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博士論文

整合式資料探勘技術在預測股票市場應用之研究

研 究 生：林光甫
指導教授：黃欽印教授

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Application of Integrated Data Mining Techniques in Stock Market Forecasting

By
Philip K.P. Lin

Advisor：Prof. Chin-Yin Huang

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學生：林光甫　　　　　　　　　　　　　　　　　　指導教授：黃欽印 教授

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摘　要

股票市場不確定性高很難準確性預測，很多研究學者針對股票投資提出許多方法或模式尋求最大獲利的概率，這些方法或模式的整體勝率卻過低以致無法應用在實務上，最主要原因之一是股市的上下激烈震盪，因此目前研究方向聚焦在提高股票交易準確性預測，本研究提出一套解決方案，針對股票交易準確性預測的特殊需求，整合各種不同資料探勘的方法，支援股票交易的決策制訂，方法包含由上而下的交易理論，類神經網路，股票技術分析， 和動態式時間系列方法，並以貝氏機率為其系統架構，本文特舉兩個實例來驗証這套方案之交易投資報酬.第一實例是台積電，時間軸涵蓋 240 交易日，從 2011 年 2 月 16 日到 2013 年 1 月 23 日，84 筆交易透過本系統模擬完成， 投資報酬率 54%，勝率為 80.4%，這期間台積電股價上升 25%，每股從 78.5 元升至 101.5 元.第二實例是長榮海運，同樣的時間軸 240 交易日，64 筆交易透過本系統模擬完成，投資報酬率 128%，從台積電和長榮海運的投資報酬率，本研究對股票交易準確性預測提供一套確實有效的解決方案.

關鍵字詞：預測， 決策制訂， 由上而下的交易， 類神經網路， 動態式時間系列， 貝氏機率

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Student：Philip K.P.Lin　　Advisor： Chin-Yin Huang

Department of Industrial Engineering and Enterprise Information
Tunghai University

ABSTRACT

Stock market is considered too uncertain to be predictable. Many individuals have developed methodologies or models to maximize the probability of making a profit in their stock investment. The overall hit rates of these methodologies and models are generally too low to be practical for real-world application. One of the major reasons is the huge fluctuation of the market. Therefore, the current research focus in the stock forecasting area is to improve the accuracy of stock trading forecast. This paper introduces a scheme that addresses the particular need. The system integrates various data mining techniques and supports the decision making for stock trades. The proposed system embeds the top-down trading theory, artificial neural network theory, technical analysis, dynamic time series theory, and Bayesian probability theory as its bases. To experimentally examine the trading return of the presented algorithm, two examples are studied. The first uses the Taiwan Semiconductor Manufacturing Company (TSMC) dataset that covers an investment horizon of 240 trading days from Feb. 16th, 2011 to January 23th, 2013. 84 transactions were made using the proposed approach and the investment return of the portfolio was 54% with an 80.4% hit rate during a 12-month period in which the TSMC stock price increased by 25% (from $NT 78.5 to $NT 101.5). The second example examines the stock data of Evergreen Marine Corporation, an international marine shipping company. 64 transactions were made following the same algorithm and the investment return of the portfolio was 128% in 12 months. Given the remarkable investment returns in trading the example TSMC and Evergreen stocks, the proposed system demonstrates promising potentials as a viable tool for stock market forecasting.

Keywords：Forecasting, Decision-making, Top-down trading, Artificial neural network, Dynamic time series, Bayesian probability

致謝詞

1986 年我完成碩士論文”電子試算表與一般用途語言”，當時 Microsoft Excel 尚未誕生，我的論文就是設計一套電子試算表(Spreadsheet)，具備一般用途語言之功能， 相當於 Excel 下的 VBA，應用於 Digital VAX 11/750 系統上實現，我的 Co-advisor 謝聰智教授曾建議我創業.29 年後，我的論文“整合式資料探勘技術在預測股票市場應用之研究”利用資料探勘技術來預測股票市場之決策，關連到海量資料(Big data) 之分析和探勘，使用的載具是 Excel，程式語言正是 VBA.

1995 年 6 月 李登輝總統在美國康乃爾大學演講 “Always in My Heart”,其中內容提到” Some say that it is impossible for us to break out of the diplomatic isolation we face， but we will do our utmost to "demand the impossible." 2010 年暑假全家到美國 Florida State University 遊學回來後，決定攻讀博士班，試試自己半百年紀是否仍有能力挑戰最高學程? Demand the impossible?

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“萬軍之耶和華說:不是倚靠勢力、不是倚靠才能、乃是倚靠我的靈、方能成事.”如果我的論文研究有一點點成就和貢獻，一切榮耀都歸給上帝.

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目錄

摘　　要 1
ABSTRACT 2
致謝詞 3
目錄 4
表目錄 5
圖目錄 6
1.Introduction........1
2. Literature review and related work........11
2.1 Application of neural network in stock markets........11
2.2 Application of technical analysis in stock markets........15
2.3 Application of time series in stock markets........17
2.4 Application of Bayesian network and data mining in stock markets........19
3. The proposed methodology –Integrated Data Mining Techniques 23
3.1 Top down trading approach........24
3.2 Hybrid intelligent stock forecasting method........29
3.3 Technical analysis........29
3.4 Bayesian Probability (BP)........48
3.5 Dynamic Time Series Theory........50
3.6. Artificial neural networks training........53
4. Experimentation setup and test results........ 57
4.1 Experimentation simulation and system verification........ 57
4.2 One year period........61
4.3 First period: 12/24/2012– 01/23/2013........63
4.4 Second Period 10/30/2012– 01/23/2013........64
4.5 Third period 08/06/2012–01/23/2013........66
4.6 Summary of TSMC stock performance........67
4.7 Application to the Evergreen stock........68
5. Conclusions........70
References........71
Appendix........78

表目錄

Table 2.1 Summary of modeling techniques....................22
Table 3.1 Summary of technical indicators....................47
Table 3.2 Results of prior probability and posterior probability calculated by BP..................49
Table 4.1 The design model of trading forecasting simulation ……………………………57
Table 4.2 The performance comparison of investment in TSMC..68
Table 4.3 The performance comparison of investment in Evergreen 69

圖目錄

Figure 3.1 Block diagram showing the operation procedure of the system............................24
Figure 3.2 Taiwan Stock Index formed a pivot point in 2008.11.21.......................................25
Figure 3.3 Semiconductor group gave a clear signal that the trend was upward in November of 2008..26
Figure 3.4 MediaTek stock formed a pivot point in 2008.12.12……………………………27
Figure 3.5 TSMC stock formed a pivot point in 2008.11.21. ....……..…28
Figure 3.6 stochastic KD index application in TSMC………………………..…..………..32
Figure 3.7 Williams %R index application in TSMC………………………………………...33
Figure 3.8 RSI %R index application in TSMC……..…………………….………...…...36
Figure 3.9 Psychological line index application in TSMC……………………..……………...38
Figure 3.10 Bias index application in TSMC……………………….……………………..…...39
Figure 3.11 ADX index application in TSMC……………………………………..……..……...42
Figure 3.12 Moving average index application in TSMC……………………….……….......44
Figure 3.13 MACD index application in TSMC………………………………….…............46
Figure 3.14 the closed loop structure of adaptive exponential smoothing methods…………....51
Figure 3.15 performance comparisons between the adaptive alpha and the other alpha values..53
Figure 3.16 the learning layer of ANN structure……………………………..………………56
Figure 3.17 MSE decreases after a period of training in TSMC……………………...…...…56
Figure 3.18 TSMC training confusion matrix has been trained to distinguish between "Buy", "Sell" and 'Hold"……………………………………………………………………….………57
Figure 4.1 simulation of stock price flat and the return of investment is 92.7%.....................58
Figure 4.2 simulation of stock price up and the return of investment is 67.7%.......................59
Figure 4.3 simulation of stock price down and the return of investment is 23.7%..................60
Figure 4.4 the moving hit rate in the period of 240 trading days……………………….………62
Figure 4.5 the returns of investment and the variation of stock price in a year………………62
Figure 4.6 the moving hit rate in the first period of 20 trading days in TSMC………………63
Figure 4.7 the returns of investment and the variation of stock price in the first period……. 64
Figure 4.8 the moving hit rate in the second period of 60 trading days………………………65
Figure 4.9 the returns of investment and the variation of stock price in the 2nd period ...…...66
Figure 4.10 the moving hit rate in the third period of 120 trading days…………………….....66
Figure 4.11 the returns of investment and the variation of stock price in the third period…….67

1. Introduction

Forecasting stock investment return is an important financial issue that has been given a lot of attentions (Matias and Reboredo, 2012). In the last decade, a number of intelligent systems and hybrid models have been proposed for making trading decisions in an attempt to outperform the main market and be profitable in stock investment (Atsalakis and Valavanis, 2009b). Many individuals have developed methodologies or models to maximize the probability of making a profit in their stock investment. Atsalakis (2011) adopted the Elliot wave theory and a neuro-fuzzy approach. They presented the WASP (Wave Analysis Stock Prediction) system, which was based on the neuron-fuzzy architecture that utilized the Elliott Wave Theory. The system showed a tendency to achieve hit rates in the 60% mark which was significantly better than forecasting with the help of a coin. Unfortunately, the overall hit rates of these methodologies and models are generally below 70(Atsalakis *et al.,* 2011). It is difficult for an investor to make profit using these methodologies or models in real-world stock trading. The nature of stock market prediction requires the combining of several computing techniques synergistically rather than exclusively. It is essential to clarify as predicting the ‘stock market trend.’ In reality, it is impossible to predict the future absolute value of the stocks on a daily basis. However, based on the assumption that is largely supported by real case studies that with appropriate training over any (uptrend, down-trend and flat) horizon one could have enough indicators to forecast the trend with significant accuracy. Future trends may be predicted to some extend based on some key indicators and past behavior.

Forecasting requires the knowledge of the dominant market variables that ‘explain’ stock market behavior which is both dynamic and volatile. Due to system uncertainties and other unknown (random) factors, every stock market model is approximate. Thus, once model uncertainty is acknowledged, soft computing techniques emerge as the best candidates chosen over standard benchmark linear models to deal with such problems (Atsalakis *et al.*, 2011). One of the best ways to model the market value is the use of expert systems with artificial neural networks (ANN), which is void of standard formulas and can easily adapt the changes of the market. In literature, many artificial neural network models are evaluated against statistical models for forecasting the market value. It is observed that in most of the cases ANN models give better results than other methods (Guresen *et al.,* 2011). The proposed system in this research is a hybrid intelligent forecast system combined with ANN. It may predict with significant accuracy stock price trends using historical stock market prices from the Taiwan Stock Exchange (TSE) and gives very encouraging results. The trend of the Taiwan Semiconductor Manufacturing Company (TSMC) stock and the Evergreen Marine Corporation stock were predicted with an 80.4% or higher accuracy. This percentage of accuracy corresponds to a 4 ratio 1 (80.4/19.6) of making a 54% profitable stock transaction in a year-long window in which the global recession was at its height and most trading was non-profitable. All case studies performed on the returns of the TSE stocks result in 80% or higher accuracy. In the sections that follow, we propose a system that integrates various data mining techniques to support the stock trading decision making. The system also incorporates the theory of top-down trading and tandem trading pioneered by Jesse Livermore (Livermore, 1940). The theory was found useful in stock forecasting. Analysis of top-down analysis in stock prediction is vital for two important reasons. One is the top-down analysis of the market direction. The investor must know the overall trend of the market before making a trade. This applies to the stock market, the industry group and individual stocks. The method is to probe whether the market, the industrial group, or the stock is headed up, down or sideways (Leung *et al.*, 2000). Then, the individual stock is investigated by the system integrated with data mining techniques including artificial neural network theory, technical analysis, dynamic time series theory, and Bayesian probability theory.

In this research’s approach, we start with checking the main market. The step is to know which way the overall market is headed: up, down, or sideways. Secondly, we examine the specific industry group to make sure that the group is moving in the same direction in order to increase the chance of making a profit on the trade. Thirdly, we review the sister stocks to see if the stock is moving in the same direction. In the fourth step, all three factors are examined at the same time; that is, considering the overall market, the industry group and the sister stocks simultaneously. It can be clearly seen how the system works when all factors are in unison. Lastly, the system that integrated data mining techniques is employed to attain the stock up/down prediction (Chavarnakul and Enke, 2009, Zarandi *et al.*, 2012).

The remaining sections of this paper are organized as follows. Section 2 gives the background of the related studies. Section 3 introduces the system of data mining techniques used in this study and Section 4 provides results of the approach using the daily TSE stock price. The final section gives the conclusion and recommendations for future research. This paper contributes to the study of intelligence forecasting. It would also help realize profitable stock transactions if properly implemented. The key successful factors of this research is to find the method to obtain the significant inputs for ANN and the gate of MSE is able to be reached in the desired level $3x10^{-2}$. It stands for the convergence of learning and the weight matrix is useful for forecasting in future. Therefore, the proposed approach that integrated various data mining techniques has achieved remarkable results.

The assumption and the limitation in this study is the selection of stock. The company performance is correlated to stock price (market give their assessment of the company's share price), rather than specific speculation or on-purpose manipulation of stock price. One early Livermore lesson was "trade only the leaders in any particular industry group." "Don't play in the junkyard with the weaker stocks. Don't try to fish for the bargain stock, the as yet undiscovered stock in an industry group. Rather, go with the proven leaders! In the long run, you will be much better off. This single piece of advice can greatly assist a trader in the decision-making process. If you cannot make money with the leaders of a stock group, it is unlikely that you can make money at all in that group" (Livermore, 1940, Smitten, 2005).

2. Literature review and related work

Many financial analysts and stock market investors seem convinced that they can make profits by employing one technical analysis approach or another to predict stock market. Some use time series models expressed by financial theories for forecasting a series of stock price data. ANN is usually chosen as a stock prediction tool besides other methods. Yet, these approaches cannot be employed alone because they are not directly applicable to predict the market value which is always subject to external impact. The nature of the stock market is affected by system uncertainties and other unknown (random) factors. Prediction requires combining several computing techniques synergistically rather than exclusively. Thus it necessarily indicates the hybrid use of technical analysis, time series forecasting, Bayesian probability and possibly ANN. In the following a review is given to the recent development of hybrid approach for the prediction of the stock market.

2.1 Application of neural network in stock markets

This section provides some of the applications of neural network in stock markets. The main advantage of neural networks is that they can approximate any nonlinear function to an arbitrary degree of accuracy with a suitable number of hidden units. Mandziuk and Jaruszewicz (2011) introduced an experimental evaluation of a neuron-genetic system for the prediction of the short-term stock index. The buy/sell signals generated by the technical analysis, MACD, Williams, Move Averages (MA) and Relative Strength Indicator (RSI) are considered for stock trading. Their results showed that prediction based on the neuron-genetic model worked well during both uptrend and downtrend.

The appraoch developed by Tan et al. (2008) involves the use of technical analysis and neuro-fuzzy. They proposed a novel RSPOP Intelligent Stock Trading System, that combines the superior predictive capability of RSPOP FNN and the use of widely accepted Moving Average and Relative Strength Indicator Trading Rules. The system is demonstrated empirically using real live stock data to achieve significantly higher Multiplicative Returns than a conventional technical rule trading system. It is able to outperform the buy-and-hold strategy and generate several folds of dollar returns over an investment horizon of four years. The Percentage of Winning Trades was increased significantly from an average of 70% to more than 92% using the system as compared to the conventional trading system; demonstrating the system’s ability to filter out erroneous trading signal. This paper presents empirical results on live stock data and demonstrated that the RSPOP FNN can contribute to more accurate prediction and the creation of a highly profitable trading system. The ability to filter out losing trades is certainly a significant contribution to stock investors, because it not only enhances their portfolio performance but also enable them to capitalize on winning opportunities otherwise missed when engaged in losing trades.

Atsalakis et al. (2009a) suggest Wave Analysis Stock prediction based on the neuro-fuzzy. The techniques were used to forecast the trend of the stock prices and results derived. The Elliott wave principle was connected with the Fibonacci sequence, the Fibonacci sequence of numbers derived from the addition of the previous two numbers. Elliott’s wave theory cannot constantly explain the market perfectly but the fuzzy estimates of the market behavior accurately to improve the stock market forecasting. Atsalakis et al. (2011) presents the WASP (Wave Analysis Stock Prediction) system, a system based on the neurofuzzy architecture, which utilizes aspects from the Elliott Wave Theory, presented by Ralph Nelson Elliott. This theory has been found to be extremely useful and accurate, particularly in problems of forecasting. A neuro-fuzzy logic technique has been used to forecast the trend of the stock prices and the results derived are very encouraging. The system showed a tendency to achieve hit rates in the 60% mark which was significantly better than forecasting with the help of a coin. Elliott believed that there are nine cycles, of different durations, the bigger of which, is formed by the smaller ones. From largest to the smallest cycles, there are: (1) Grand Super-Cycle, (2) Super-Cycle, (3) Cycle, (4) Primary, (5) Intermediate, (6) Minor, (7) Minute, (8) Minute and (9) Sub-minute.

The approach by Abraham et al. (2001) incorporated the principal component analysis and ANN. This paper deals with the application of hybridized soft computing techniques for automated stock market forecasting and trend analysis. This study makes use of a neural network for one day ahead stock forecasting and a neuro-fuzzy system for analyzing the trend of the predicted stock values. It analyzed the 24 months stock data for Nasdaq-100 main index as well as six of the companies listed in the Nasdaq-100 index. Input data were preprocessed using principal component analysis and fed to an artificial neural network for stock forecasting. In this paper, they used Nasdaq-100 main index values and six other companies listed in the Nasdaq-100 index. Apart from the Nasdaq-100 index; the other companies considered were Microsoft Corporation, Yahoo! Inc. , Cisco Systems Inc. , Sun Microsystems Inc. , Oracle Corporation and Intel Corporation. The development of powerful communication and trading facilities has enlarged the scope of selection for investors.

Enke and Thawornwong (2005) introduced an information gain technique used in machine learning for data mining to evaluate the predictive relationships of numerous financial and economic variables. Neural network models for level estimation and classification are then examined for their ability to provide an effective forecast of future values. A cross validation technique is also employed to improve the generalization ability of several models. The results show that the trading strategies guided by the classification models generate higher risk-adjusted profits than the buy-and-hold strategy, as well as those guided by the level-estimation based forecasts of the neural network and linear regression models.

Defu et al. (2007) dealt with the application of well-known neural network technique, multilayer back-propagation neural network, in financial data mining. A modified neural network forecasting model is presented, and an intelligent mining system is developed. The system can forecast the buying and selling signs according to the prediction of future trends to stock market, and provide decision-making for stock investors. The simulation result of seven years to Shanghai composite index shows that the return achieved by this mining system is about three times as large as that achieved by the buy-and-hold strategy, so it is advantageous to apply neural networks to forecast financial time series, so that the different investors could benefit from it (Defu et al., 2007). Accurate volatility forecasting is the core task in the risk management in which various portfolios' pricing, hedging, and option strategies are exercised.

Tae (2007) proposes hybrid models with neural network and time series models for forecasting the volatility of stock price index in two view points: deviation and direction. It demonstrates the utility of the hybrid model for volatility forecasting. This model demonstrates the utility of the neural network forecasting combined with time series analysis for the financial goods (Tae, 2007).

Vaisla and Bhatt (2010) proved that neural network (NN) outperform statistical technique in forecasting stock market prices. They have showed it through a method to forecast the daily stock price using neural network and then the result of the neural network forecast is compared with the Statistical forecasting result. They have proved that neural network, when trained with sufficient data, proper inputs and with proper architecture, can predict the stock market prices very well. On the other hand, statistical technique though be well built but their forecasting ability is reduced as the series become complex. Therefore, NN can be used as a better alternative technique for forecasting the daily stock market prices.

Lu (2010) proved from the experimental results that the integrated independent component analysis (ICA)-based de-noising scheme with neural network proposed for stock price prediction model outperforms the integrated wavelet de-noising technique with BPN(back propagation network) model, the

BPN model with non-filtered forecasting variables, and a random walk model. According to the experiments, the author has concluded that the proposed method can effectively detect and remove the noise from stock prices/indices and improve the forecasting performance.

2.2 Application of technical analysis in stock markets

Technical analysis and fundamental analysis are two major stock market analyzing methods used to predict short- and long-term stock trends, respectively. For most investors, it is more valuable to accurately predict market trends and daily value movements because one would want to invest in the stock at the right time when the market is on the upward trend market (Ausloos and Ivanova, 2002, Edwards et al., 2007). Fundamental analysis considers commercial factors, such as financial statements, management ability, business competition and market conditions, in order to determine the intrinsic value of a given stock. Technical analysis helps recognize the price patterns according to the extrapolations from historical price patterns.

In technical analysis method, chart patterns and technical indicators are the two major analyzing tools. Charting patterns such as head-and-shoulder and flag use stock charts to study the movement of the stock prices. Technical indicators such as RSI and moving average are produced by specific equations to examine market signals and help investors make trading decisions. Technical analysts widely use market indicators of many sorts, some of which are mathematical transformations of price, often including up and down volume, and advance/decline data. Popular technical indicators are usually classified into two major functions: trend and momentum (Liu and Lee, 1997).

Senthamarai et al. (2010) used data mining technology to discover the hidden patterns from the historic data that have probable predictive capability in their investment decisions. The prediction of stock market is a challenging task of financial time series predictions. There are five methods namely Typical price, Bollinger bands, Relative strength index (RSI), Chaikin Money Flow indicator (CMI), Stochastic Momentum Index (SMI) used to analyzed the stock index. In this paper the author got the profitable signal is 84.24% using Bollinger Bands rather than MA, RSI and CMI.

Abdulsalam et al. (2010) used the moving average (MA) method to uncover the patterns, relationship and to extract values of variables from the database to predict the future values of other variables through the use of time series data. The advantage of the MA method is a device for reducing fluctuations and obtaining trends with a fair degree of accuracy. This techniques proven numeric forecasting method using regression analysis with the input of financial information obtained from the daily activity equities published by Nigerian stock exchange.

