in the rules of trading except that their values may change dynamically in different parts of the trend instead of remaining constants.

In this case, some additional technical analysis that helps determining the buying and selling positions in real-time is desirable for adjusting the P' and Q' . Relative Strength Index (RSI) is one of the popular approaches for this purpose. RSI is a technical momentum indicator that compares the magnitude of recent gains to recent losses in an attempt to determine overbought and oversold conditions of an asset. The advantage is that it reflects signals of overbought or oversold in real time as the market progresses. It is calculated using the following formula:

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

$$RS = \frac{AU(t)}{AD(t)}$$

$$AU(t) = \frac{Up(t) + Up(t-1) + \dots + Up(t-n+1)}{n}$$

$$AD(t) = \frac{Down(t) + Down(t-1) + \dots + Down(t-n+1)}{n}$$

where AU is average price upward in n periods, AD is average price downward in n periods, n is the number of RSI periods that is usually taken as 14 by most analysts.

One example is given below in Figure 5, the RSI ranges from 0 to 100. An asset is deemed to be overbought once the RSI approaches the 70 level, meaning that it may be getting overvalued and is a good candidate for a pullback. Likewise, if the RSI approaches 30, it is an indication that the asset may be getting oversold and therefore likely to become undervalued. According to [9], the following three observations are classical and well known by stock market technical analysts.

- Above 50, the internal strength of the market is considered bullish; below there, considered bearish.
- Above 70 is a bullish danger zone, considered to represent an overbought market that will correct sooner or later.
- Below 30 is a bearish danger zone, considered to represent an oversold market that will rally sooner or later.

The ideas that hold true for oscillators in general hold true with the RSI . The oscillator will frequently turn around before the price does – for example, a price still rising that is accompanied by a falling RSI produces a bearish divergence between price and oscillator, a major warning that the uptrend is running out of steam.

Note that 70 and 30 are typical values for RSI_{max} and RSI_{min} respectively. These two thresholds can be arbitrarily chosen by traders. In our experiments, we set RSI_{max} and RSI_{min} to be 60 and 40 that narrows the range by an offset of 10 for less-risky trading.

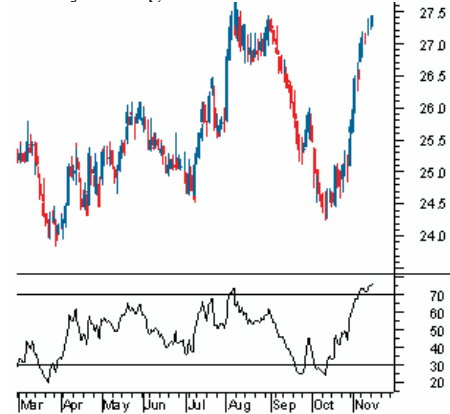


Figure 5. Figure 5. Illustration of RSI and its maximum and minimum thresholds (Source: Investopedia)

A trader using RSI should be aware that large surges and drops in the price of an asset will affect the RSI by creating false buying or selling signals. The RSI is best used as a valuable complement to other stock-picking tools. In our adaptive $P&Q$ strategy, RSI is used as a main reference index in calculating P' and Q' in real-time. By studying the interaction of how the indicator reacts to the market, we can derive the criteria as follow, which depict the situation ready for a position to open.

For long position, at P'

1. Price is advancing
2. $RSI(t)$ is greater than $EMA(RSI(t))$
3. $EMA(RSI(t))$ is less than 40 or greater then 60

For short position, at Q'

1. Price is declining
2. $RSI(t)$ is less than it $EMA(RSI(t))$
3. $EMA(RSI(t))$ is less than 40 or greater then 60

The following diagram shows an example of a long position opened at time 10:35 after the long position criteria are met, and closed out at time 13:36¹ when the short position criteria are met. The values of P' and Q' now change adaptively and dynamically according to and along with the RSI . As the trading goes, the criteria assess the fluctuating trend of the market and trigger positions to be open or close.

¹ In Hong Kong stock market there's a two hours break between morning and afternoon sessions, to avoid this discontinuation on the chart, we shifted the time backward, and joined this two sessions into one, so 13:36 is equivalent to 15:36.