2.3 Application of time series in stock markets

Time series data is characterized as large in data size, high dimensionality and update continuously. Moreover, the time series data is always considered as a whole instead of individual numerical fields. As, a large set of time series data is from stock market, dimensionality reduction is an essential step before many time series analysis and mining tasks. In stock markets, many types of time series models such as statistical time series model, fuzzy time series model, and advanced time series model based on artificial intelligence algorithms were advanced by academic researchers to forecast stock price. Some drawbacks are issued for these models as follows: (1) mathematical assumptions are required for statistical time series models; (2) the forecast from fuzzy time series model is a linguistic value that is not as accurate as statistical time series; and (3) a proper threshold is not easy to be produced by advanced time series model and the forecasting algorithm is unintelligible.

There was a novel price-pattern detection method that looked for certain price-patterns "price trend" and " price variation" contained in the time series variables that can be used to forecast the stock market. To deal with these problems, Chen et al. (2011) explored pattern recognition and time series forecasting. From model verification using a nine-year period of Taiwan stock market index (TAIEX) as experimental datasets, it is shown that the proposed model outperforms three listing fuzzy time series. The stock price-patterns with higher similarity are used the pattern basis for forecasting. Additionally, to promote forecasting accuracy, an adaptive model is utilized in forecasting process of the proposed model. After implementing the experiment, three major advantages for the proposed model are issued as follow: (1) no mathematic assumptions about observations are required to form forecasting algorithms and the computer system using the proposed algorithms is easy to build up with lower complexity; (2) the proposed model produce accurate forecasts based on "stock price-patterns" that are understandable for common investors instead of "statistical formula" or "fuzzy logic relations" that are complicated words for common investors; and (3) by using multi-period adaptation model, the proposed method can produce self-modified forecasts to reach better accuracy when stock market go flat and to make smaller loss when stock market fluctuates violently.

Fu et al. (2008) have represented financial time series according to the importance of the data points. With the concept of data point importance, a tree data structure, which supports incremental updating, has been proposed to represent the time series and an access method for retrieving the time series data point from the tree, which is according to their order of importance, has been introduced. This technique is capable of presenting the time series in different levels of detail and facilitates multi-resolution dimensionality reduction of the time series data. The authors have proposed different data point importance evaluation methods, a new updating method and two dimensionality reduction approaches and evaluated them by a series of experiments. Finally, the application of the proposed representation on mobile environment has been demonstrated (Fu et al., 2008).

Yu and Huarng (2010) used neural network because of their capabilities in handling nonlinear relationship and also implement a new fuzzy time series model to improve forecasting. The fuzzy relationship is used to forecast the Taiwan stock index. In the neural network fuzzy time series model where as in-sample observations are used for training and out-sample observations are used for forecasting. The drawback of taking all the degree of membership for training and forecasting may affect the performance of the neural network. To avoid this take the difference between observations. These reduce the range of the universe of discourse.

2.4 Application of Bayesian network and data mining in stock markets

Bayesian network is the graphical model which can represent the stochastic dependency of the random variables via the acyclic directed graph. Hoeting et al. (1999) proposed a coherent mechanism for accounting for this model uncertainty. Standard statistical practice ignores model uncertainty. Data analysts typically select a model from some class of models and then proceed as if the selected model had generated the data. This approach ignores the uncertainty in model selection, leading to over-confident inferences and decisions that are more risky than one thinks they are. Bayesian model averaging (BMA) provides a coherent mechanism for accounting for this model uncertainty. Several methods for implementing BMA have recently emerged. BMA provides improved out-of sample predictive performance.

Zuo and Kita (2012a) described the price earnings ratio (P/E ratio) forecast by using Bayesian network. Firstly, the use of clustering algorithm transforms the continuous P/E ratio to the set of digitized values. The Bayesian network for the P/E ratio forecast is determined from the set of the digitized values. NIKKEI stock average (NIKKEI225) and Toyota motor corporation stock price are considered as numerical examples. The results show that the forecast accuracy of the present algorithm is better than that of the traditional time-series forecast algorithms in comparison of their correlation coefficient and the root mean square error.

Zuo and Kita (2012b) presented a Bayesian network technique to predict the up/down analysis of the daily stock indexes and the result were compared with the psychological line and trend estimation technical analyses, and are popular algorithms which are well-known by the traders. The application of Bayesian network to the up/down rate analysis of the stock index was presented in this study.

The network was determined according to the K2 algorithm with K2 metric as the network score from the up/down rates of the stock indexes; FTSE100, DOW30 and Nikkei225. The network was applied for predicting the improvement in the FTSE100 in 2007. The present algorithm showed almost 60% correct answer rate, which is higher than the results by the traditional algorithms such as psychological line and the trend estimation. Although the correct answer rate of the psychological line showed the similar accuracy, the number of investments is much smaller than that of the present algorithm. Therefore, the vertical investment revealed that total profit of the Bayesian network was much greater than the others. The average correction rate of their algorithm was almost 60%, which is almost equal to or higher than the technical psychological line (50-59%) and the trend estimation (50-52%).

Cui and et al. (2010) adopts the Bayesian variable selection (BVS) using informative priors to select variables for binary response models and forecasting for direct marketing. The variable sets by forward selection and BVS are applied to logistic regression and Bayesian networks. The results of validation using a holdout dataset and the entire dataset suggest that BVS improves the performance of the logistic regression model over the forward selection and full variable sets while Bayesian networks achieve better results using BVS. Thus, Bayesian variable selection can help to select variables and build accurate models using innovative forecasting methods.

Lu and Chen (2009) employed decision tree-based mining techniques to explore the classification rules of information transparency levels of the listed firms in Taiwan’ s stock market. Moreover, the multi-learner model constructed by boosting ensemble approach with decision tree algorithm has been applied. The numerical results show that the classification accuracy has been improved by using multi-leaner model in terms of less Type I and Type II errors. In particular, the extracted rules from the data mining approach can be developed as a computer model for the prediction or the classification of good/poor information disclosure potential and like expert systems.

In this study, over 60 related scientific articles applied to stock market forecasting have been reviewed. Results are presented in terms of summary tables. Table 1 demonstrates modeling benchmarks of each author’s specific approach and techniques; such techniques include artificial neural networks (ANNs), Fussy logic, Time series, Technical analysis, Data mining, Bayesian network, Principal component analysis (PCA) and Top down trading method.

Table 2.1 Summary of modeling techniques

Articles \ Model	ANNs	Fuzzy	Time series	Technical analysis	Data mining	Bayesian	PCA	Top down trading
Abraham et al.(2001)	●	●					●	
Atsalakis et al.(2011)	●	●		●				
Atsalakis and Valavanis(2009a)	●	●						
Ausloos and Ivanova (2002)				●				
Billah et al.(2006)			●					
Bramer M. (2013)					●			
Chavarnakul and Enke (2009).	●	●		●				
Chen et al.(2003)	●							
Chen et al.(2008)		●	●					
Chen et al.(2012)			●	●				
Chenoweth et al.(1996)	●			●				
Cremers (2002).						●		
Cui et al.(2010)						●		
Dai et al.(2012)	●						●	
Defu et al.(2007)	●		●					
de Faria et al.(2007)	●				●			
Edward et al.(2007)				●				
Enke and Thawornwong(2005)	●				●			
Esfahanipour and Aghamiri(2010).	●	●						
Fu et al.(2008)			●					
Guresen et al.(2011)	●							
Hajizadeh et al.(2010)					●			
Hoeting, et al.(1999)						●		
Hornik et al.(1989)	●							
Jang et al.(1997)	●	●						
Jie and Hui (2008)					●			
Johnson and Sakoulis (2008).						●		
Kanas (2001).	●							
Kannan et al.(2010)					●			
Kao et al.(2013)	●						●	
Kim and Lee (2004).	●							
Kim et al.(2006)					●			
Leigh et al.(2002)				●				
Leigh et al.(2006)				●				
Leung et al.(2000)					●			
Liao et al.(2008)					●			
Lim and WuncshII (1999).		●		●				
Liu and Lee (1997)				●				
Livemore (1940)								●
Lo (2010)				●				
Lu (2010)	●						●	
Lu and Chen (2009).					●			
Mandziuk and Jaruszewicz (2011).	●	●						
Matias and Reboredo (2012).	●		●					
Mizuno et al.(1998)	●			●				
Oh and Kim (2002).	●							
Ohama et al.(2005)	●							
Olaniyi et al.(2010)					●			
Reboredo et al.(2012)	●							
Shaarawy and Broemeling (1984).						●		
Smitten, R.(2005).								●
Spiegelhalter et al.(1992)						●		
Tae (2007).	●		●					
Tan et al.(2008)	●	●						
Taylor(2004).			●					
Tsai et al.(2010)						●		
Vaisla and Bhatt(2010),	●							
Wang and Chan (2007).				●	●			
Wu et al.(2001)	●	●						
Yu and Huarng(2010).	●	●	●					
Zarandi et al.(2012)	●	●						
Zuo and Kita (2012b).						●		
Zuo and Kita (2013a).						●		

3. The proposed methodology –Integrated Data Mining Techniques

This paper presents a system that incorporates the top-down trading theory first introduced by Jesse Livermore (1940) and various data mining techniques. Livermore believed that stock trends follow a trend line that can be used to forecast both in the long- and short-term. He published this particular idea in 'How to Trade in Stock' ' in 1940. Using stock data he concluded that stock-group behavior was an important indication to overall market direction, whether they are big or small - an indication embraced by the Wall Street but ignored by most traders. He believed stock-groups often provided the key to changes in trends. As the favored groups of the moment became weaker and collapsed, a correction in the overall market was usually on the way. The same thing happened in year 2000 dot.com bubble and year 2009 financial market collapse. The leaders flipped and fell first, and the others followed. Figure 3 depicts the block diagram of the system. The system can be classified into two categories, one is Top down trading approach and the other is Hybrid intelligent stock forecasting method.

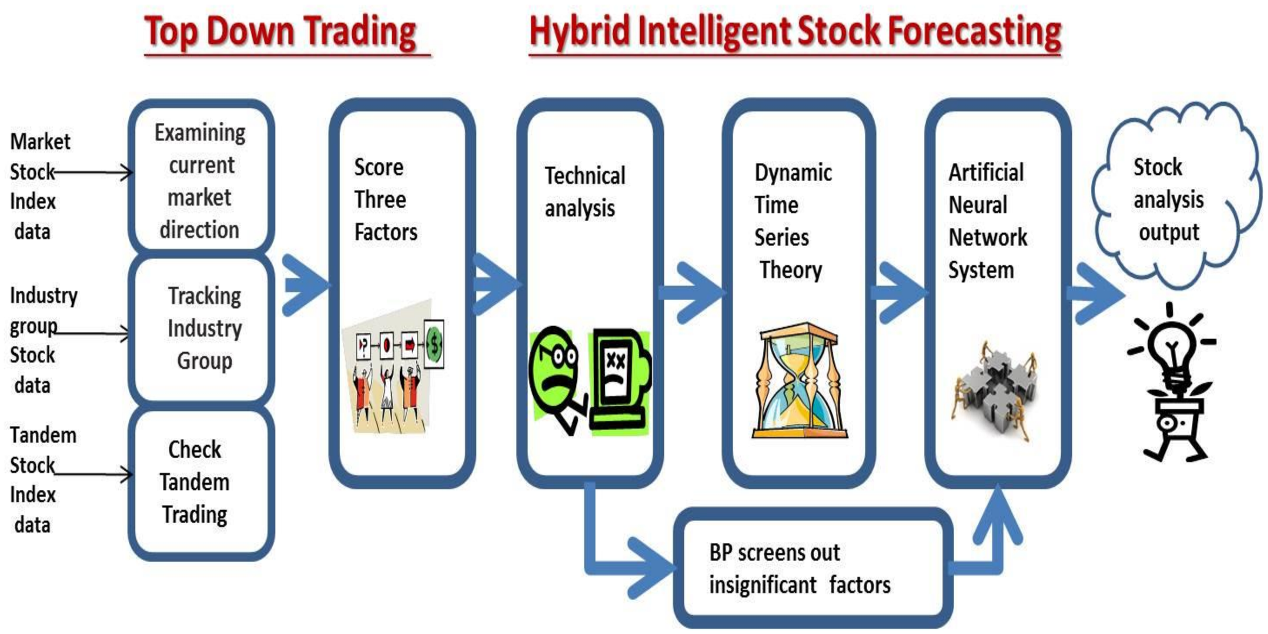

Figure 3.1 Block diagram showing the operation procedure of the system

3.1 Top down trading approach

Top down forecast approach utilizes the aspects from the theory of top down trading and tandem trading, presented by Jesse Livemore. This theory has been found to be useful in problems of stock forecasting. Analysis of top down analysis is vital for probing the market direction. The investor must know the overall trend of the market before making a trade. This applies to the market, the industry group and individual stocks. The basic thing is to probe which way the market is headed, up, down, or sideways. The main idea behind top down trading is that a rising tide lifts all boats. So if you can find where the tide is going up, then you can also find stocks that are going up. That means top down trading is concerned with finding the best stocks within the best sectors within the best industries in the market. Instead of bottom fishing for bargains, you look at what’s working and let the momentum do the work for you. As Chinese proverb says "The nest eggs will survive." Detail descriptions of the Top down forecast approach are as follows.

Step 1—examining current market direction

The first step is to survey and to establish the current market direction and to investigate if the current line of least resistance is positive, negative or neutral (Livermore, 1940). It is essential to make sure the least resistance lines are in the direction of the investor's trade before entering the trade. Figure 3.2 shows that the Taiwan Stock Index (TSI) began its recovery in November of 2008 where a pivot point was formed and basic direction was changed.

Figure 3.2 Taiwan Stock Index formed a pivot point in 2008.11.21

Step 2: Tracking the Industry Group

The second step is to check the specific Industry Group. Since the trades of TSMC are of interest, the Semiconductor Industry Group is checked out to make sure that the group is moving along the line of least resistance, in order to increase the chance of making a profit on the selected trade. Stocks do not move alone. When they move, they move in a group. The Semiconductor Industry Group began its recovery in November of 2008, the same time Taiwan Stock Index began its recovery in Figure 3.3. In July/August, it gave a clear signal that the line of least resistance was upward. The signals confirmed each other that the trend was now heading to the upside.

Figure 3.3 Semiconductor group gave a clear signal that the trend was upward in November of 2008

Step 3: Checking Tandem Trading

Tandem Trading involves comparing two stocks of the same group by comparing the stock of interest in trading with its sister stocks. To trade in TSMC, the Taiwan MediaTek is examined as a sister stock. Both stocks bottomed out in December of 2008 and gave a signal, by a pivotal point, that the line of least resistance was positive. Because the broker/dealers are also often an important bellwether group for what the market may do in the future, this chart action (see Figure 3.4) was a precursor of what was to come in the overall market.

Figure 3.4 MediaTek stock formed a pivot point in 2008.12.12.

Figure 3.5 TSMC stock formed a pivot point in 2008.11.21.

Step 4: Scoring the Three Factors

In the fourth step, the previous three factors, namely the market, the Industry Group, and the Tandem stocks, are examined all together. It can be clearly seen in Figs. 2-5 that all factors are in unison. All the signals in the figures show a bottoming out in November and a reversal in trend, clearly indicating that the line of least resistance was now upward in direction. The step provides the trend reference of the individual stock for further analysis in the fifth step. The steps to score the three factors are described as follows.

Step 4.1: If the TSI and individual stock value are the same (upward, downward or flat), the score is 1 and -1 otherwise.

Step 4.2: If the industry group and individual stock value are the same (upward, downward or flat), the score is 1 and -1 otherwise.

Step 4.3: If the tandem stock and individual stock value are the same (upward, downward or flat), the score is 1 and -1 otherwise.

Step 4.4: Sum up the scores of Steps 1~3. The summed score is considered one of the key factors in ANN.

3.2 Hybrid intelligent stock forecasting method

Lastly, after all the trend lines are confirmed and the score is made, the next step is to make prediction of the future stock values. In this category, we make use of integrated data mining techniques for stock forecasting. Our approach is able to identify and predict the profits or losses in the next one day, two days, three days and four days in the stock counter (Atsalakis and Valavanis, 2009a). The information is vital for the investor to buy at the start of an uptrend and to sell off just before the trend reverses and the stock counter goes into a decline. Since the stock market behaves dynamically, integrated data mining techniques can provide a suitable approach to figure the behavior patterns (uptrend, down-trend and flat) of the stock price from the stock dataset (Jang et al. 1997). Since the stock dataset does not show the correlation with stock behavior patterns, the techniques including technical analysis, Bayesian probability, dynamic time series, and ANN are integrated to figure the patterns from those massive and non-meaningful data. More details are elaborated in the following subsections.

3.3 Technical analysis

Technical analysts believe that investors collectively repeat the behavior of the investors that preceded them. To a technician, the emotions in the market may be irrational, but they exist. Because investor behavior repeats itself so often, technicians believe that recognizable (and predictable) price patterns will develop on a chart. Recognition of these patterns can allow the technician to select trades that have a higher probability of success. Technical analysis is not limited to charting, but it always considers price trends.

Technical analysis employs models and trading rules based on price and volume transformations, such as the relative strength index, moving averages, regressions, inter-market and intra-market price correlations, business cycles, stock market cycles or, classically, through recognition of chart patterns. Technical analysis stands in contrast to the fundamental analysis approach to security and stock analysis. Technical analysis analyzes price, volume and other market information, whereas fundamental analysis looks at the facts of the company, market, currency or commodity. All the technical indicators utilized in this study are summarized in Table 3.1.

3.3.1 Stochastic KD

The Stochastic Indicator is based on the observation that as the trend of a stock’s price increases, the daily closes tend to be closer to the upper end of the recent price range. Conversely, as the trend of stock’s price decreases, the daily closes tend to be closer to the lower end of the recent price range. The stochastic values simply represent the position of the market on a percentage basis versus its range over the previous n-period sessions. The percentage scale runs from zero to 100%. There are three primary stochastic values used in this study.

Raw Stochastic(RSV) - the most basic value representing the stochastic value for each period.

%K - the first smoothing of the raw stochastic, usually with n-period exponential moving average.

%D - the smoothing of the %k value, usually with another m-period exponential moving average.

To calculate the stochastic RSV, %K and %D:

RSV= 100* (closing price - n-period low) / (n-period high - n-period low)

%K= (2/3 old %K + 1/3 RSV).

%D = (2/3 old %D + 1/3 %K).

Example of stochastic KD index application shows %k line and %d line in Figure 3.6, we develop a KD setting rule.

Rule 1:“Buy” when either %k or %d falls below a specific level (usually 20%) and then rises above that level. Buy when the %k line starts to rise above the %d line, the target value is identified as “Buy”, labeled as "1".

Rule 2: “Sell”, labeled as "-1" if Sell when either %k or %d rises above a specific level (usually 80%) and then falls below that level, sell when the %k line start to fall below the %d line.

Rule 3: If not in the cases of the above, the target value is identified as “Hold”, labeled as “0”.

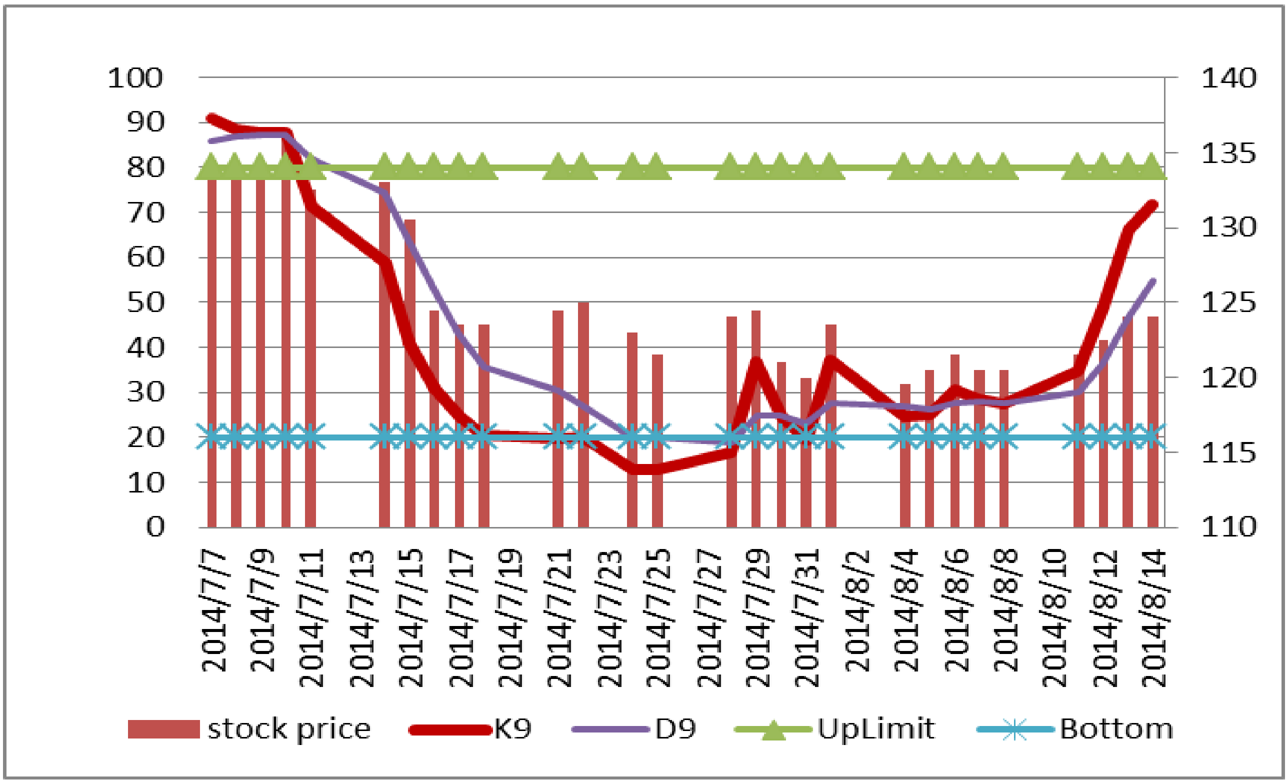

Figure 3.6 stochastic KD index application in TSMC

3.3.2 Williams %R

Williams Percent R indicates overbought/oversold market conditions, and is expressed as a percentage, ranging from zero to 100%. Its purpose is to detect whether a stock or commodity market is trading near the high or the low, or somewhere in between, of its recent trading range. The formula for the Williams Percent R is

$$\%R = 100 * (\text{high N days} - \text{close today}) / (\text{high N days} - \text{low N days})$$

Williams used a 10 trading day period and considered values %R above 80 as oversold and below 20 as overbought. Example of Williams %R index application is shown in Figure 3.7, we develop a Williams %R setting rule.

Rule 1:“Buy” when values %R above 80 as oversold, the target value is identified as “Buy”, labeled as "1".

Rule 2: “Sell”, labeled as "-1" if values %R below 20 as overbought.

Rule 3: If not in the cases of the above, the target value is identified as “Hold”, labeled as “0”.

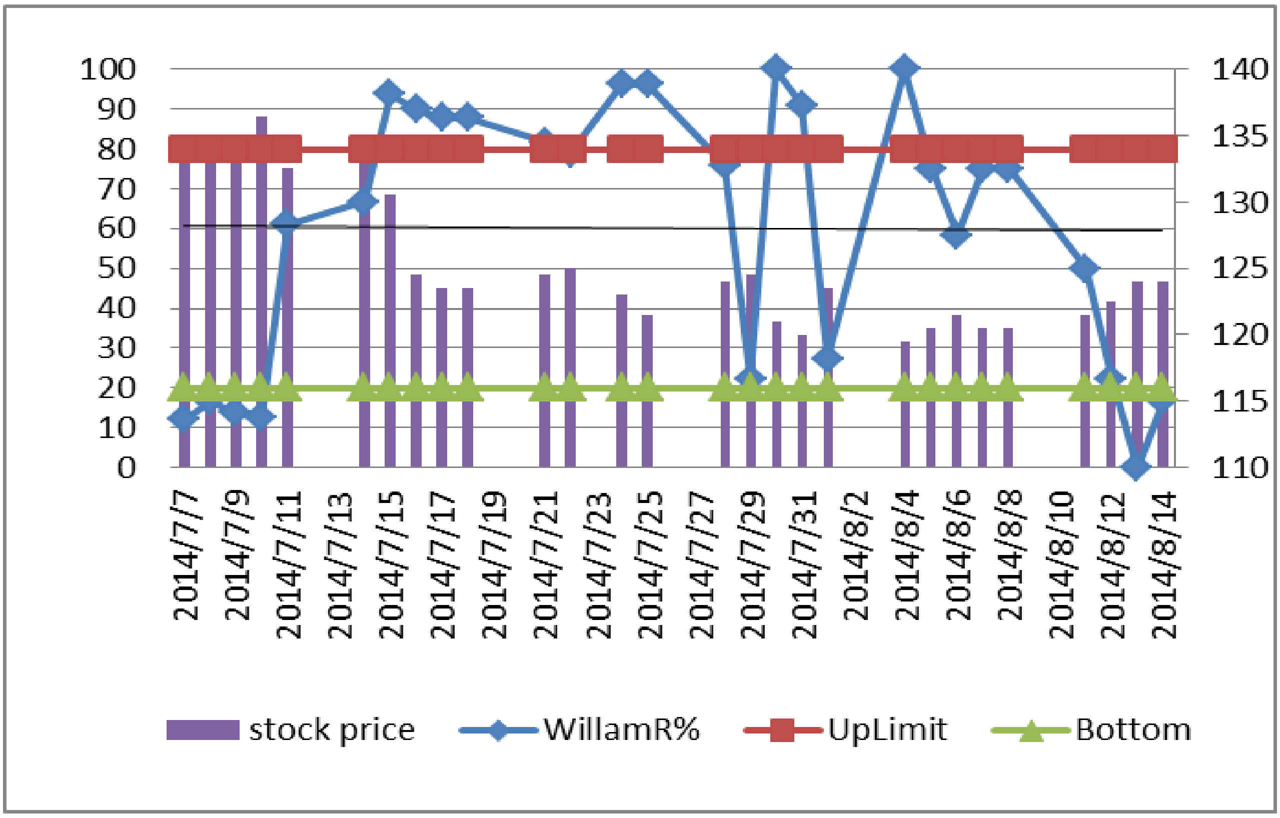

Figure 3.7 Williams %R index application in TSMC

3.3.3 Relative Strength Index

The Relative Strength Index (RSI) is basically an internal strength index which is adjusted on a daily basis by the amount by which the market rose or fell. The RSI is classified as a momentum oscillator, measuring the velocity and magnitude of directional price movements. Momentum is the rate of the rise or fall in price. The RSI computes momentum as the ratio of higher closes to lower closes: stocks which have had more or stronger positive changes have a higher RSI than stocks which have had more or stronger negative changes. It is most commonly used to show when a market has topped or bottomed. A high RSI occurs when the market has been rallying sharply and a low RSI occurs when the market has been selling off sharply. The RSI is expressed as a percentage, and ranges from zero to 100%. The formula for the RSI is

- A=An Average of upward price change=EMA(U, n)
- B=An Average of downward price change=EMA(D, n)
- Relative Strength=100-100/(1+A/B)

For each trading period an upward change U or downward change D is calculated. Up periods are characterized by the close being higher than the previous close:

U= closenow – closeprevious

Conversely, a down period is characterized by the close being lower than the previous period's (note that D is nonetheless a positive number), D= closeprevious – closenow

If the last close is the same as the previous, both U and D are zero. Example of RSI index (RSI(6D)-6 day and RSI(12D)-12 day) application is shown in Figure 3.8, we develop a RSI index setting rule.

Rule 1:“Buy” when either RSI(6D) or RSI(12D) falls below a specific level (usually 20%) and then rises above that level. Buy when the RSI(6D) line starts to rise above the RSI(12D) line, the target value is identified as “Buy”, labeled as "1".

Rule 2: “Sell”, labeled as "-1" if Sell when either RSI(6D) or RSI(12D) rises above a specific level (usually 80%) and then falls below that level, sell when the RSI(6D) line start to fall below the RSI(12D) line.

Rule 3: If not in the cases of the above, the target value is identified as “Hold”, labeled as “0”.

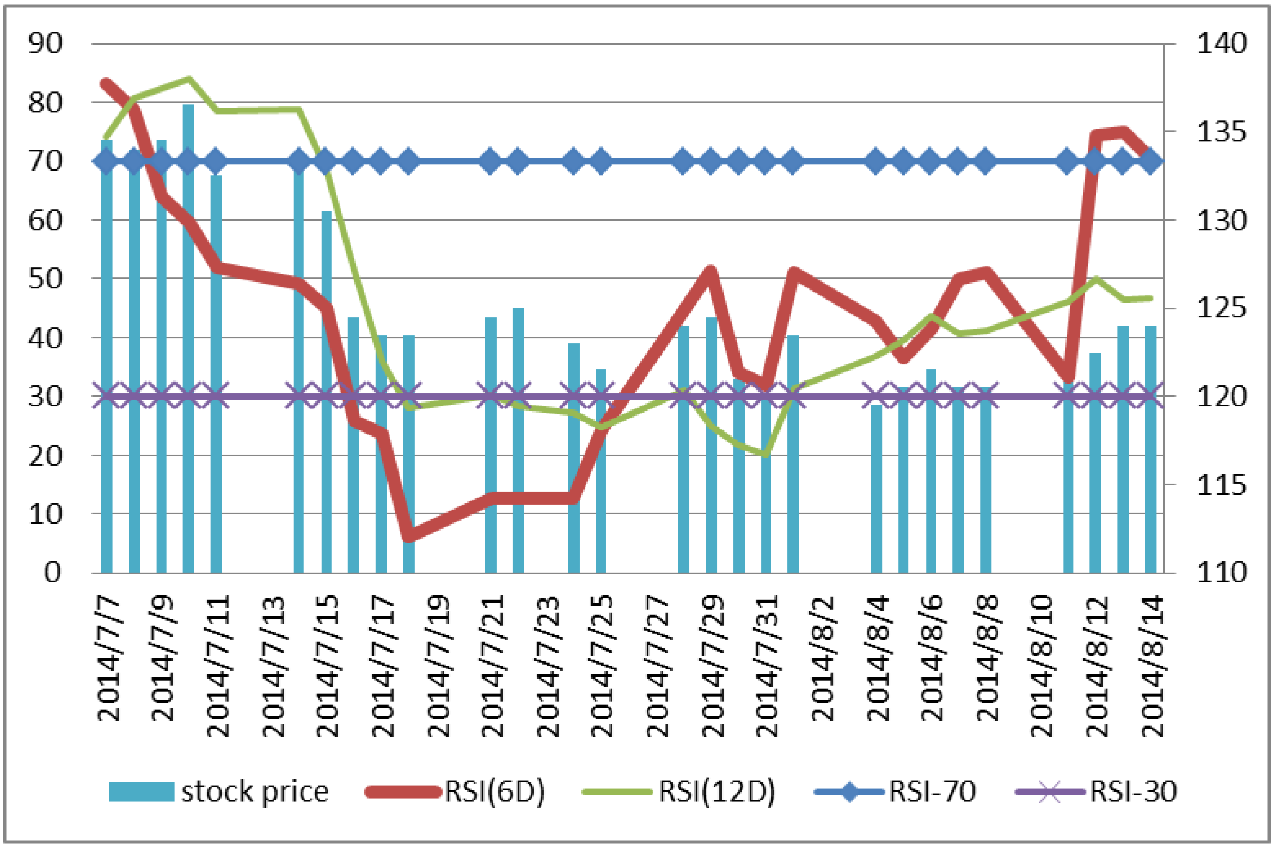

Figure 3.8 RSI index application in TSMC

3.3.4 Psychological line %P

PSY shows the ratio of number of rising period over the total period. Its value lies between 0 and 100. It reflects the buying power in relation to the selling power in the market. It is a very simple indicator as it shows the ratio of rising period to total which indicates control of buyers and sellers. Divergence between price and PSY helps to give strong reversal indications. To calculate the Psychological line %P:

%P=100*(number of rising period over the total period)/(number of the total period)

If %P value is above 75, means that buyers are in control of the price.

If %P value is below 25, means sellers are in control of the price. Example of Psychological line index (12-day) application is shown in Figure 3.9, we develop a PSY %P setting rule:

Rule 1:“Buy” when values %P above 80 as oversold, the target value is identified as “Buy”, labeled as "1".

Rule 2: “Sell”, labeled as "-1" if values %R below 20 as overbought.

Rule 3: If not in the cases of the above, the target value is identified as “Hold”, labeled as “0”.

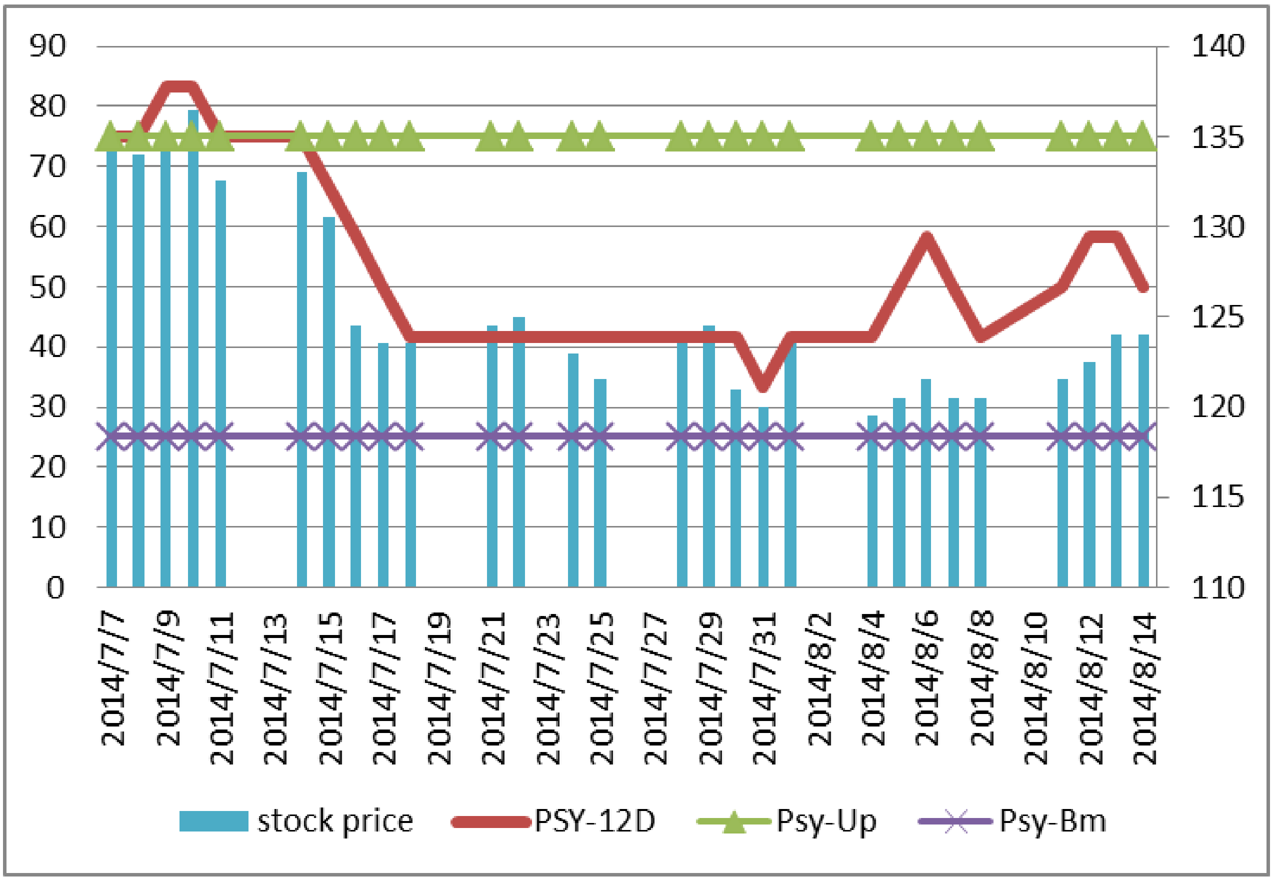

Figure 3.9 Psychological line index application in TSMC

3.3.5 Bias Indicator

The Bias Indicator is defined in terms of time and price. The Bias Indicator is used to measure the offset level between daily stock price and a period moving average line. The price eventually comes back to the neighboring price of moving average when the stock price is far off the moving average line. The price will be in balance state with moving average line. The Bias Line Indicator is a useful trade filter. Take only long trades when prices are above the Bias Line and only short trades when prices are below it. To calculate the Bias indicator,

Bias(n) = (close(today) － Average close(last n days))/ Average close(last n days)

BIAS index setting rules:

Rule 1:“Buy” when either Bias(10) < -4.5% or Bias(20) < -7% , the target value is identified as “Buy”, labeled as "1".

Rule 2: “Sell”, labeled as "-1" if Sell when either Bias(10) > 4.5% or Bias(20) >7%.

Rule 3: If not in the cases of the above, the target value is identified as “Hold”, labeled as “0”.

Example of Bias index (10-day and 20-day) application is shown in figure 3.1.5.

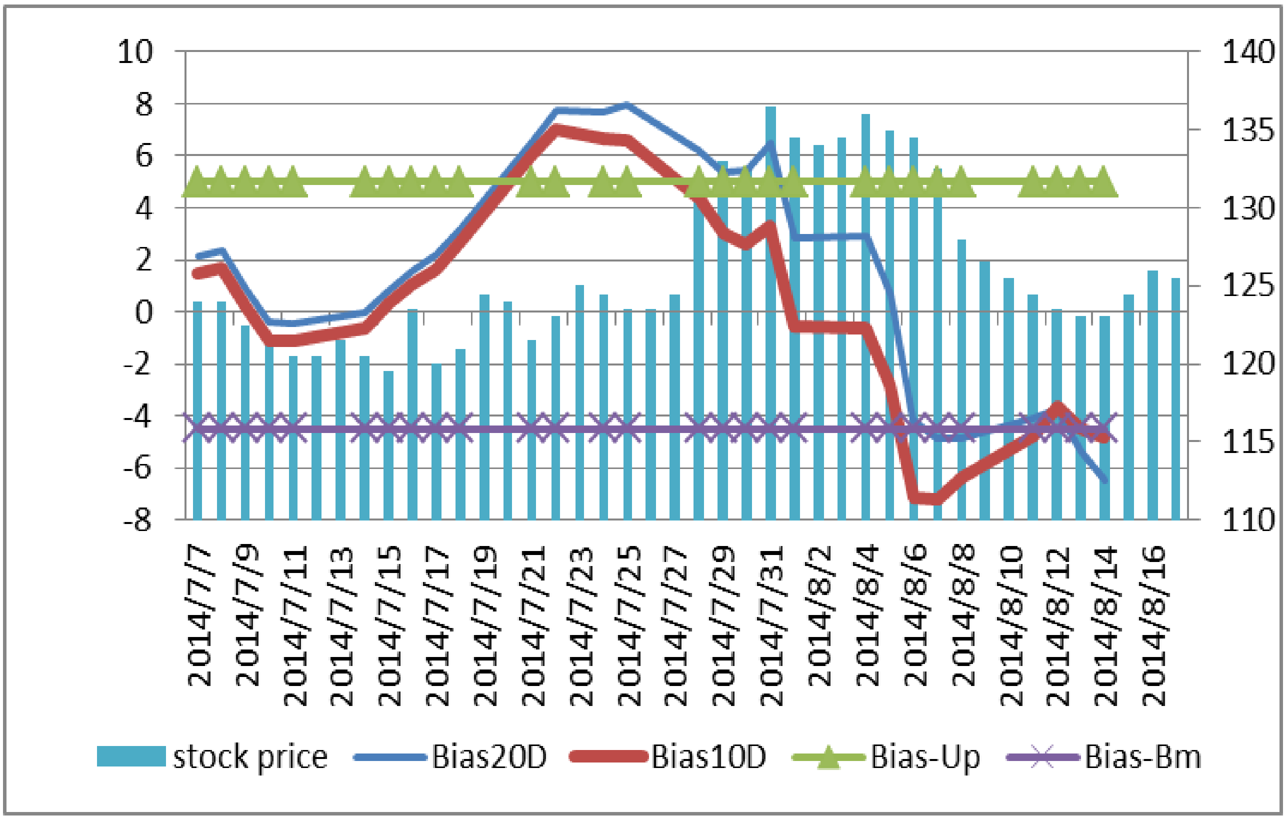

Figure 3.10 Bias index application in TSMC

3.3.6 ADX Indicator

The ADX Indicator (average directional movement index) determines the market trend. When used with the up and down directional indicator values, +DI and -DI, the DMI is an exact trading system. The standard interpretation for using the ADX is to establish a long position whenever the +DI crosses above the -DI. You reverse that position, liquidate the long position and establish a short position, when the -DI crosses above the +DI. The ADX is a combination of two other indicators, the positive directional indicator (abbreviated +DI) and negative directional indicator (-DI). The ADX combines them and smooth the result with an exponential moving average. To calculate the ADX indicator:

To calculate +DI and −DI, one needs price data consisting of high, low, and closing prices each period (typically each day).

One first calculates the directional movement (+DM and −DM):

UpMove = today's high − yesterday's high

DownMove = yesterday's low − today's low

if UpMove > DownMove and UpMove > 0,

then +DM = UpMove,

else +DM = 0

if DownMove > UpMove and DownMove > 0,

then −DM = DownMove,

else −DM = 0

+DI = 100 times exponential moving average of +DM divided by average true range

−DI = 100 times exponential moving average of −DM divided by average true range

The range of a day's trading is simply high-low. The true range extends it to yesterday's closing price if it was outside of today's range.

True range = max [(high – low), abs(high – closeprev), abs(low- closeprev)]

The average true range is an N-day exponential moving average of the true range values. The true range is the largest of the:

- Most recent period's high minus the most recent period's low
- Absolute value of the most recent period's high minus the previous close
- Absolute value of the most recent period's low minus the previous close

The exponential moving average is calculated over the number of periods selected, and the average true range is an exponential average of the true ranges.

Then: $ADX = 100\ (+DI - -DI) / (+DI + -DI)$

For some traders, the most significant use of the ADX is the turning point concept. First, the ADX must be above both DI lines. When the ADX turns lower, the market often reverses the current trend. The ADX serves as a warning for a market about to change direction. Stop using any trend following system when the ADX is below both DI lines. The market is in a choppy sidewise range with no discernible trend. Example of ADX index (ADX, DI+ and DI-) application is shown in Figure 3.11. It is a momentum indicator, such as the stochastic, that allow traders to determine whether the market is trending or not and to what extent.

ADX index setting rules:

Rule 1:"Buy" when while a value above 30, signals a strong trend, the target value is identified as "Buy", labeled as "1".

Rule 2: "Sell", labeled as "-1" if ADX value that is lower than 20, indicates that the trend is weak,

Rule 3: If not in the cases of the above, the target value is identified as "Hold", labeled as "0".