Figure 6. Figure 6. P' and Q' are determined by the criteria of adaptive strategy.

To program this strategy into an automated trading simulator, the following pseudo-code is used:

Pseudo code of Adaptive $P&Q$ Rules

```
Repeat
Compute  $RSI(t)$  and  $EMA(RSI(t))$ 

If price is advancing at  $t$ 
  If  $RSI(t) > EMA(RSI(t))$  and  $40 < EMA(RSI(t)) < 60$ 
    If no position opened
      Open a long position,  $P'$ 
    Else if short position opened
      Close out short position,  $Q'$ 
Else if price is declining at  $t$ 
  If  $RSI(t) < EMA(RSI(t))$  and  $40 < EMA(RSI(t)) < 60$ 
    If no position opened
      Open a short position,  $Q'$ 
    Else if long position opened
      Close out long position,  $P'$ 
  If end of market
    Close all opened position
Until Market Close
```

V. SIMULATION EXPERIMENTS AND RESULTS

The purpose of this simulation experiment is to verify that the effects of $P&Q$ strategies in applying trend following, and to compare the static and adaptive $P&Q$ strategies. Most importantly the simulator is to prove the possibilities that TF can yield profits in market trading, by strictly following the rules in a computer program.

Our experiment simulates intraday trading on Hang Seng future contract, which is stored in data file with daily records in year 2008; with a total size of 355 days. Hang Seng Index is founded in 1969 November, it is composed of 36 different securities including some well-known companies such as Li Ka Shing's Cheung Kong, HSBC holdings and China Mobile. It is the second largest stock market in Asia in total capital that is worth of USD \$1.6 trillion by 2007 January.

We use the indices as our to-be-estimated target to represent the average of all companies and balanced portfolios which approximates the overall market returns. The reason that we use indices rather than individual stocks is that we suppose the market index can balance the bias for choosing stocks and eliminate the influence of single stock.

One important resultant variable in our simulation is the returns on investment (ROI) on common shareholder's equity. In this study, we are going to use the average ROI of overall stock in a specified market as a performance indicator for comparing the two variants of trend following strategies.

The ROI is calculated based on the assumption that one contract is traded with the initial capital of HKD 100,000, the average monthly ROI is the total ROI divided by the number of months in the length of the simulation.

- Read in the stock market data from a file.
- Calculate the EMA and RSI for some given values of parameters, such as n the period of time.
- Feed the data into the two $P&Q$ strategies, static and adaptive, and generate the buying and selling signals - During the simulation, when the reversal of trend gives rise to P and Q conditions, then our trading strategy regard this situation as a buying signal and selling signal respectively.
- Simulate the trading by calculating the profits each day and subtract costs if there is a trade.
- Run this for many values of n and summarize the results including the ROI.

The following diagram shows the simulation of both strategies with respect to the Hang Seng index performance as a base line. The base line could represent a buy-and-hold strategy that suffers an overall depreciation in value when the whole trend is sinking down in performance as shown in the diagram. The two $P&Q$ strategies of TF however in contrast, are gaining in increasing the values of the initial capital; the lines show that profits can be reaped even during those bad times when the market index was going down.

The dates are normalized, taking the starting date of the input data as the initial date in the simulation. Figure 8 shows a snapshot of daily profits gained and daily losses incurred on a daily basis. In general, when the total trading events are averaged out, there are more profits than losses both in magnitudes and in counts.

Table 1 shows a summary list of results extracted from the simulation graph in Figure 7. It shows in comparison of the performance of the static and adaptive versions of $P&Q$ strategies in trend-following. Overall, we can see that the adaptive $P&Q$ outperforms the static one because the rules of opening and closing a positions can be better estimated based on real-time RSI. They are adaptive in real-time to the ever changing market trend. Both trend-following strategies however are yielding impressive results in average monthly ROI, amounted to 67.67% and 75.63% respectively based on our simulation results.

CONCLUSION

Technical trading can be predictive or reactive. Trend followers just follow the trend, they don't predict the trend. This enables traders to focus on the market and not get emotionally involved. Trend followers expect and handle losses with objectivity and detachment.