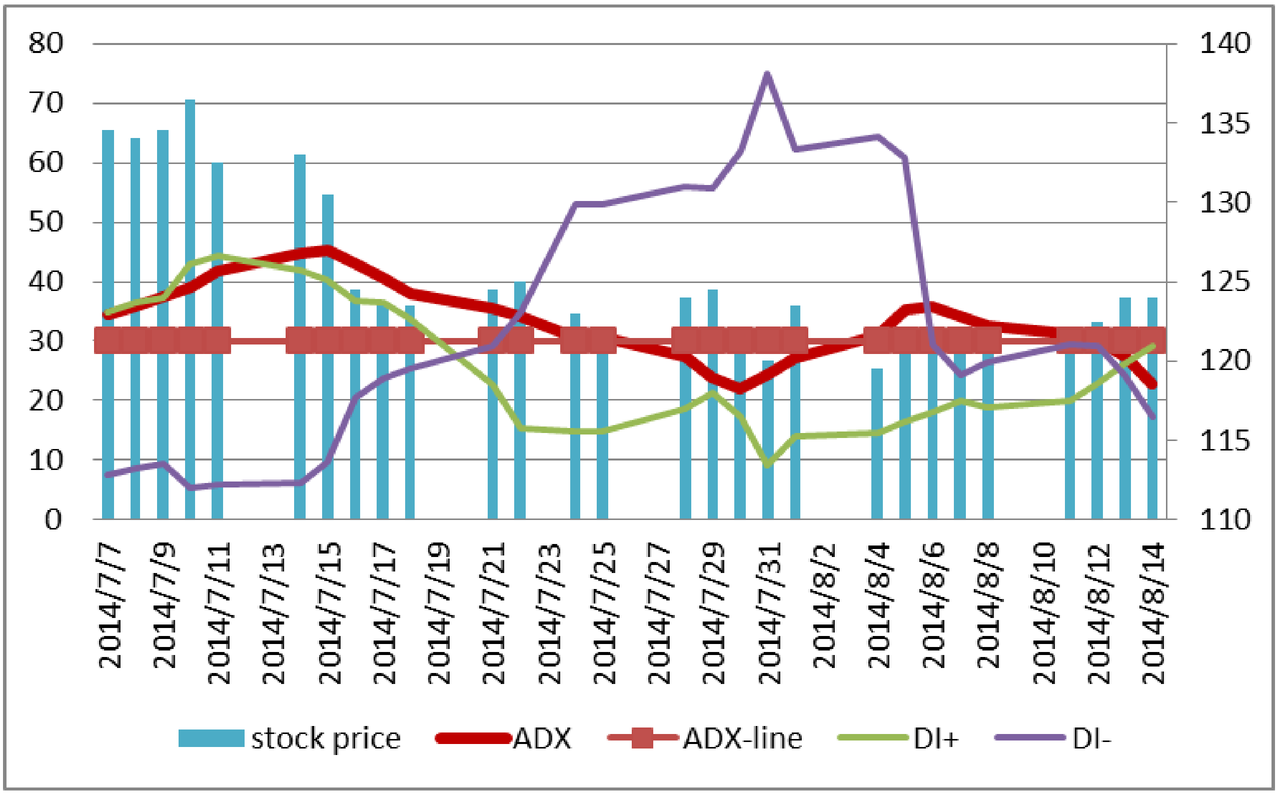

Figure 3.11 ADX index application in TSMC

3.3.7 Moving Averages

A moving average is the average price of a contract over the previous n-period closes. The moving average is used to observe price changes. The effect of the moving average is to smooth the price movement so that the longer-term trend becomes less volatile and therefore more obvious. When the price rises above the moving average, it indicates that investors are becoming bullish on the commodity. When the price falls below, it indicates a bearish commodity. As well, when a moving average crosses below a longer-term moving average, the study indicates a down turn in the market. When a short-term moving average crosses above a longer term moving average, this indicates an upswing in the market. The longer the period of the moving average, the smoother the price movement is.

Longer moving averages are used to isolate long-term trend. To calculate the moving average indicator:

For a n-day sample of closing price, the mean of the previous n days' closing prices. If those prices are PM, PM-1 ,⋯.PM-(n-1) , then the formula is

$$MA = (PM + PM\text{-}1 , +\cdots. + PM\text{-}(n\text{-}1)) / n$$

Example of MA index (5-day, 22-day and 66-day) application is shown in Figure 3.12 and MA index setting rules:

Rule 1:“Buy” when MA(5D) > MA(22D) >MA(66D), the target value is identified as “Buy”, labeled as "1".

Rule 2: “Sell”, labeled as "-1" if Sell when MA(5D) < MA(22D) <MA(66D)

Rule 3: If not in the cases of the above, the target value is identified as “Hold”, labeled as “0”.

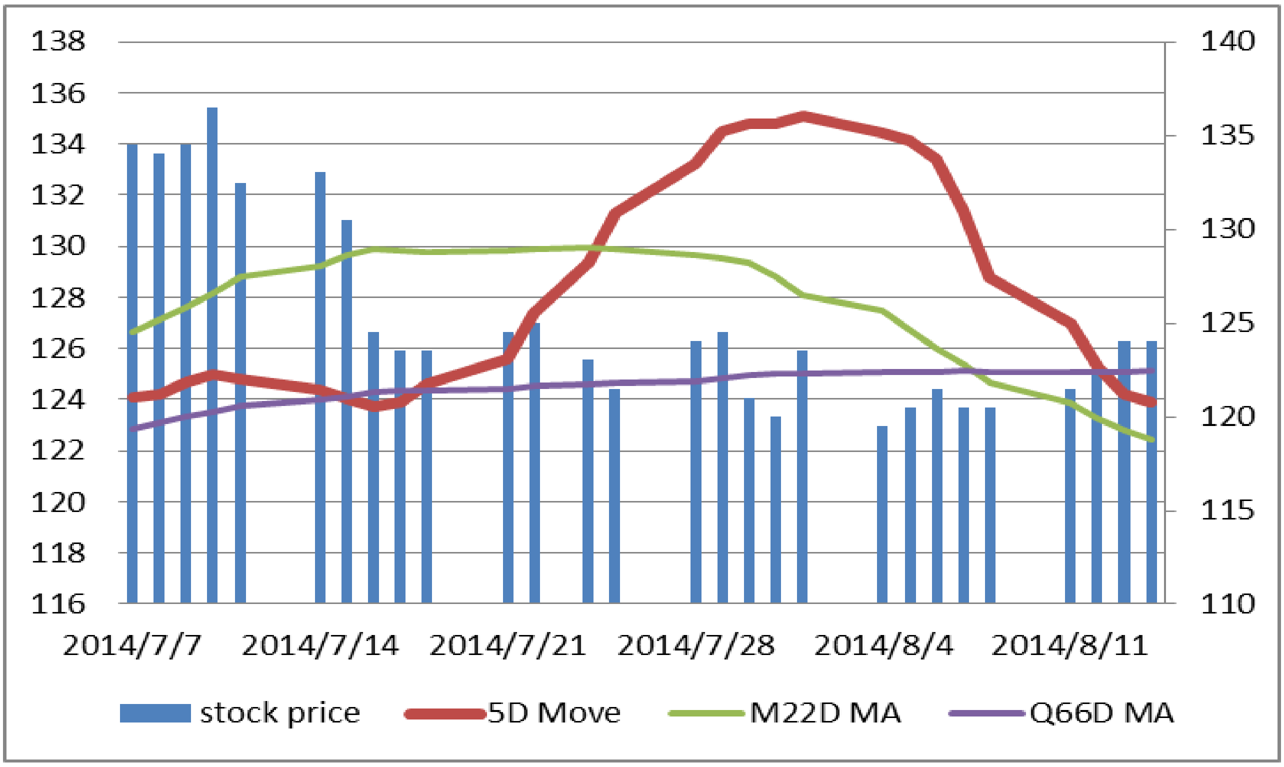

Figure 3.12 Moving average index application in TSMC

3.3.8 MACD Oscillator

The MACD Oscillator is the difference between a short-term and a long-term moving average. The three parameters are the number of periods for the short-term moving average, long-term moving average and the moving average of the resulting MACD Oscillator. In signal processing terms, the MACD is a filtered measure of the derivative of the input (price) with respect to time. A MACD crossover of the signal line indicates that the direction of the acceleration is changing. The MACD line crossing zero suggests that the average velocity is changing direction. The histogram can also help in visualizing when the two lines are approaching a crossover. Though it may show a difference, the changing size of the difference can indicate the acceleration of a trend. A narrowing histogram suggests a crossover may be approaching, and a widening histogram suggests that an ongoing trend is likely to get even stronger. To calculate the MACD indicator:

MACD = EMA[stockPrices,12] – EMA[stockPrices,26]

signal = EMA[MACD,9]

DIF = MACD – signal

An exponential moving average (EMA) is a type of infinite impulse response filter that applies weighting factors which decrease exponentially. The weighting for each older datum point decreases exponentially, never reaching zero. The graph at right shows an example of the weight decrease. The EMA for a series Y may be calculated recursively:

$S_1 = Y_1$,

$S_t = \alpha * Y_t + (1-\alpha) * S_{t-1}$, for $t > 1$

Where the coefficient α represents the degree of weighting decrease, a constant smoothing factor between 0 and 1. A higher α discounts older observations faster. Yt is the value at a time period t. St is the value of the EMA at any time period t. Example of MACD index (MACD and DIF) application is shown in Figure 3.13, MACD target setting rules:

Rule 1:“Buy” when the DIF line starts to rise above the MACD line, the target value is identified as “Buy”, labeled as "1".

Rule 2: “Sell”, labeled as "-1" when the DIF line start to fall below the MACD line.

Rule 3: If not in the cases of the above, the target value is identified as “Hold”, labeled as “0”.

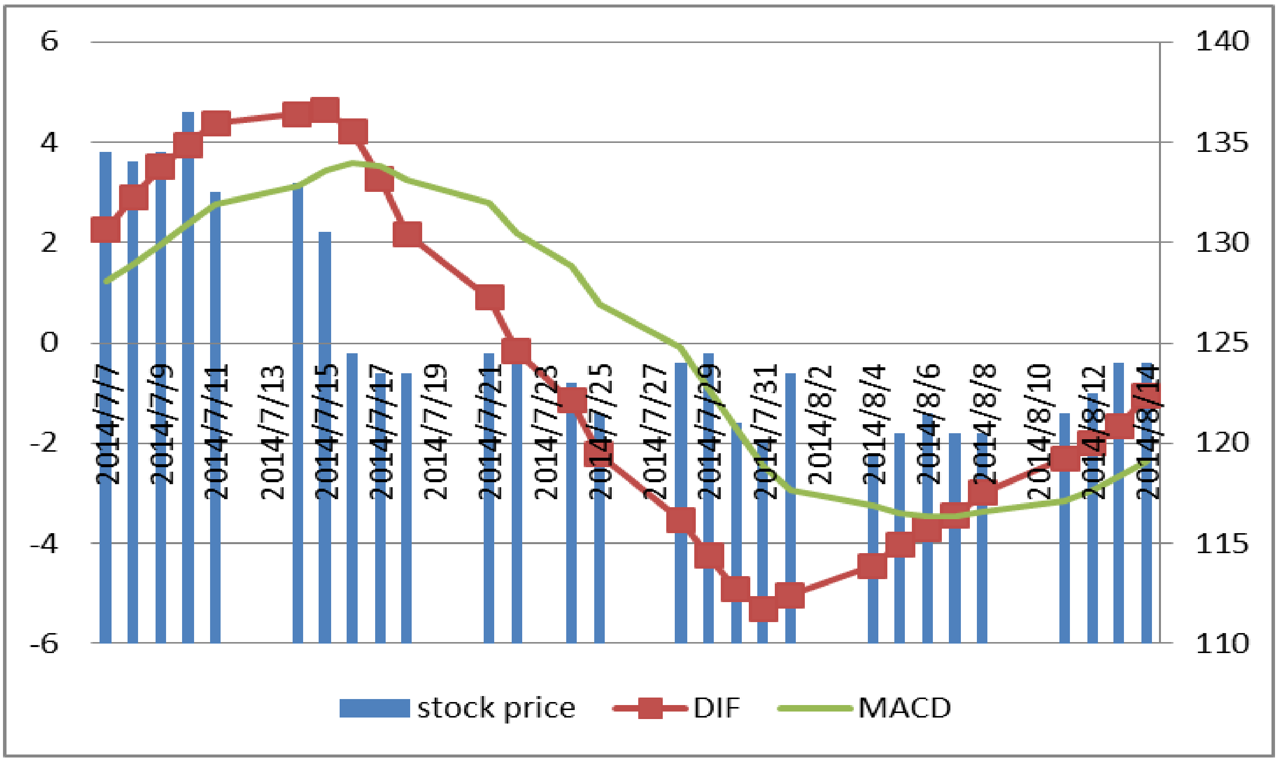

Figure 3.13 MACD index application in TSMC

Table 3.1 Summary of technical indicators

Technical indicator	Main Type	Function Purpose
Stochastics KD	**Momentum**	Represent the position of the market on a percentage basis versus its range over the previous n-period sessions.
Willam %R	**Momentum**	Detect whether a stock is trading near the high or the low or in between of its recent trading range.
RSI	**Momentum**	Measure the velocity and magnitude of directional price movements.
PSY line	**Momentum**	Show the ratio of rising period to total which indicates control of buyers and sellers.
Bias	**Momentum**	Detect the offset level between daily stock price and a period moving average line.
ADX	**Trend**	Determined directional movement by comparing the difference between two consecutive lows with the difference between the highs.
MA	**Trend**	Smooth the price movement so that the longer-term trend becomes less volatile therefore obvious.
MACD	**Trend**	Work as a filtered measure of the derivative of the stock price with respect to time.

3.4 Bayesian Probability (BP)

Bayesian probability is a method used to update the probability estimates for a hypothesis once additional evidences is learned. Bayesian inference is closely related to subjective probability, often called "Bayesian probability". There are many useful functions in Bayesian probability. One is probabilistic learning. BP can calculate explicit probabilities for hypothesis, among the most practical approaches to certain types of learning problems. Each training example can incrementally increase or decrease the probability that a hypothesis is correct. Prior knowledge can be combined with observed data. Even when Bayesian methods are computationally intractable, they can provide a standard of optimal decision making against which other methods can be measured (Spiegelhalter *et al.* 1993, Tsai *et al.* 2010). The formula of BP is expressed as below.

Given n mutually exclusive and exhaustive events E_1, E_2, E_n such that $P(E_i) \neq 0$ for all i, we have for $1 \leqq i \leqq n$;

$$P(E_i|F)=\frac{P(F|E_i)P(E_i)}{P(F|E_1)P(E_1)+P(F|E_2)P(E_2)+\cdots+P(F|E_n)P(E_n)} \quad (1)$$

$P(E_i)$ = Prior probability, $P(E_i|F)$= Posterior probability

Table 3.2 tabulates several technical indicators calculated by BP. It also gives the result of prior probability and posterior probability. The value of each technical indicator stands for the performance accuracy of the individual stock according to the recent 300 trading days. The result can provide a standard of optimal decision making for selecting significant technical indices. We then ignore the technical indicators with low values and select the significant ones. The values of the selected indictors become the inputs of the neural network in the next step. BP screens out the unnecessary technical indicators to preempt possible losing trades. Table 3.2 depicts the results of prior probability and posterior probability calculated by BP over 300 days. For example, P (Stock Up) is a prior probability, stands for the counts of stock price up during this period, divided by 300 days. P (Stock Down) stands for the counts of stock price down during this period, divided by 300 days. The same rule to P(Non) means holds. From this table, we select MA, ADX and William as candidates of significant technical indicators for the ANN in this research.

Table 3.2 Results of prior probability and posterior probability calculated by BP

MA	Bias	MACD	RSI	ADX	K-D	William	PSY
P(Stock UP)	P(Stock UP)	P(Stock UP)	P(Stock UP)	P(Stock UP)	P(Stock UP)	P(Stock UP)	P(Stock UP)
0.23	0.6	0.3	0.1	0.23	0.42	0.23	0.05
P(Stock Down)	P(Stock Down)	P(Stock Down)	P(Stock Down)	P(Stock Down)	P(Stock Down)	P(Stock Down)	P(Stock Down)
0.43	0.2	0.2	0.3	0.2	0.41	0.27	0.06
P(Non)	P(Non)	P(Non)	P(Non)	P(Non)	P(Non)	P(Non)	P(Non)
0.35	0.2	0.5	0.6	0.57	0.17	0.5	0.9
P(Up｜UP)	P(Up｜UP)	P(Up｜UP)	P(Up｜UP)	P(Up｜UP)	P(Up｜UP)	P(Up｜UP)	P(Up｜UP)
0.61	0.48	0.17	0.5	0.51	0.47	0.62	0.45
P(Down｜Down)	P(Down｜Down)	P(Down｜Down)	P(Down｜Down)	P(Down｜Down)	P(Down｜Down)	P(Down｜Down)	P(Down｜Down)
0.48	0.3	0.3	0.11	0.44	0.41	0.4	0.17

3.5 Dynamic Time Series Theory

Exponential smoothing is a technique that can be applied to time series data to either produce smoothed data or make forecast. Time series data themselves are a sequence of observations. The exponential smoothing model for forecasting does not eliminate any past information but adjust the weights given to the past data that older data get increasingly less weight. Each new forecast is based on an average that is adjusted each time there is a new forecast error. The proportion of the error that will be incorporated into the forecast is called the exponential smoothing factor and is identified as α. The raw data sequence is often represented by x_t and the output of the exponential smoothing algorithm is commonly written as Equation (2), which may be regarded as the best estimate of what the next value of x will be. The simplest form of exponential smoothing is given by the formula below,

$$S_1 = X_0$$

$$S_t = \alpha * X_{t-1} + (1-\alpha) * S_{t-1} = S_{t-1} + \alpha * (X_{t-1} - S_{t-1}), \qquad t > 1 \qquad (2)$$

where α is the *smoothing factor*, and $0 < \alpha < 1$. In other words, the smoothed statistic S_t is a simple weighted average of the previous observation x_{t-1} and the previous smoothed statistic S_{t-1}. Values of α close to one have less of a smoothing effect and give greater weight to recent changes in the data, while values of α closer to zero have a greater smoothing effect and are less responsive to recent changes (Billah *et al.* 2006).

Adaptive exponential smoothing methods allow a smoothing parameter to change over time, in order to adapt to changes in the characteristics of the time series. However, these methods tend to produce unstable forecasts and have performed poorly in empirical studies (Taylor 2004, Entorf *et al.* 2012). We present a new adaptive method, which enables a smoothing parameter to be modeled as a linear combination function of the trading volume, trend, and momentum. Figure 3.14 illustrates the closed loop structure of the adaptive exponential smoothing method, where V(i) is the volume indicator of the i^{th} day, T(i) is the trend indicator of the i^{th} day, M(i) is the momentum indicator of i^{th} day, and α(i) is the smoothing factor of the i^{th} day. D(i) is the actual stock value of the i^{th} day, F(i) is the forecast stock value at time i and Z(i) is the deviation of the forecast value at time i. Note that only the smoothing factor of each day at its first processing step is controlled using the deviation between the predicted stock value at the final stage and actual value for the final stage.

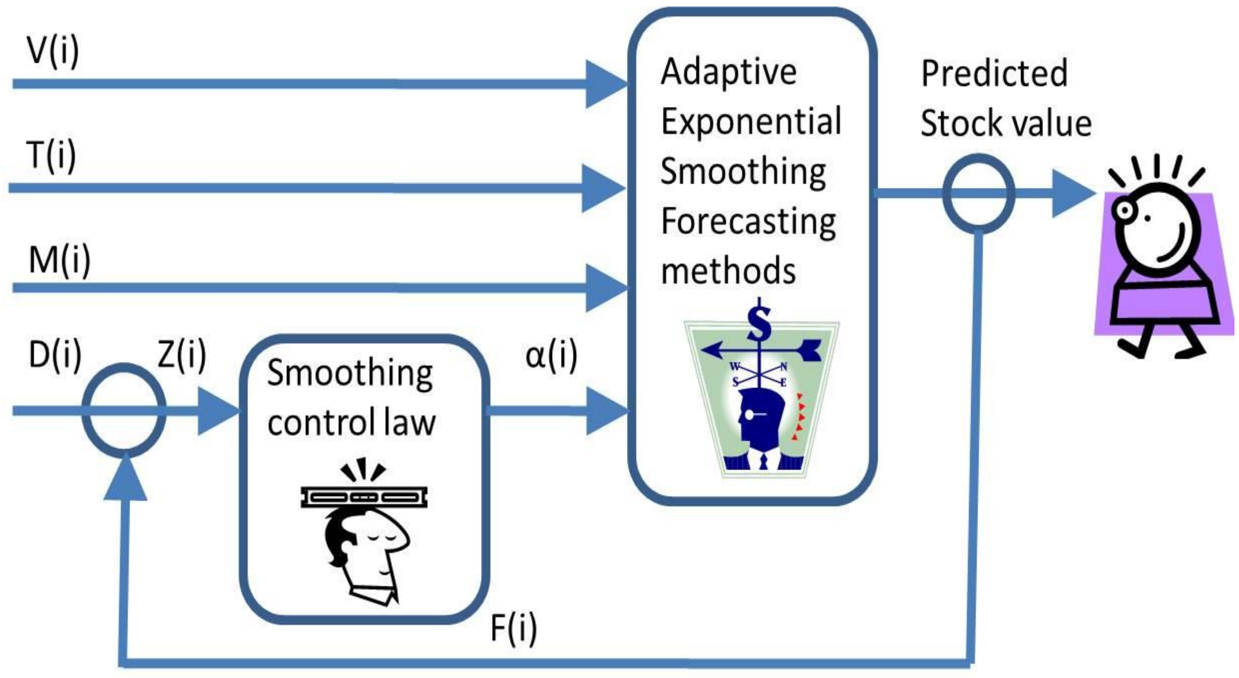

Figure 3.14 the closed loop structure of adaptive exponential smoothing methods

The simplest form of adaptive exponential smoothing is given by the formula below,

$$F(i)= \alpha(i)*D(i-1)+(1-\alpha(i))*F(i-1) \qquad (3)$$

where $\alpha(i)=\alpha(i-1) + \beta*(V(i) +T(i)+M(i))$ and β is a small coefficient value less than 0.05 and is used to fine tuning $\alpha(i)$ according to the following setting steps:

Step 1: V(i) is the volume indicator of the i^{th} day.

- If the stock transaction volume of today is more than twice of yesterday's volume, then V(i) =1
- If the stock transaction volume of today is less than half of yesterday's volume, then V(i) = -1
- Otherwise, V(i) = 0

Step 2: T(i) is the trend indicator of the i^{th} day,

- If Bias (10) < -11%, then T(i) =1
- Else, If Bias (20) > 7% % , then T(i) = -1
- Otherwise, T(i) = 0

Step 3: M(i) is the momentum indicator of i^{th} day

- If ADX >=30, then M(i) =1
- Otherwise, M(i) = 0

The adaptive exponential smoothing α is used to examine the performance of the exponential smoothing with fixed α. The investment horizon is 60 days, from September 2012 to November 2012. Figure 3.15 compares the performance of the adaptive exponential smooth alpha to those of 3 distinct alpha values at 0.3, 0.4

and 0.5.   It is seen in Figure 3.15 that the adaptive alpha follows the actual stock up/down value much closely than the other three lines. The adaptive exponential smoothing target setting rules is as follows.

Rule 1: As the forecasting stock value increases and the up value is over the stock transaction tax, the target value is identified as “Buy”, labeled as "1".

Rule 2: “Sell”, labeled as "-1" if the forecasting stock value decreases and the down value is more than the stock transaction tax.

Rule 3: If not in the cases of the above, the target value is identified as “Hold”, labeled as “0”.

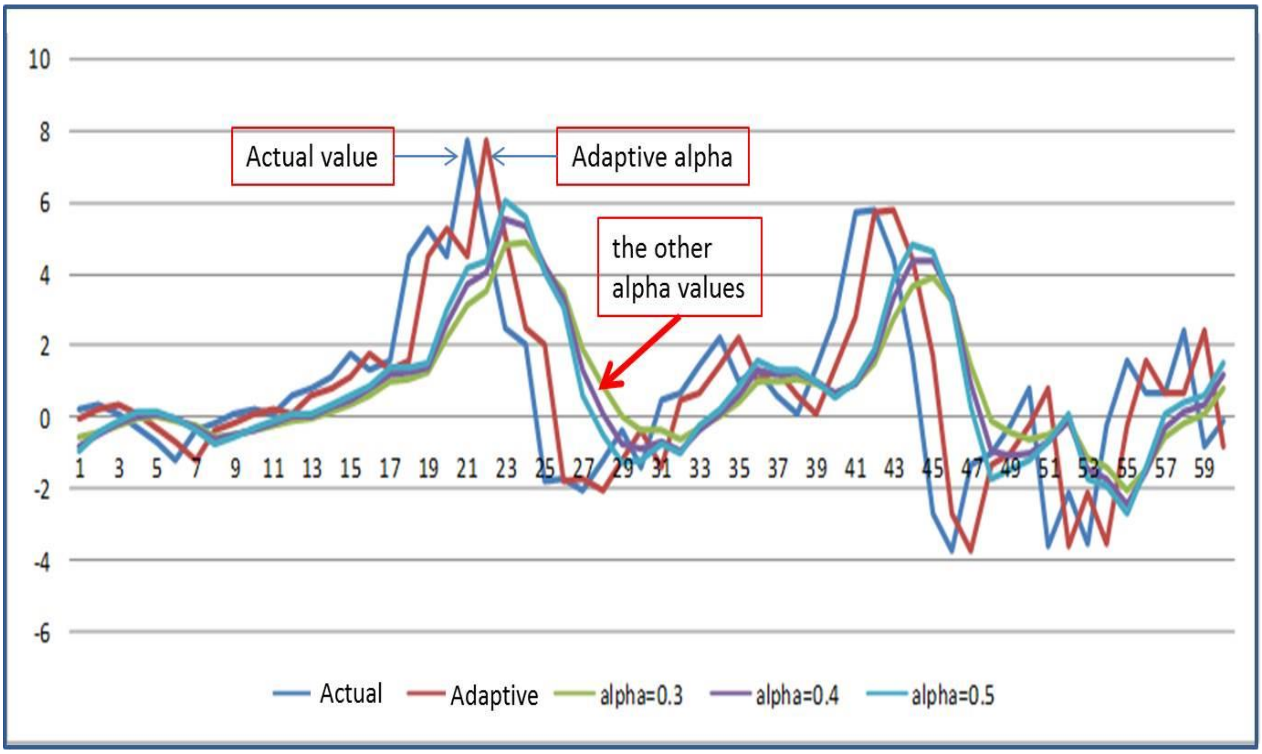

Figure 3.15 performance comparisons between the adaptive alpha and the other alpha values

3.6. Artificial neural networks training

Many ANN models have been evaluated against statistical models for market forecast. It is observed that in most cases ANN models give better result than other methods (Chen *et al.* 2003) The most commonly used neural network technique in pattern recognition is Multi- Layer Perceptron (MLP) for the classification problems. MLP architecture using back propagation (BP) algorithm has gone into the application field of ANN to stock price prediction. Two important characteristics of the MLP are its nonlinear processing elements (PEs, applying the sigmoid function in this research) and their massive interconnectivity. Sigmoid functions all share a similar S shape that is essentially linear in their center and nonlinear toward their bounds that are approached asymptotically. To find the optimal neural weights by the back-propagation algorithm based on mathematically training a network in order to minimize the error of a cost function such as the Mean Squares Errors (MSE), it is required that the sigmoid function is easily differentiable, thus permitting the evaluation of increment of weights via the chain-rule for partial derivatives (Yonaba et al., 2010). The back-propagation rule propagates the errors through the network and allows adaptation of the hidden PEs. The MLP is trained with error correction learning, which means that the desired response for the system must be known. Learning typically occurs by example through training, where the training algorithm iteratively adjusts the connection weights. When the network is adequately trained, it is able to generalize relevant output for a set of input data. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples. MSE is the average squared difference between outputs and targets. Since the forecasting problem has been converted to a classification problem (Hajizadeh *et al.* 2010), we develop a new target setting rules.

Rule 1: As the stock value increases and the up value is over the stock transaction tax, the target value is identified as “Buy”, labeled as "1".

Rule 2: “Sell”, labeled as "-1" if the stock value decreases and the down value is more than the stock transaction tax.

Rule 3: If not in the cases of the above, the target value is identified as “Hold”, labeled as “0”.

The desired ANN response is the target value set to reflect the actual stock performance (Wang and Chan, 2007). In this study, the ANN input data include the top down scores, selected key technical indicators and the forecasting value, totally five input data. Three output units are “Buy,” “Sell” and ‘Hold”, respectively. The number of hidden neurons is 20. The diagram of ANN training layer is shown in Figure 3.16.

The standard operation procedure to perform ANN system is as following three steps:

Training => Validation => Testing.

We set aside some samples for validation and testing. The percentage of training data is set 70%, validation is 15% and 15% for testing data. The gate of MSE is set $3x10^{-2}$. Figure 3.17 depicts the MSE decreasing after 57 epochs in TSMC.

The ANN system is trained to distinguish among “Buy,” “Sell” and “Hold” A confusion matrix summarizes the results of testing the algorithm for further inspection (Simon and Simon, 2010). Figure 3.18 shows the classification results for the whole testing period. It shows a sample set of 144 stock up/down values: 68 Buys, 66 Sells, and 40 Holds. Each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. All correct predictions are located in the diagonal of the table, so it is easy to visually inspect the table for errors, as they will be represented by any non-zero values outside the diagonal. Figure 3.18 shows the true positive rate of "Buy," "Sell" and "Hold" as 98.5%, 97% and 97.5%, respectively. Overall, the true positive rate is 97.7%.

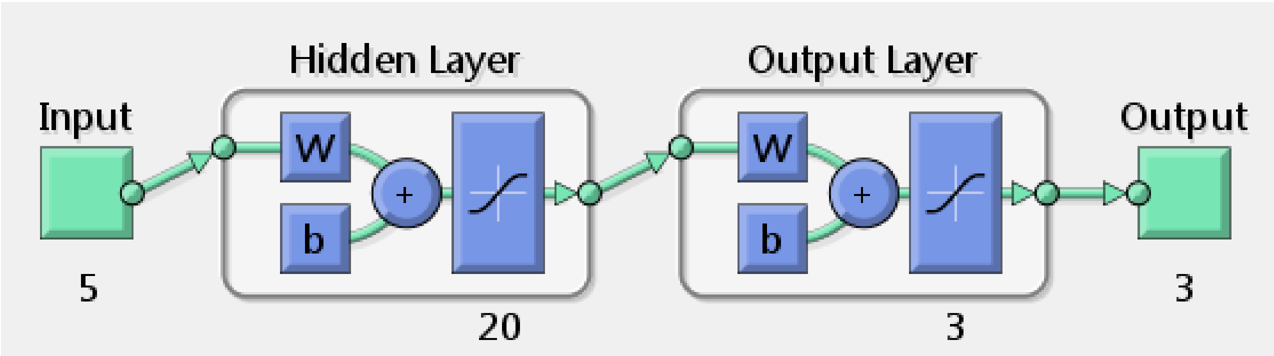

Figure 3.16 the learning layer of ANN structure

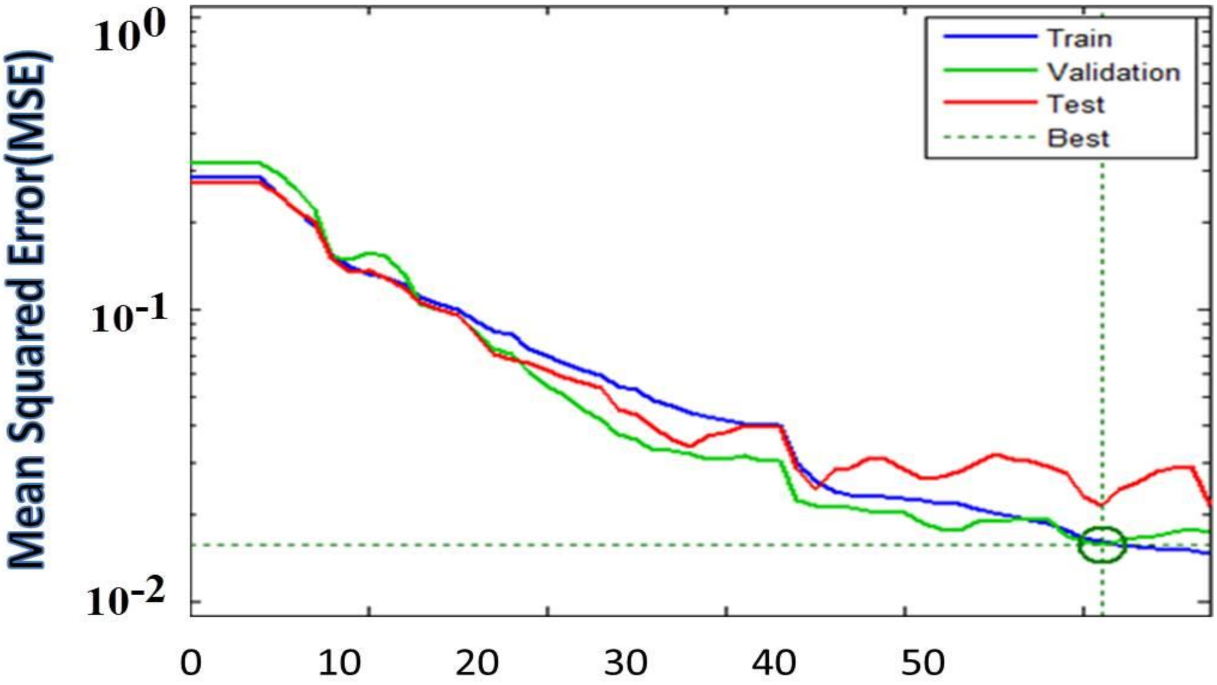

Figure 3.17 MSE decreases after a period of training in TSMC

		Target Class (Predicted)			Total	True Positive Rate
		Buy	Sell	Hold		
Output Class (Actual)	Buy	67	1	0	68	98.50%
	Sell	1	64	1	66	97.00%
	Hold	0	1	39	40	97.50%

Figure 3.18 TSMC training confusion matrix has been trained to distinguish between "Buy", "Sell" and 'Hold"

4. Experimentation setup and test results

4.1. Experimentation simulation and system verification

Three case studies of simulation are used to verify and to validate the system correction. Case one is Taiwan UMC company, a global semiconductor foundry that provides advanced technology and manufacturing for applications spanning every major sector of the IC industry. UMC's robust foundry solutions allow chip designers to leverage the company's leading-edge processes. Case two is Taiwan HannStar Display Corporation, which is specialized in the manufacturing of TFT-LCD products and these main applications are in notebook computer displays and desktop computer monitors. Case three is Taiwan Calin Technology Co. Ltd., which is specialized in aspherical glass molding lenses and provides complete vertical integration process capability with advanced excellent mechanical equipment. The design model of simulation is based on the parameters of stock price up, down and flat during short period(40 days), medium period(50 days) and a longer period(120 days). The table is shown as Table 4.1

Case 1: over 40 days trading days, UMC stock price began with NT$13.25 on April 25th, 2013 and end up NT$13 on July 21rd, 2013. The rate of corresponding stock price over this period is almost flat (from 13.25 to 13) – but an investment return reaches 92.7.6%!(See Figure 4.1).

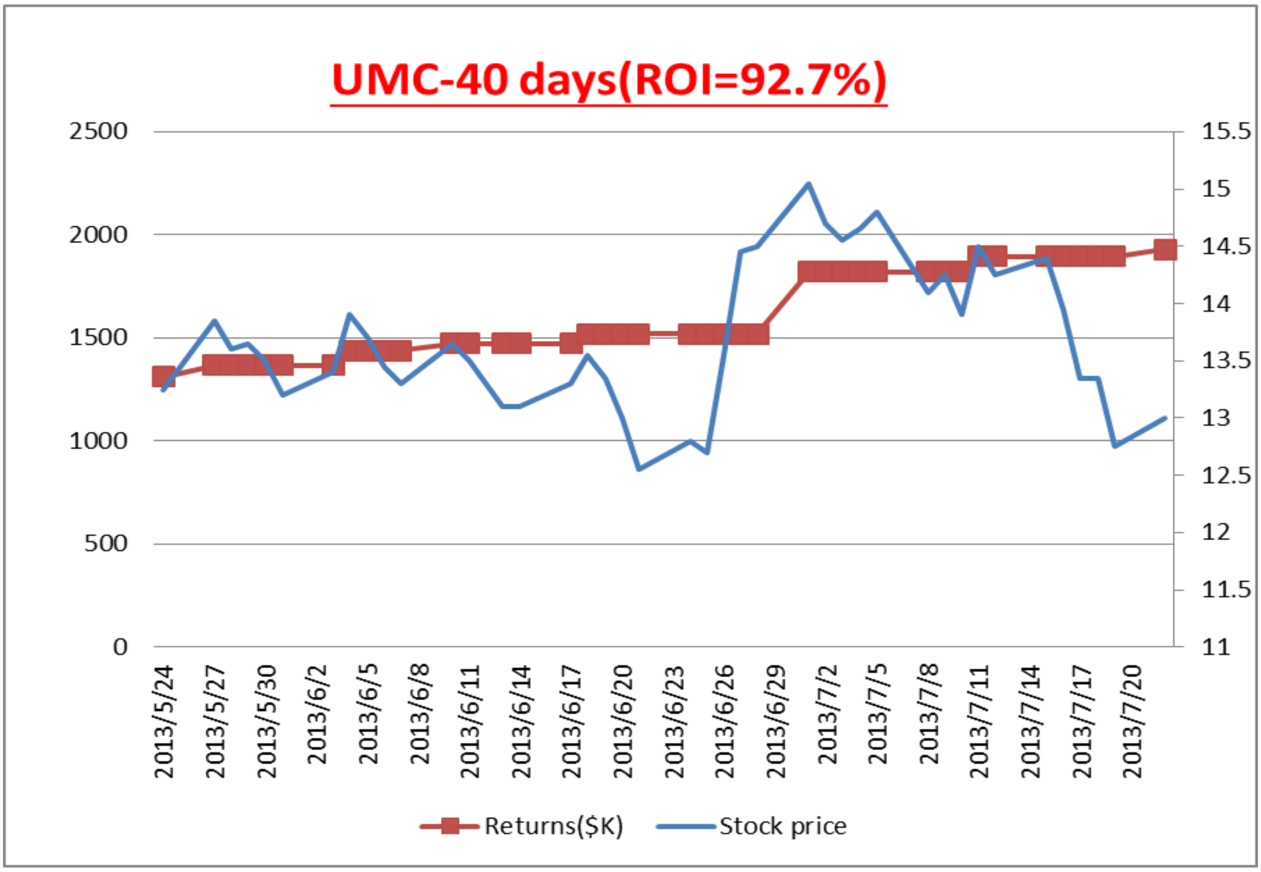

Figure 4.1 simulation of stock price flat and the return of investment is 92.7%

Case 2: over 120 days trading days, Hannstar stock price began with NT$40 on November 18th, 2012 and end up NT$13 on May 7rd, 2013. The rate of corresponding stock price over this period is increasing – but an investment return reaches 67.7%! (See Figure 4.2).

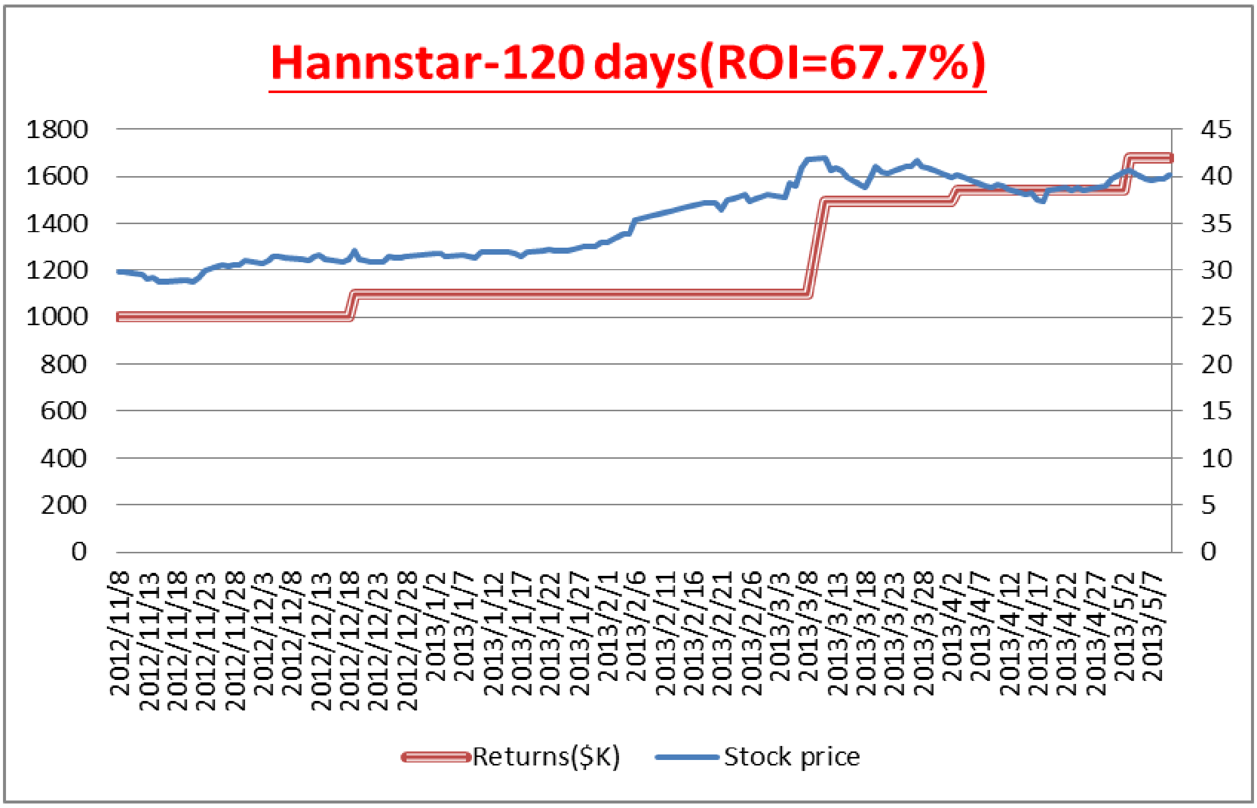

Figure 4.2 simulation of stock price up and the return of investment is 67.7%

Case 3: over 50 days trading days, Calin stock price began with NT$ 33.5 on October 2th, 2013 and end up NT$27 on December 10, 2013. The rate of corresponding stock price over this period is decreasing – but an investment return reaches 23.7%! (See Figure 4.3).

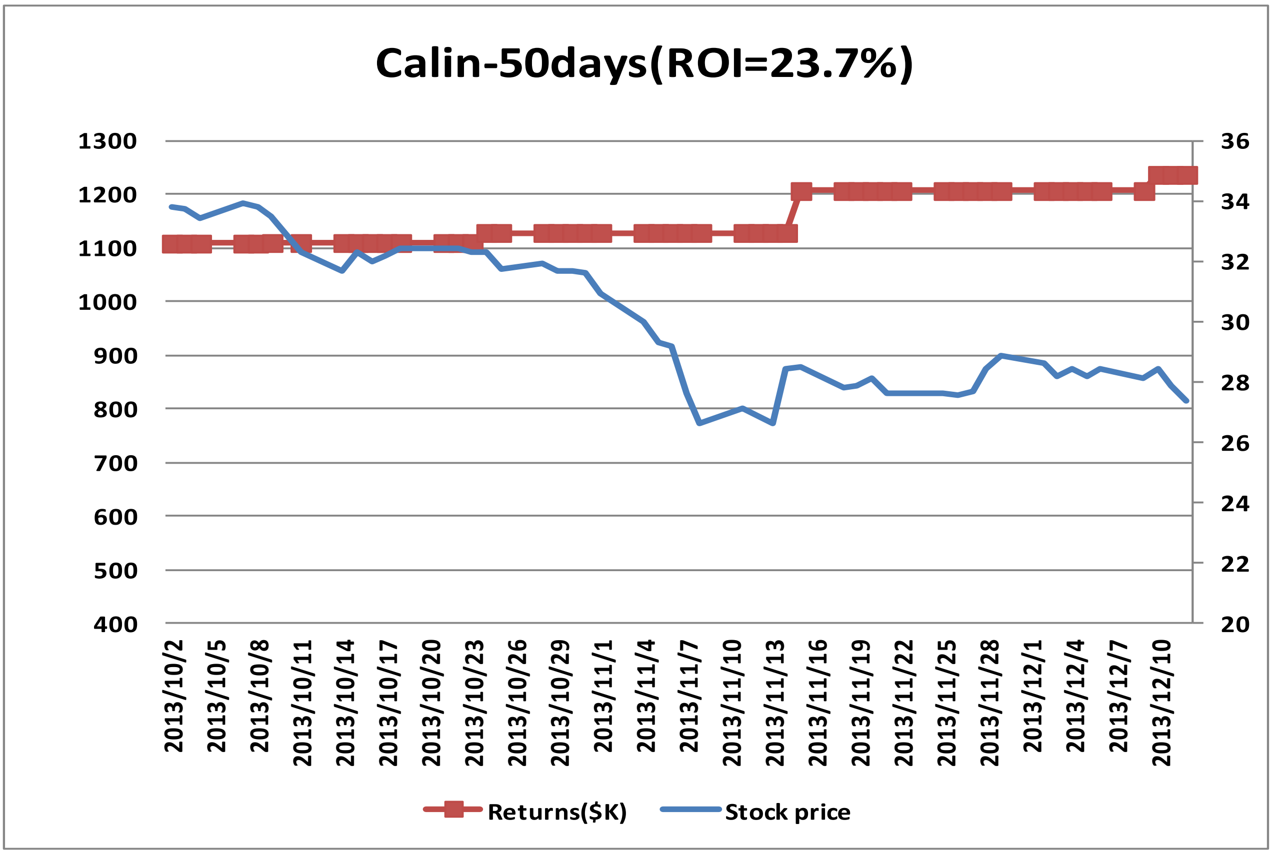

Figure 4.3 simulation of stock price down and the return of investment is 23.7%

Table 4.1 The design model of stock trading forecasting

Time period \ Stock price	Down	Flat	Up
40 days		UMC	
50 days	Calin		
120 days			Hannstar

4.2 One year period

240-trading-day stock data were considered for training and evaluating the performance of the presented approach. The system was retrained daily. A paper portfolio of NT$1,000,000 was the initiation investment. Stocks were bought whenever the forecast was positive, and the position was closed when the forecast became negative. Transaction costs were taken into consideration and were amount to 0.6% of the individual stock trading price. The system was coded in Microsoft VBA and the neural network analysis was run in MATLAB. It is noted that this period also includes the great recession, European debt crisis and the fiscal cliff of the United States in 2012.