It is believed that trend following strategies can be used for profitable trading in stock market. The idea is to automate the buying or selling process depending on the position of the price relative to a long time moving average value. We tried to verify this TF phenomenon by adhering to the trading rules. Such rules are used in TF but in the past they were manually defined. In this project we formulated the TF trading rules and their parameters heuristically, and

we programmed them into a simulator. The contribution of this work forms a cornerstone for future development of automated trading system based on TF principles which are discussed in section 3. Two different TF strategies namely static $P&Q$ and adaptive $P&Q$ are proposed and our simulation results show that they give positive trading profits even when the stock market index is declining at the bad times. We would be testing TF strategies with more data.

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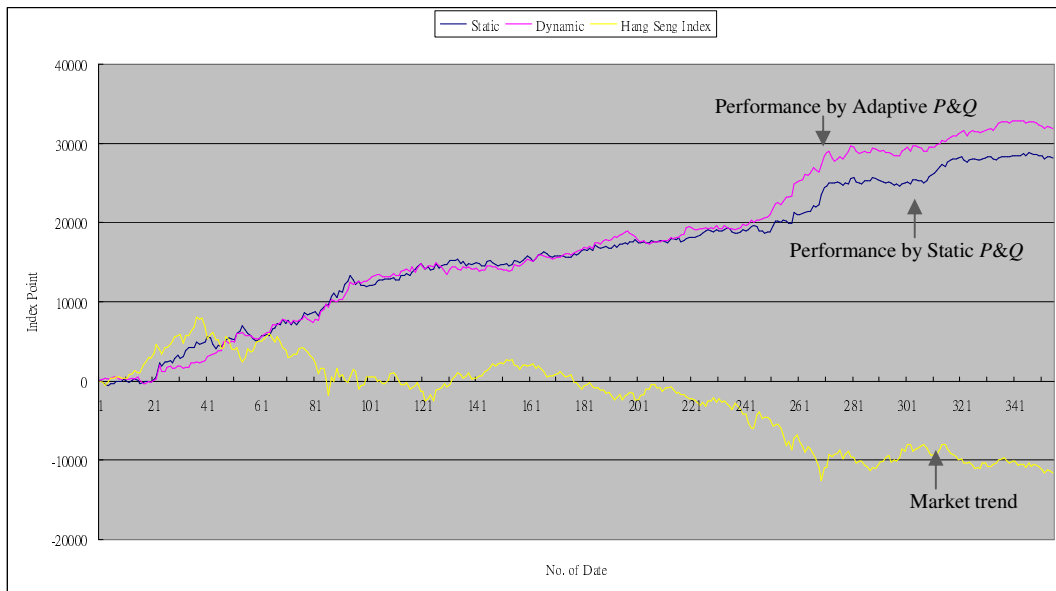


Figure 7. Simulation experiment of trading on Hang Seng Index using trend-following strategies.

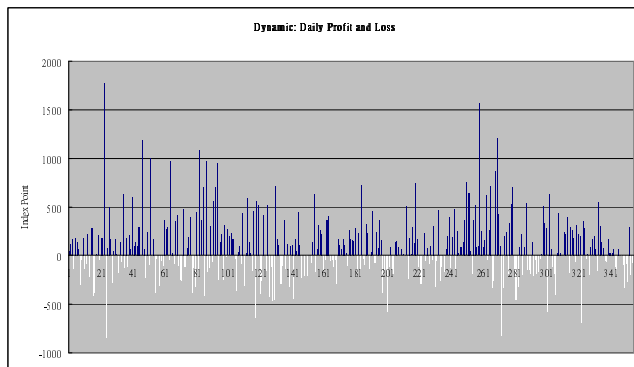


Figure 8. Daily profits and losses occurred in the adaptive $P&Q$ TF trading.

TABLE I. SUMMARY OF RESULTS FROM THE SIMULATION EXPERIMENT

Simulation	Static	Dynamic
Total Index Point	28151	31896
Net Worth (HKD)	1407550	1594800
Total Trade	900	1370
Cost (Commission in HKD)	54000	82200
P&L (Net Worth - Cost)	1353550	1512600
Average Monthly ROI	67.67%	75.63%
ROI	1353.55%	1512.60.6%