TSMC stock was tested first. Experiments were carried out on a personal computer. The rate of accuracy of the proposed approach was 81%. The moving hit-rate is illustrated in Figure 4.4 which shows the hit rate since the first day of this period. A hit rate is a term used to describe the success rate of an effort. This rate compares the number of times an initiative was a success against the number of times it was attempted. The moving hit-rate of TSMC converges towards 0.8. The TSMC stock price began with NT$78.5 on Feb.16th, 2012 and reached NT$101 on January 23rd, 2013. The corresponding stock price increasing rate over this period is 23% – an investment return of 53.6%! (See also Figure 4.5).

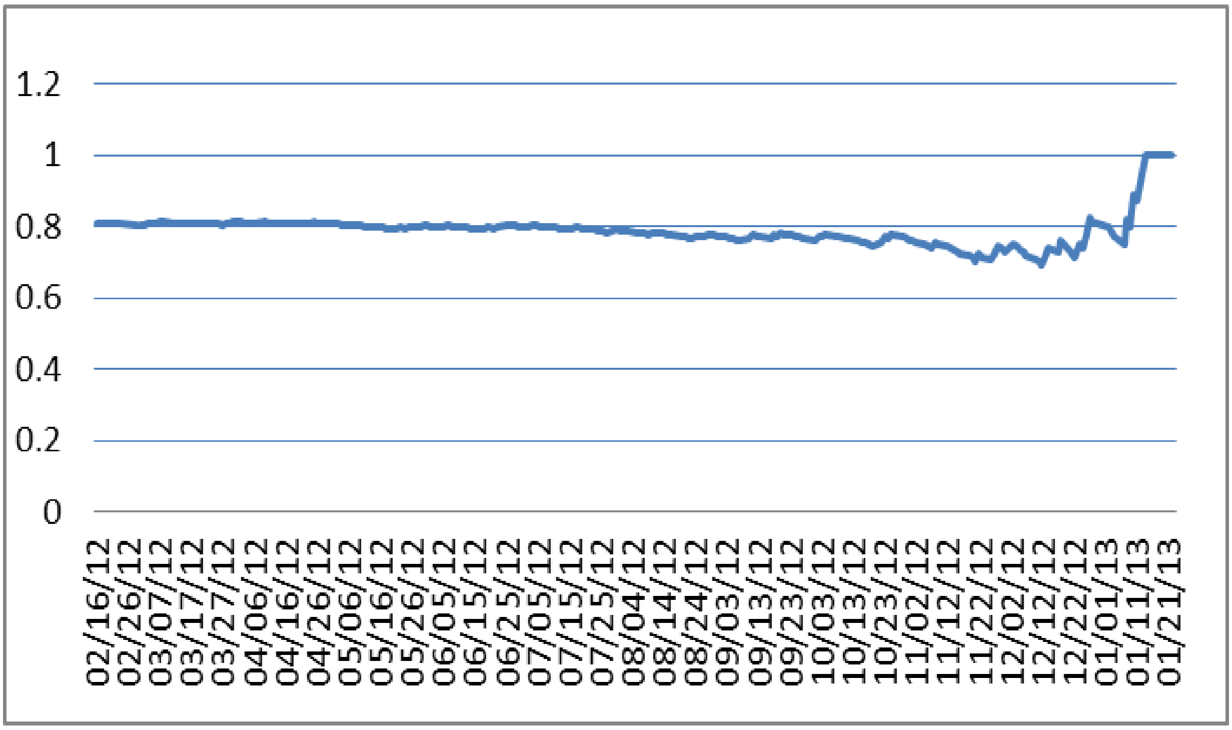

Figure 4.4 the moving hit rate in the period of 240 trading days

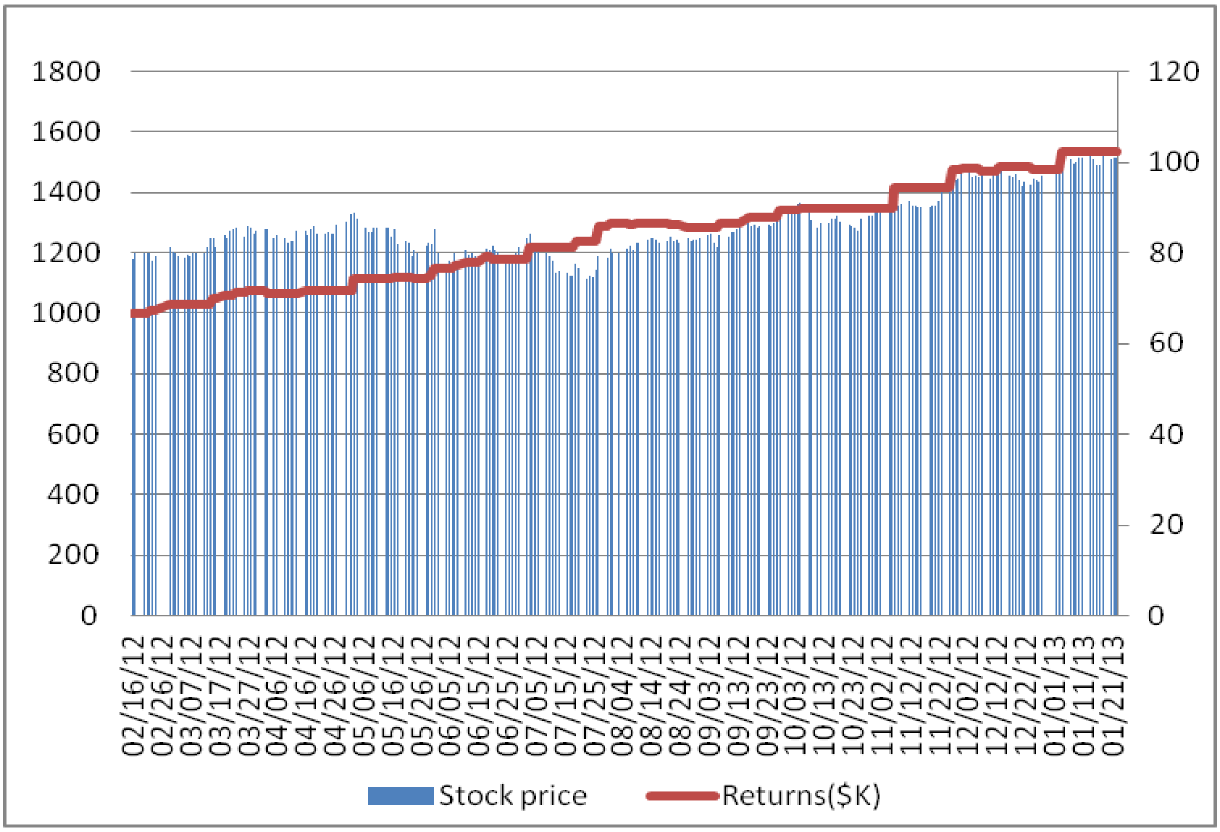

Figure 4.5 the returns of investment and the variation of stock price in a year

To compare the performances of different time periods, this period is broken into three sub-periods; namely, one month, one quarter and a half year. In Section 4.6, the system is again applied to the Evergreen stock to compare the investment performance.

4.3 First period: 12/24/2012 – 01/23/2013

For each period, the result includes the portfolio return being compared to the initial investment of NT$1million. The moving hit rate is a diagram which shows the hit-rate since the first day of this period. The return of investment is 3.6%. The accurate rate of this period is 70%. It can be seen in Figure 4.6 that the moving hit-rate converges towards 0.8. The TSMC stock price rose from NT$95 to NT$101.5, the stock price increasing rate of the period is up 5% as shown in Figure 4.7.

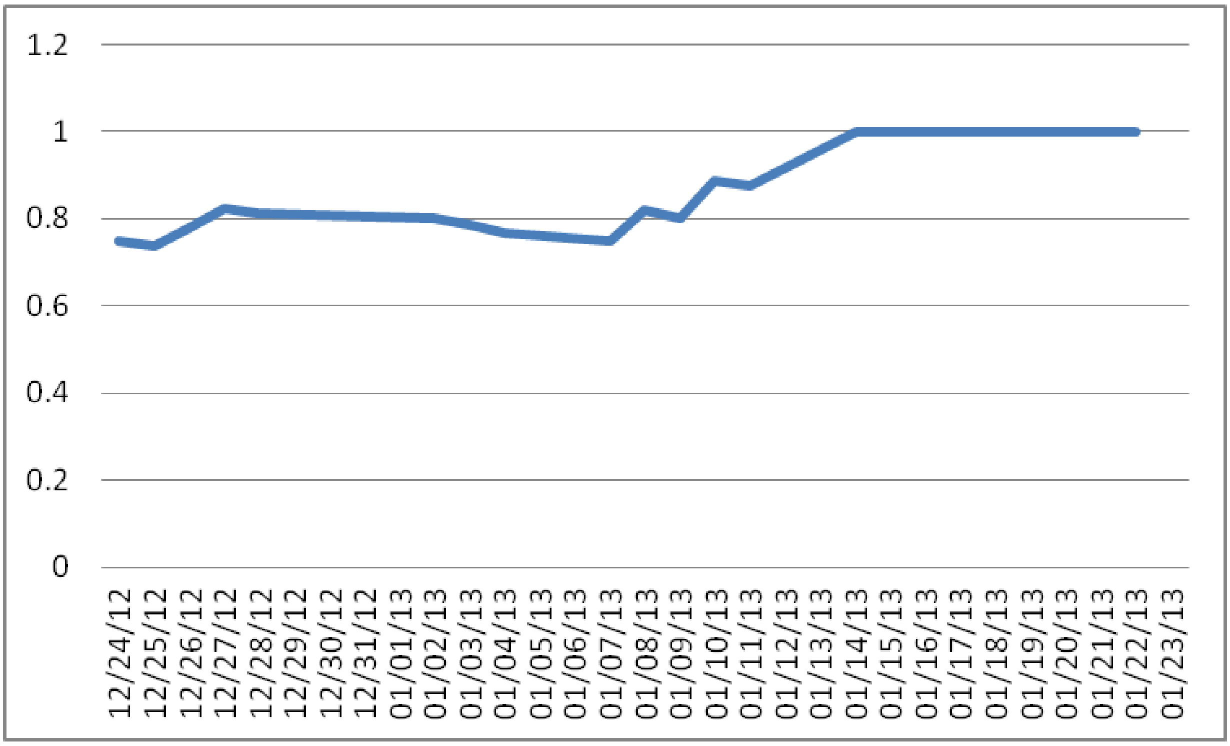

Figure 4.6 the moving hit rate in the first period of 20 trading days in TSMC

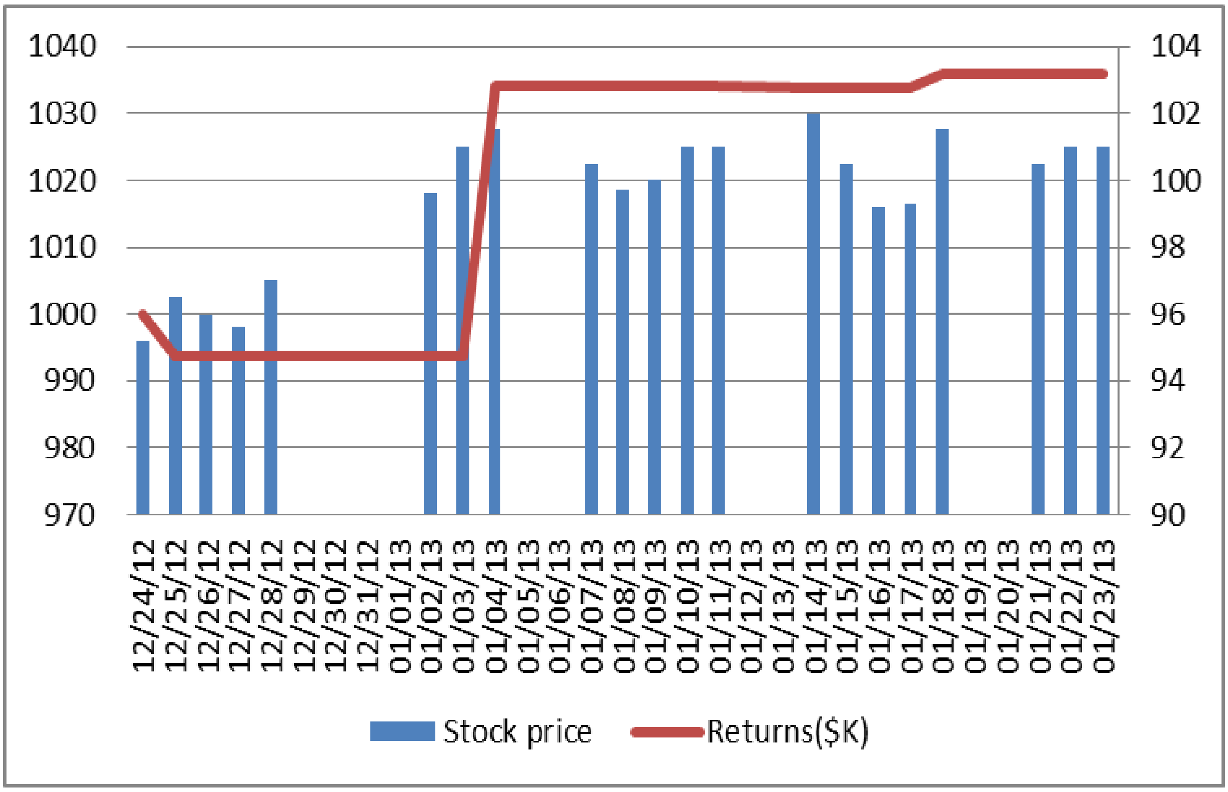

Figure 4.7 the returns of investment and the variation of stock price in the first period

4.4 Second Period 10/30/2012 – 01/23/2013

During this second period of 60 trading days, the results are even better. Again, the results include the portfolio return being compared to the initial investment of NT$1million. The return of investment achieves 8.6%. The rate of accuracy of this period is 75%. It can be seen in Figure 4.8 that the moving hit-rate converges towards the 81% region. The TSMC stock price increased from NT$88 to NT$101.5, the up rate of this period is up 12% as seen in Figure 4.9.

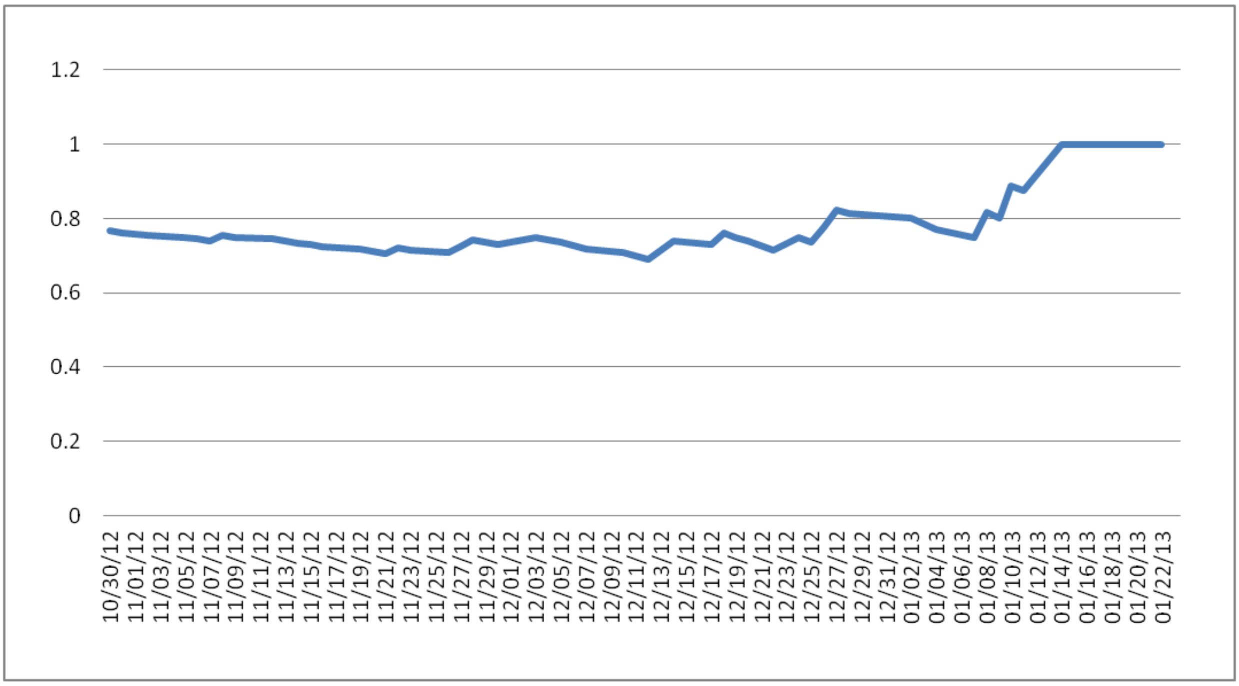

Figure 4.8 the moving hit rate in the second period of 60 trading days

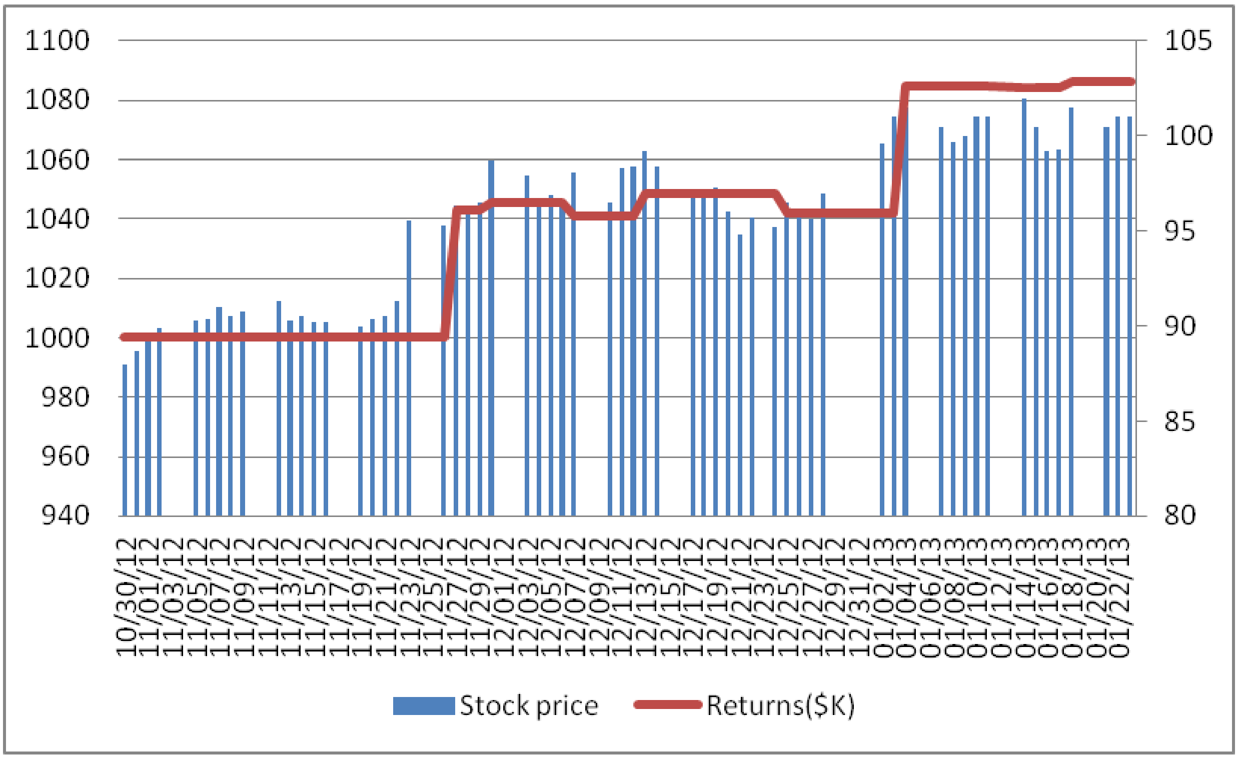

Figure 4.9 the returns of investment and the variation of stock price in the 2nd period

4.5 Third period 08/06/2012 – 01/23/2013

The portfolio return as compared to the initial investment is again considered. The return of investment achieves 18.7%. The rate of accuracy of this period is 77.5%. It is seen in Figure 4.10 that the moving hit-rate converges towards 0.8. The stock price began from NT$81 to NT$101.5, while the increasing rate of the stock price during this period is up 19% up, as indicated in Fig. 17.

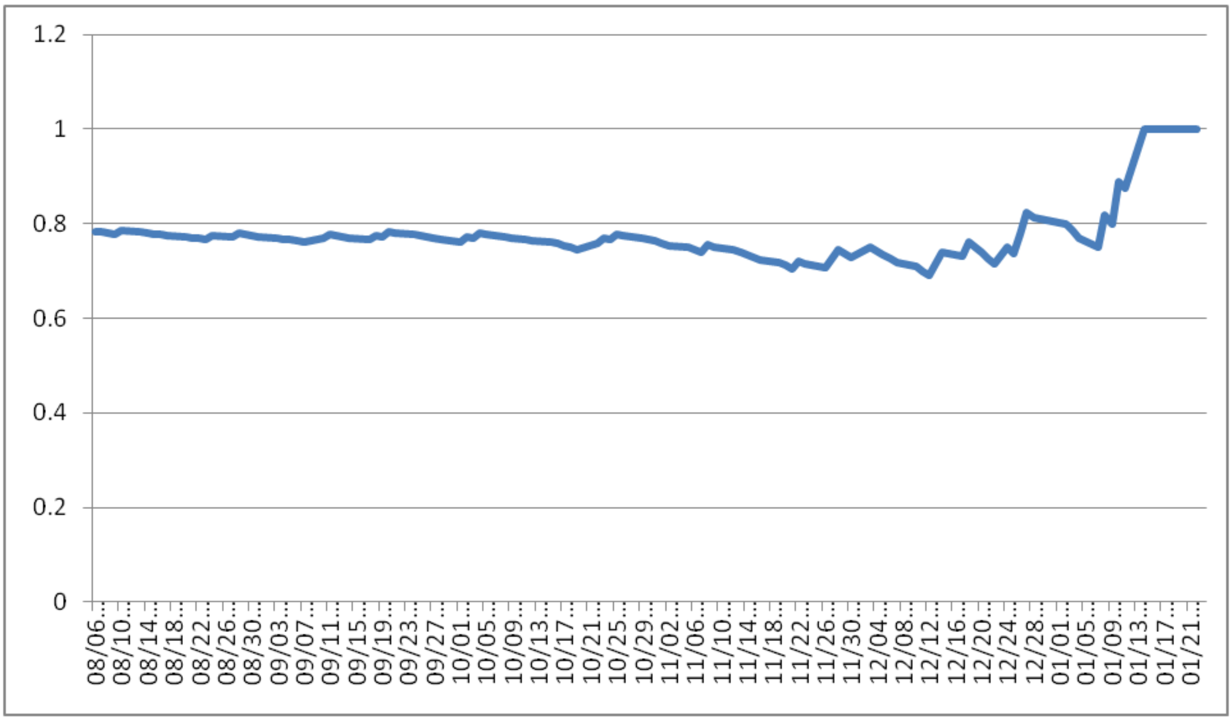

Figure 4.10 the moving hit rate in the third period of 120 trading days

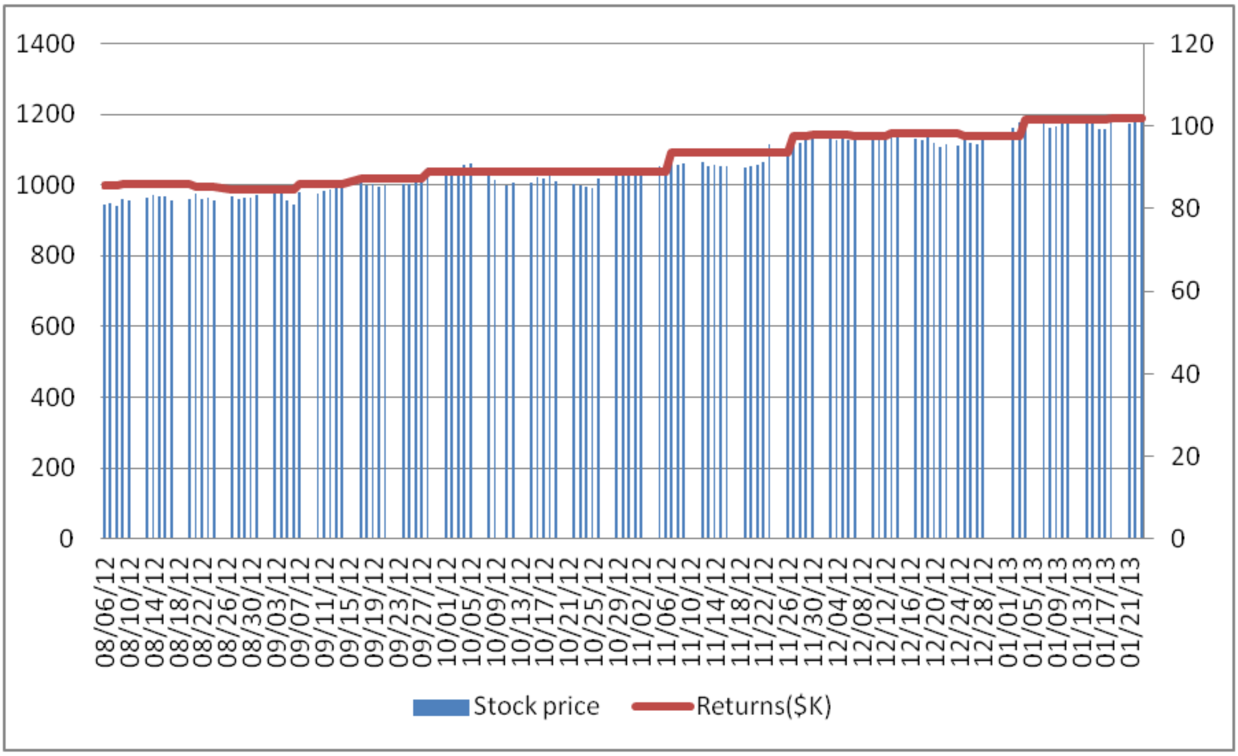

Figure 4.11 the returns of investment and the variation of stock price in the third period

4.6 Summary of TSMC stock performance

The performances of different periods of TSMC are summarized in Table The proposed system made 82 transactions in the stock market during this period of 240 trading days. This gave a rough average of 1 transaction for every 3 days. While the stock value increased by 23%, the return of the portfolio during the whole period was 53.6% with an 81% accuracy rate. The total trading period was also divided into three sub-periods that cover one month, one quarter and 6-month, respectively. The result of each period is summarized as follows:

- The accurate rates achieved were 70%, 75% and 77.5%, respectively.
- The rates of the stock price were 5% up, 12% up and 19% up, respectively.
- The returns of investment were 3.6%, 8.6% and 18.7%, respectively.

Table 4.2 the performance comparison of investment in TSMC

Performance results of different phases in TSMC			
Phase	Accurate Rate(%)	stock up/down(%)	Returns(%)
1st period(A month)	70	5	3.6
2nd period(A quarter)	75	12	8.6
3rd period(A half year)	77.5	19	18.7
One year period	81	23	53.6

4.7 Application to the Evergreen stock

The approach is also applied to Evergreen the same as in TSMC. The Evergreen stock was tested with an initial paper portfolio of NT$1,000,000. 240-trading-day Evergreen stock data were considered for training and evaluating the performance of the system which was retrained daily. Transaction costs were taken into consideration and were amount to 0.6% of the individual stock trading price.

The proposed system made 64 Evergreen stock transactions in the market during this period of 240 trading days. This gave a rough average of 1 transaction for every 4 days. Although the stock value dropped by 7.7% in this period, the return of the portfolio during the whole period still made a 128.4% in profit with an 88% accuracy rate. To study the performance of different periods, we divide the periods into one month, one quarter, six months and one year. The result of each period is summarized as follows:

- The rates of the stock price were 6.6% down, 5% up and 14.6% up, respectively.
- The returns of investment were 8.4%, 26.7% and 53.3%, respectively.
- The accurate rates achieved were 88%, 93% and 94%, respectively.

Table 4.3 the performance comparison of investment in Evergreen

Performance results of different phases in Evergreen

Phase	Accurate Rate(%)	stock up/down(%)	Returns(%)
One month	88	-6.6	8.4
One quarter	93	5.0	26.7
A half year	94	14.6	53.3
One year	96	-7.7	128.4

5. Conclusions

The proposed approach that integrated various data mining techniques has achieved remarkable results. The investment returns of the TSMC and Evergreen stocks were 53.6% and 128.4 % for the trading days considered. The system was retrained daily. As all sub-periods of the TSMC and Evergreen trading generated profits for various trading days, it is evident that the proposed system is highly effective for stock forecast. Instead of giving a straight tool, this research proposes a methodological system to handle the stock forecast. Every stock may have different structures in the top-down theory, the dynamic time series, and ANN, and have different choices in the technical analysis and the Bayesian probability. Hence, applications of the methodological system are not limited to the TSMC and Evergreen stocks.

In our future work, we will apply the proposed system to the popular Nasdaq-100 index of Stock Market as well as some of the companies listed in the Nasdaq-100 index. Additionally, justifying the decision based on the proposed system by applying linguistic fuzzy-set approach to include experts' opinions, the impact factor from either global or local events and company own breaking news are also our future research.

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Appendix

Example code of VBA program

本程式為 EXCEL VB， 主要程式化技術指標值並且算出該指標之管理內涵， 呼應在論文 Table 3.1 Technical index summary 提到各項技術指標， 分類如下：

Technical indicator	Main Type	Function Purpose
Stochastics KD	**Momentum**	Represent the position of the market on a percentage basis versus its range over the previous n-period sessions.
Willam %R	**Momentum**	Detect whether a stock is trading near the high or the low or in between of its recent trading range.
RSI	**Momentum**	Measure the velocity and magnitude of directional price movements.
PSY line	**Momentum**	Show the ratio of rising period to total which indicates control of buyers and sellers.
Bias	**Momentum**	Detect the offset level between daily stock price and a period moving average line.
ADX	**Trend**	Determined directional movement by comparing the difference between two consecutive lows with the difference between the highs.
MA	**Trend**	Smooth the price movement so that the longer-term trend becomes less volatile therefore obvious.
MACD	**Trend**	Work as a filtered measure of the derivative of the stock price with respect to time.

1. 移動平均線

移動平均(Moving Average， MA)是某變數之前 n 個數值的未作加權算術平均，以時間的長短劃分，移動平均線可分為短期、中期、長期幾種，一般短期移動平均線 5 天與 10 天；中期有 20 天、60 天；長期有 120 天及 240 天。

長、中、短期移動平均線，可以判研市場的多重傾向。如果三種移動平均線併列上漲，該市場呈多頭排列；如果三種移動平均線併列下跌，該市場呈空頭排列。

移動平均計算方式:

N 日移動平均線＝N 日收市價之和／N

MA = (PM + PM-1 ， +…. + PM-(n-1)) / n

通常短線操作的投資人，慣用 5 日和 10 日移動平均線，

所以 5 日線和 10 日線，被股市投資人稱為 短期移動平均線，簡稱「短線」。

1. 收盤價>5 日均線>10 日均線 :多頭市場

→通常表示短線呈現上漲趨勢的多頭市場

2. 收盤價<5 日均線<10 日均線 :空頭市場
→通常表示短線呈現下跌趨勢的空頭市場

3. 5 日均線<收盤價<10 日均線 :盤整市場
→通常表示短線呈現橫向趨勢的盤整市場

2. MACD

MACD 基本原理 是運用 兩條不同速度的 股價指數平滑移動平均線來計算兩者間的差離狀態(DIF)，然後再對 DIF 進行指數平滑移動平均，即為 MACD 線。

簡而言之，MACD 就是 對長期與短期的移動平均線 收斂或發散的徵兆，加以雙重平滑處理，用來判斷 買賣股票的時機與訊號。

指數平滑移動平均線(EMA):

每天股價有不同比重，加權平均一般的移動平均 認為每天的股價都有它的重要性，所以把每天的股價直接平均。

但常常會發生 只要其中一天的股價的漲幅較大，就會影響 移動平均的數值。

但事實上，最近發生的資料 應該比較重要，所以應該 用較大的比重 計算。

因此，EMA 就是依不同天 用不同的權重，計算出來的。

DIF 線:

2 條不同天期的 EMA 相減 DIF 是利用 短期與長期的指數移動平均 相減，計算出來的。

一般使用短期為 12 日，長期為 26 日。

MACD 線:

用 DIF 再取一次移動平均計算出 DIF 後，再取 DIF 的移動平均，就是 MACD 線。

一般用 DIF 的 9 日移動平均。

MACD 指標 最初由 DIF 與 MACD 兩條線 組成，

DIF(快)短期，判斷股價趨勢的變化。

MACD(慢)長期，判斷股價大趨勢。

1. 快線(DIF) 向上突破 慢線(MACD)。→買進訊號

2. 快線(DIF) 向下跌破 慢線(MACD)。→賣出訊號

3. 乖離率(BIAS)

乖離率(BIAS)代表的 就是投資者的平均報酬率。

當股價漲離平均成本很多的時候，就可能會有大的獲利賣壓出現，讓股價往均線跌回。

當股價跌出平均成本太多的時候，攤平或逢低的買盤可能會進入，讓股價往均線漲回，

這樣的狀況會使股價向平均成本靠近。

乖離率告訴我們 股票是不是漲太多了，移動平均線是一條趨勢線，因此就趨勢而言，

股價一定會 傾向靠近平均線 來移動，股價遠離平均線 變遠的話，往平均線修正的機率就會上升，

而且離得越遠，股價拉回的機會就越大，因此就算股票是在多頭的走勢中，

如果漲離均線太遠的話，短期下跌的機率反而是很大的。

3.1.當 收盤價 大於 移動平均價時的乖離 ，稱為 正乖離。

3.2.當 收盤價 小於 移動平均價時的乖離，稱為 負乖離。

結合 均線與正負乖離，看出股價短期的波動訊號

A.當股價觸碰到「正乖離線」，不要 追高買進，

未來幾天可能會有一波 股價下跌的修正。

B.當股價觸碰到「負乖離線」，不要 殺低賣出，

未來幾天可能會有一波 股價上漲的反彈。

N 日 bias = [（當日收盤價 – N 日移動平均價）÷ N 日移動平均價] x 100

乖離率指標的研判功能

10 日乖離率達到-4.5%以下是買進時機，+5.0%以上是賣出時機。
20 日的乖離率達到--7.0%以下是買進時機，+8.0%以上是賣出時機

4. KD

KD 指標(隨機指標) 用來判斷股價強弱、找到反轉點，KD 指標，又叫隨機指標。
它最主要的假設是股票位於上漲波段時，收盤價會往當日價格波動的最高收斂，
而當股價位於下跌段時，收盤價就會朝向當日價格波動的最低價收斂。

所以 KD 指標 是一個用來 判斷股價強弱趨勢 及 尋找轉折點 的重要技術指標。

一般 KD 指標的參數設定為 9 日，計算 K 和 D 時，所取的平滑值就用 3，
因此指標的參數上可以看到(9，3，3)這樣的參數在算 KD 之前，我們必須先計算 未成熟隨機值(RSV)。

RSV 的意義是 最近 9 天內， RSV 的中文叫 未成熟隨機值，
它的意義是『在最近九天裡，今天的股價 是強還是弱』也就是把 9 天內的股價總波動當分母，當天收盤價跟 9 天內最低點的差 當作分子，衡量當天收盤價在這 9 天內相對位置是強勢還是弱勢。
K 值就是 取 RSV 的加權移動平均，當日的 RSV 占 1/3 權重，而過去的 K 值 占 2/3 權重。
D 值則是 取 K 值的加權移動平均，當日 K 值 占 1/3 權重，過去的 D 值 占 2/3 權重。
經過兩次平滑，D 值因為速度慢(這是為了取其穩定)，K 值就成為較快速的轉折了。

KD 指標的研判功能

KD 值 可客觀的表現 市場過熱或過冷

最常使用的 2 種時機是：

A.1. KD >80 時，為高檔超買訊號，市場過熱，股價要開始 "跌" 了。

A.2. KD <20 時，為低檔超賣訊號，市場過冷，股價要開始 "漲" 了。

5. <u>RSI 指標</u>

RSI 用來測量市場買賣力量的強弱程度。

不過在現實的市場中， 無法統計真正供應者與需求者的數量，因此，RSI 的計算上， 只得利用買賣（多空）雙方爭鬥的結果－收盤價格的漲跌為基礎， 來評估市場買力的強弱。

以 14 日的周期參數為例， RSI 將 14 天當中漲勢的總和， 也就是每日收盤價減前一日收盤價的正值總和， 看成買方的總力量， 也就是 14 天的「總買力」；

14 天當中跌勢的總和， 也就是每日收盤價減前一日收盤價的負值總和， 看成賣方的總力量， 也就是 14 天的「總賣力」。

因此在計算 RSI 時， 必須要先求得 14 天當中， 每日收盤價跟前一日收盤價相比的漲跌幅度。

將漲幅與跌幅分成兩邊，

將 14 日漲幅總和除以 14，即為 14 日漲幅平均值；

將 14 日跌幅總和除以 14，即為 14 日跌幅平均值。

RSI 將漲幅平均值視為買力，跌幅平均值視為賣力。

RSI 指標的研判功能

RSI 值永遠介於 0 與 100 之間，

A.1. 頭部或底部形成徵兆：

RSI 在 70 以上表示買超現象，

在 30 以下為賣超現象。

A.2 虛弱反轉：

RSI 值在 70 以上或 30 以下的反轉， 是市場趨向反轉的強烈訊號。

A.3. 背離訊號：

在實際的日線圖上， 頭部的形成是一頭比一頭高， 而在 RSI 的線型上，卻出現一頭比一頭低的情形， 就是所謂的背離訊號。 此種背離，顯示了價格虛漲的現象， 意味著較大的反轉下跌的前兆。

6. <u>DMI 趨向指標</u>

趨向指標（Directional Movement Index）它的基本原理是在商品價格漲跌中，藉由創新高價或是新低價的動能（±DM）來判斷多空力道，進而尋求買賣雙方力量的均衡點，以探究雙方互動下價格波動的循環過程。

首先先算出+DM 與-DM－

1. 用當日最高價減去前一日最高價：+DM＝HIGH-HIGH[1]。

2. 用前一日最低價減去當日最低價：-DM＝LOW[1]-LOW。

3. 如果+DM 大於-DM，而且+DM 大於 0，則「真實+DM」= +DM。

如果+DM 小於等於 0，則「真實+DM」= 0。

4. 若+DM 小於-DM，而且-DM 大於 0，則「真實-DM」= -DM，

如果-DM 小於等於 0，則「真實-DM」= 0。

接下來要計算+DM(14)與－DM(14)的數值，這邊使用 14 天舉例－

起始值可先用前 14 天的「真實+DM」的平均值做為第一天的+DM(14)，

用前 14 天的「真實-DM」的平均數做為第一天的-DM(14)，

而後的 DM 值計算如下：

當日+DM(14)＝前一日的+DM(14)×(13/14) + 當日真實+DM×(1/14)

當日-DM(14)＝前一日的-DM(14) ×(13/14) + 當日真實-DM×(1/14)

再來要計算 TR 值，也就是所謂的真實區間值，算法如下:

1. 為當日最高價減去當日最低價。
2. ｜H(t)-C(t－1)｜ 為當日最高價減去前一日收盤價的絕對值。
3. ｜C(t－1)-Lt｜為前一日收盤價減去當日最低價絕對值。

然後取上面三者的最大值，

所以 TR＝MAX (H(t)-L(t)，｜H(t)-C(t－1)｜，｜C(t－1)-L(t)｜)。

接著再計算 TR(14)－

起始值計算比照 DM(14)之計算方式，取前 14 根做平均數。

當日 TR(14)＝前一日 TR(14)×(13/14) +今日 TR×(1/14)。

然後再計算 DI 值－

+DI(14)＝+DM(14)/ TR(14) × 100

-DI(14)＝-DM(14)/ TR(14) × 100

最後要計算 DX 及 ADX 值。

ADX（趨向平均線）是用來判別 14 日內價格變動趨勢的明顯度，計算如下：

先算出 DX 值：DX＝｜(+DI 14)- (-DI14)｜/ ((+DI14)+ (-DI14)) ×100。

再算出 ADX 值：起始值計算一樣取前 14 根的值做平均數。

當日 ADX(14)＝前一日 ADX × (13/14) + 今日 DX × (1/14)。

DMI 進場交易策略

當+DI 由下往上穿越-DI 時，就啟動買進訊號；

當+DI 由上往下穿越-DI 時，就啟動賣出訊號。

7. 心理線

簡稱為 PSY 稱它為人氣指標心理線，是一種企圖以指標化的方式，亦即利用某一特定天數期間內，以行情上漲天數的比例值，來揣摸投資人是趨向於買方或賣方的心理事實，並依據投資人高賣低買的交易心態，來做為市場進出的參考。

PSY 公式如下：
PSY=(UPn / n) * 100
其中 UPn 值為 n 日內行情上漲的天數。

PSY 之研判原則
A.1 當 PSY 大於 75 時，代表上漲出現的頻率已高到多數樂觀人的水準，也就是股價到達買超區，這個時候盤勢反轉向下的可能性大增。

A.2. 當 PSY 小於 25 時，代表下跌發生的頻率已高到多數
悲觀者的預期程度，也就是股價到達了賣超區，此時應留意盤勢將反轉向上。

8. William

由美國人賴利．威廉斯(Larry Williams)在 1973 年出版的"我如何賺到 100 萬(How I Made A Million Dollars)"一書中所發明，當時稱為威廉超買超賣指標，簡稱威廉%R，是判斷個股在某一段時間內超買超賣狀況的有效指數。

公式計算如下：

%R= [-(收盤價－n 日之最高價)／(n 日內最高價－n 日最低價)] x 100

William 之研判原則:
%R 在>80 為超賣區。
%R<20 為超買區

```
‘==============================================================

Sub KPIindex() ' 將技術指標值算出

 k = 300
 n = 10 ' Number of attributes
 m = 11 ' Conversion starts

;======================================================
    ‘◎趨勢指標
    ' ‘指數＞月線－短多
    ' ‘指數＜月線－短空
    ' ‘月線＞季線－中多
    ' ‘月線＜季線－中空

    Cells(1， m - 2).Value = "10D Move"     'Bi-weekly data

    Cells(1， m - 1).Value = "5D Move"     'weekly data

    Cells(1, m).Value = "M22D MA"

    Cells(1, m + 1).Value = "Q66D MA"

    Cells(1, m + 2).Value = " MoveIndex" ' m+2

   '==============================================================

   For i = 1 To k   ' 平均線計算

     Cells(i + 1, m - 2).Value = 0
```

```
For j = 1 To 10 ' 10 Day index

   Cells(i + 1, m - 2).Value = Cells(i + 1, m - 2).Value + Cells(i + j + 1, 2).Value

Next j

Cells(i + 1, m - 2).Value = (Cells(i + 1, m - 2).Value) / 10 '

 '============================================================

Cells(i + 1, m - 1).Value = 0

For j = 1 To 5 ' 5 Day index

   Cells(i + 1, m - 1).Value = Cells(i + 1, m - 1).Value + Cells(i + j + 1, 2).Value

Next j

Cells(i + 1, m - 1).Value = (Cells(i + 1, m - 1).Value) / 5 '

 '============================================================

 Cells(i + 1, m).Value = 0

For j = 1 To 20      ' Monthly   20Day index

   Cells(i + 1, m).Value = Cells(i + 1, m).Value + (Cells(i + j + 1, 2).Value)

Next j
```

```
Cells(i + 1, m).Value = (Cells(i + 1, m).Value) / 20   '

 '==============================================================

Cells(i + 1, m + 1).Value = 0

For j = 1 To 60    ' 60 Day index (m+1)

   Cells(i + 1, m + 1).Value = Cells(i + 1, m + 1).Value + (Cells(i + j + 1, 2).Value)

Next j

Cells(i + 1, m + 1).Value = (Cells(i + 1, m + 1).Value) / 60

Next i

‘******************

For i = k To 1 Step -1   '            '   "sp>5d,20d,60d"
```

' 股價會帶領均線向上發展，價格在均線上方，故以股價>5 日、20 日、60 日均線作篩選，可篩選過濾掉仍在盤整區的標的，並選出開始轉強的。

'K 線表現價格與氣勢-所以在本程式中設定股價漲幅>3%(可選擇 3%~7%)，並設定 K 線型態為不留上影線或上影線小 stock price >= 0.9 max.

```
If Cells(i + 1, 2).Value >= Cells(i + 1, m - 1).Value And Cells(i + 1, 2).Value >= Cells(i + 1, m).Value And Cells(i + 1, 2).Value >= Cells(i + 1, m + 1).Value And Cells(i + 1, 2).Value >= 0.9 * Cells(i + 1, 7).Value And Cells(i + 1, 4).Value >= 3 Then

    Cells(i + 1, m + 2).Value = 1

ElseIf Cells(i + 1, m).Value >= Cells(i + 1, m + 1).Value And Cells(i + 1, m - 1).Value > Cells(i + 1, m).Value And Cells(i + 1, 2).Value > Cells(i + 1, m - 1).Value Then
```

```
Cells(i + 1, m + 2).Value = 1

'6 日移動平均線往下跌破 26 日移動平均線，而今日的 6 日移動平均數小於昨日的 6 日移動平均數，
' 今日的 26 日移動平均數小於昨日的 26 日移動平均數，即為 6 日線與 26 日線的「死亡交叉」。

ElseIf Cells(i + 1, m).Value <= Cells(i + 2, m).Value And Cells(i + 1, m - 1).Value <= Cells(i + 1, m).Value And Cells(i + 1, m - 1).Value <= Cells(i + 2, m - 1).Value Then

Cells(i + 1, m + 2).Value = -1

' 日<週<月

ElseIf Cells(i + 1, 2).Value <= Cells(i + 1, m - 1).Value And Cells(i + 1, m - 1).Value <= Cells(i + 1, m).Value Then

Cells(i + 1, m + 2).Value = -1

'"日線<季線,賣出 1"

ElseIf Cells(i + 2, 2).Value >= Cells(i + 2, m + 1).Value And Cells(i + 1, 2).Value < Cells(i + 1, m + 1).Value And Cells(i + 1, 7).Value < Cells(i + 1, m + 1).Value Then

Cells(i + 1, m + 2).Value = -1

Else

Cells(i + 1, m + 2).Value = 0

End If

Next i
```

```
‘===================================================================

 ' 10 日乖離率達到-4.5%以下是買進時機，+5.0%以上是賣出時機。25 日的乖離率達到-7.0%以下是買進時機，+8.0%以上是賣出時機

' 。72 乖離率達到-11.0%以下是買進時機，+14.0%以上是賣出時機。在多頭行情中，會出現多次高價，
' 太早賣出會錯失一段行情，可於先前高價之正乖率點賣出，反之，在空頭市場時，亦會使負乖離率加大，可於前次低價之負乖離時買進。

 Cells(1, m + 3).Value = "Bias20D"

 Cells(1, m + 4).Value = "Bias10D"

 Cells(1, m + 5).Value = "BiasIndex"

 bia = m + 5 ' reecord the bias location

For i = 1 To k
  ' Bias(m+5) Check 10-d and 20-d weighted moving average with the present stock price

Cells(i + 1, m + 3).Value = 100 * (Cells(i + 1, 2).Value - Cells(i + 1, m).Value) / Cells(i + 1, m).Value
   '22 日  m  移動平均線

  ' Bias 10 days
Cells(i + 1, m + 4).Value = 100 * (Cells(i + 1, 2).Value - Cells(i + 1, m - 2).Value) / Cells(i + 1, m - 2).Value
   '10 日  m  移動平均線

Next i

For i = k To 1 Step -1
```

```
    If Cells(i + 1, m + 3).Value <= -7 Then ' Bias 20 days

       Cells(i + 1, m + 5).Value = 1

     ElseIf Cells(i + 1, m + 3).Value >= 8 Then

       Cells(i + 1, m + 5).Value = -1

   ' 10 日乖離率達到-4.5%以下是買進時機，+5.0%以上是賣出時機。

     ElseIf Cells(i + 1, m + 4).Value <= -4.5 Then

       Cells(i + 1, m + 5).Value = 1

     ElseIf Cells(i + 1, m + 4).Value >= 5 Then

         Cells(i + 1, m + 5).Value = -1

   Else
         Cells(i + 1, m + 5).Value = 0

   End If

 Next i
'
' ========================================

 Cells(1, m + 6).Value = "DIF" 'm+6
 Cells(1, m + 7).Value = "MACD" 'm+7
 Cells(1, m + 8).Value = "MACD index" 'm+8
```

```
'==============

For i = 1 To k

    ' MACD Check 10-d and 20-d weighted moving average with the present stock price

     ' DIF(m+6)   = WMA 12 D -wma 26 D

     Cells(i + 1, m + 6).Value = Cells(i + 1, m - 2).Value - Cells(i + 1, m).Value

    '實際  MA10(m-2) - MA22(m)

Next i

Cells(k + 2, m + 7).Value = 0

For i = 1 To k ' MACD=DEM = DEM(i-1) x 0.8 + DIF x 0.2

     ' DEM (m+7)=MACD

     Cells(k + 2 - i, m + 7).Value = Cells(k + 3 - i, m + 7).Value * 0.8 + Cells(k + 2 - i, m + 6).Value * 0.2

Next i
```

' 1. 差 離 值 (DIF)： 由指數平滑異同移動平均線(MACD)中， 運用二條不同速度(長期與中期)的平滑移動平均線(EMA)所得到的差離值 DIF。

' 2. 在 DIF 向上突破 MACD 時， 應做買進切入； ' 若 DIF 從上往下跌破 MACD 時， 應做即時做原單的賣出動作， '不可新賣單進場。

' 3. 差離值(DIF)與指數平滑異同移動平均線(MACD)在 0 軸以下， 大盤屬於空頭市場， 在 DIF 向上突破 MACD 時， 應做原單的平倉不可新買單進場；

' 若 DIF 向下跌破 MACD 時， 可做賣出動作

'當 DIF、MACD 或 BAR 值大於 0 時，一般可視為多頭市場(三者之值均大於 0 時，其勢更為明顯)；反之當 DIF、MACD 或 BAR 值小於 0 時，

' 可被視為空頭市場(三者之值均小於 0 時，可視為逃命訊號)。

' 短線而言，DIF 與 MACD 均在水平軸下方，且 DIF 由下往上穿過 MACD 線(即同義於 BAR 值自下方

```
  突破水平軸)，是為買入訊號；

' 反之 DIF 與 MACD 均在水平軸上方，且 DIF 由上往下穿過 MACD 線(即同義於 BAR 值自上方貫破水
平軸)，是為賣出訊號。

' 中線而言，BAR 由下向上突破水平軸，可視為買入訊號，反之則為賣出訊號。

 ' 股價出現兩三個相對高點，但 MACD 並未伴隨出現新高點，其為賣出訊號；

' 反之股價出現兩三個相對低點，但 MACD 並未伴隨出現新低點，其為買入訊號。


For i = k To 1 Step -1        ' MaCD(m+8)   to check the turnaround signal


      'DIF > MACD DIF from - to +     when DEM >0

        '在 DIF  向上突破 MACD  時，  應做買進切入；


     If Cells(i + 1, m + 6).Value > Cells(i + 1, m + 7).Value And Cells(i + 2, m + 6).Value <= Cells(i + 2, m +
7).Value And Cells(i + 3, m + 6).Value <= Cells(i + 3, m + 7).Value Then


            Cells(i + 1, m + 8).Value = 1


     ElseIf Cells(i + 1, m + 6).Value > Cells(i + 1, m + 7).Value And Cells(i + 1, m + 7).Value > 0 And Cells(i + 1,
m + 6).Value > 0 Then


            Cells(i + 1, m + 8).Value = 1


     ' 股價出現兩三個相對低點，但 MACD 並未伴隨出現新低點，其為買入訊號。


    ' ElseIf Cells(i + 1, m + 7).Value > Cells(i + 2, m + 7).Value And Cells(i + 1, 3).Value < Cells(i + 2, 3).Value <
0 And Cells(i + 2, 3).Value < Cells(i + 3, 3).Value < 0 Then


      '     Cells(i + 1, m + 8).Value = -1


     ' 股價出現兩三個相對高點，但 MACD 並未伴隨出現新高點，其為賣出訊號；


     ElseIf Cells(i + 1, m + 7).Value < Cells(i + 2, m + 7).Value And Cells(i + 1, 3).Value > Cells(i + 2, 3).Value >
```

```
0 And Cells(i + 2, 3).Value > Cells(i + 3, 3).Value > 0 Then

            Cells(i + 1, m + 8).Value = -1

        'DIF < DEM DIF from + to -   when DEM <0
        '若 DIF 從上往下跌破 MACD 時,應做即時做原單的賣出動作，不可新賣單進場。

        ElseIf Cells(i + 1, m + 6).Value < Cells(i + 1, m + 7).Value And Cells(i + 2, m + 6).Value >= Cells(i + 2, m + 7).Value And Cells(i + 3, m + 6).Value >= Cells(i + 3, m + 7).Value Then

            Cells(i + 1, m + 8).Value = -1

        'ElseIf Cells(i + 1, m + 6).Value < Cells(i + 1, m + 7).Value And Cells(i + 1, m + 7).Value < 0 And Cells(i + 1, m + 6).Value < 0 Then

        '   Cells(i + 1, m + 8).Value = -1

        Else
            Cells(i + 1, m + 8).Value = 0

        End If

    Next i
'==========================================================================

    '何謂 RSI 黃金交叉?當短天期的 RSI 由下往上突破長天期 RSI，即是「黃金交叉」，也可視為買進訊號，
    ' 反之短天期的 RSI 由上往下跌破長天期 RSI，即是「死亡交叉」，可視為賣出訊號

    Cells(1, m + 12).Value = "RSI index" 'm+12
    rsi = m + 12 ' key index
```

' 若短期(6 日)RSI 值在 10%以下，或長期(12 日、24 日)RSI 值在 20%以下，則表示股市正處於超賣狀態，是為買進時機。

' 若短期(6 日)RSI 值在 90%以上，或長期(12 日、24 日)RSI 值在 80%以上，則表示股市正處於超買狀態，是為賣出時機。

'以 6 日 RSI 值為例，80 以上為超買，90 以上或 M 頭為賣點；20 以下為超賣，10 以下或 W 底為買點。

' 在股價創新高點，同時 RSI 也創新高點時，表示後市仍強，若未創新高點為賣出訊號。

' 在股價創新低點，RSI 也創新低點，則後市仍弱，若 RSI 未創新低點，則為買進訊號。

' 當 6 日 RSI 由下穿過 12 日 RSI 而上時，可視為買點；反之當 6 日 RSI 由上貫破 12 日 RSI 而下時，可視為賣點。

' 當出現類似這樣的訊號：3 日 RSI>5 日 RSI>10 日 RSI>20 日 RSI....，顯示市場是處於多頭行情；反之則為空頭行情。

' 盤整期中，一底比一底高，為多頭勢強，後勢可能再漲一段，是買進時機，反之一底比一底低是賣出時機。

```
For i = 1 To k ' RSI   index (m+12)

    Cells(i + 1, m + 9).Value = 0
    Cells(i + 1, m + 10).Value = 0

    For j = 1 To 12 ' 12 Day RSI value

        '12-day up
        If Cells(i + j, 3).Value >= 0 Then '股價上漲
            Cells(i + 1, m + 9).Value = Cells(i + 1, m + 9).Value * 11 / 12 + Cells(i + j, 3).Value * 1 / 12

        Else
            ' Cells(i + j, 3).Value <= 0
            Cells(i + 1, m + 10).Value = Cells(i + 1, m + 10).Value * 11 / 12 + Cells(i + j, 3).Value * 1 / 12

        End If

    Next j
```

```
    Cells(i + 1, m + 11).Value = Cells(i + 1, m + 9).Value * 100 / (Cells(i + 1, m + 9).Value - Cells(i + 1, m +
10).Value)

    '================================================

   Cells(i + 1, m + 13).Value = 0
    Cells(i + 1, m + 14).Value = 0

    For j = 1 To 6 ' 6 Day RSI value

      If Cells(i + j, 3).Value >= 0 Then

          Cells(i + 1, m + 13).Value = Cells(i + 1, m + 13).Value * 5 / 6 + Cells(i + j, 3).Value * 1 / 6

      Else
          ' Cells(i + j, 3).Value < 0
          Cells(i + 1, m + 14).Value = Cells(i + 1, m + 14).Value * 5 / 6 + Cells(i + j, 3).Value * 1 / 6

      End If

    Next j

    Cells(i + 1, m + 15).Value = Cells(i + 1, m + 13).Value * 100 / (Cells(i + 1, m + 13).Value - Cells(i + 1, m +
14).Value)

  Next i

    '============================================================

  '當 6 日 RSI(m+15)由下穿過 12 日 RSI(m+11) 而上時，可視為買點；
  '反之當 6 日 RSI 由上貫破 12 日 RSI 而下時，可視為賣點。
```

```
Cells(1, m + 15).Value = "RSI(6D)"

Cells(1, m + 11).Value = "RSI(12D)"


For i = k + 1 To 1 Step -1 ' RSI 12 Day index (m+12)


  ' 若短期(6 日)RSI 值在 10%以下，或長期(12 日、24 日)RSI 值在 20%以下，則表示股市正處於超賣狀態，是為買進時機。


  ' rsi <30 and turn up -buy

    'If Cells(i + 1, m + 15).Value <= 10 And Cells(i + 1, m + 11).Value <= Cells(i + 1, m + 15).Value Then

     If Cells(i + 1, m + 15).Value <= 10 Then

        Cells(i + 1, m + 12).Value = 1


    'ElseIf Cells(i + 1, m + 11).Value <= 20 And Cells(i + 1, m + 11).Value <= Cells(i + 1, m + 15).Value Then

    ElseIf Cells(i + 1, m + 11).Value <= 20 Then

        Cells(i + 1, m + 12).Value = 1


    ' 若短期(6 日)RSI 值在 90%以上，或長期(12 日、24 日)RSI 值在 80%以上，則表示股市正處於超買狀態，是為賣出時機。

    ' rsi >80 and turn dowmn -sell


    'ElseIf Cells(i + 1, m + 15).Value >= 90 And Cells(i + 1, m + 11).Value >= Cells(i + 1, m + 15).Value Then

    ElseIf Cells(i + 1, m + 15).Value >= 90 Then

        Cells(i + 1, m + 12).Value = -1



    ' ElseIf Cells(i + 1, m + 11).Value >= 80 And Cells(i + 1, m + 11).Value >= Cells(i + 1, m + 15).Value Then

    ElseIf Cells(i + 1, m + 11).Value >= 80 Then

        Cells(i + 1, m + 12).Value = -1
```

```
        Else

            Cells(i + 1, m + 12).Value = 0


        End If


    Next i


    ' Confused m+13, m+14, m+15 so move forward m=m+3 revised in 2014-06-11



'****************************************************************************
```

'DMI 利用計量分析方法，以較客觀性的態度，研判股價漲跌的趨勢。

' 在研判時，未摻雜個人主觀性的判斷，且能考慮股價每日的最高價、最低價及收盤價三者間的波動情形，可對股價的波動情形做完整性分析。

```
     Cells(1, m + 21).Value = "DMI"


    For i = 1 To k + 1 ' DSI   index (m+21)


        Cells(i + 1, m + 13).Value = 0

         Cells(i + 1, m + 14).Value = 0


        ' SP Highest price >= yesterday HP    +DM

       If (Cells(i + 1, 7).Value - Cells(i + 2, 7).Value) > (Cells(i + 2, 8).Value - Cells(i + 1, 8).Value) Then

            Cells(i + 1, m + 13).Value = Cells(i + 1, m + 13).Value + Cells(i + 1, 7).Value - Cells(i + 2, 7).Value


       ElseIf (Cells(i + 1, 7).Value - Cells(i + 2, 7).Value) < (Cells(i + 2, 8).Value - Cells(i + 1, 8).Value) Then


       ' SP Lowesr price <= Yesterday LP     -DM


            Cells(i + 1, m + 14).Value = Cells(i + 1, m + 14).Value + Cells(i + 1, 8).Value - Cells(i + 2, 8).Value
```

```
    End If

     ' Temporary value for Ht-Ct-1, Lt-Ct-1, Ht-Lt
     Cells(i + 1, m + 16).Value = Cells(i + 1, 7).Value - Cells(i + 2, 2).Value
     Cells(i + 2, m + 16).Value = Cells(i + 1, 8).Value - Cells(i + 2, 2).Value
     Cells(i + 3, m + 16).Value = Cells(i + 1, 7).Value - Cells(i + 1, 8).Value

        ' Obtain True range
     If Cells(i + 1, m + 16).Value >= Cells(i + 2, m + 16).Value And Cells(i + 1, m + 16).Value >= Cells(i + 3, m + 16).Value Then
         Cells(i + 1, m + 15).Value = Cells(i + 1, m + 16).Value

     ElseIf Cells(i + 1, m + 16).Value <= Cells(i + 2, m + 16).Value And Cells(i + 2, m + 16).Value >= Cells(i + 3, m + 16).Value Then
         Cells(i + 1, m + 15).Value = Cells(i + 2, m + 16).Value

     Else
          Cells(i + 1, m + 15).Value = Cells(i + 3, m + 16).Value

     End If

  Next i

    Cells(1, m + 19).Value = "DI+"
     Cells(1, m + 20).Value = "DI-"

  For i = 1 To k ' DSI DM
     Cells(i + 1, m + 16).Value = 0
     Cells(i + 1, m + 17).Value = 0
     Cells(i + 1, m + 18).Value = 0
```

```
For j = 1 To 14 ' 14 Day DM+(m+13)   and DM-(m+14) TR(m+18)

        Cells(i + 1, m + 16).Value = Cells(i + 1, m + 16).Value * 13 / 14 + Cells(i + j, m + 13).Value * 1 / 14 '+DM14

        Cells(i + 1, m + 17).Value = Cells(i + 1, m + 17).Value * 13 / 14 + Cells(i + j, m + 14).Value * 1 / 14 '-DM14


        Cells(i + 1, m + 18).Value = Cells(i + 1, m + 18).Value * 13 / 14 + Cells(i + j, m + 15).Value * 1 / 14 ' TR14

Next j

        Cells(i + 1, m + 19).Value = 100 * Cells(i + 1, m + 16).Value / Cells(i + 1, m + 18).Value ' +DI14

        Cells(i + 1, m + 20).Value = -100 * Cells(i + 1, m + 17).Value / Cells(i + 1, m + 18).Value ' -DI14


Next i

'*****************************************************************************************

Cells(1, m + 22).Value = "DX"

  For i = 1 To k '

    'DX

    Cells(i + 1, m + 22).Value = 100 * Abs(Cells(i + 1, m + 19).Value - Cells(i + 1, m + 20).Value) / (Cells(i + 1, m + 19).Value + Cells(i + 1, m + 20).Value) 'ADX 14 D

 Next i

'     '‘◎趨勢指標
  '‘ＡＤＸ＞３０　＝＞趨勢強勁
'‘ＡＤＸ＜2０　＝＞沒有趨勢
```

```
Cells(1, m + 23).Value = "ADX"     'm+23

For i = 1 To k '

    'ADX
      Cells(i + 1, m + 23).Value = 0

    For j = 1 To 10 ' 10 Day

            Cells(i + 1, m + 23).Value = Cells(i + 1, m + 23).Value * 9 / 10 + Cells(i + j, m + 22).Value * 1 / 10
'ADX 10 D

    Next j

Next i

'=================================================================
```

' 3.求出方向線(DI)--為探測股價上漲或下跌方向的指標，以 +DI 表示上升方向指標，為最近 N 日內實際上漲的動量百分比；

' 以 - DI 表示下跌方向指標，為最近 N 日內實際下跌的動量百分比。

' +DI = + DM N 日平均 / TR N 日平均

' -DI = - DM N 日平均 / TR N 日平均

```
For i = 1 To k   ' DI+ DI- to check the turnaround signal

    'DI+ > DI- DIF from - to +     BUy

    If Cells(i + 1, m + 19).Value > Cells(i + 1, m + 20).Value Then
        Cells(i + 1, m + 21).Value = 1
```

```
'DI+ < DI- DIF from + to -   Sell
ElseIf Cells(i + 1, m + 19).Value < Cells(i + 1, m + 20).Value Then
    Cells(i + 1, m + 21).Value = -1

Else
     Cells(i + 1, m + 21).Value = 0
End If

Next i
```

'**

'ADX 可作為趨勢行情是否出現的判斷依據，當行情明顯朝某一方向進行時，ADX 數值都會顯著上升。若行情呈現盤整格局時，ADX 會低於+DI 與–DI 二條線。

' 若 ADX 數值低於 20，則不論 DI 如何，均顯示市場沒有明顯趨勢。此時投資人應該退場以靜待行情的出現。

'當 ADX 持續偏高時，代表買超或賣超現象，此時則不宜順勢操作，因行情反轉的機會增加。

' 當 ADX 指數從上升趨勢轉為下降時，則代表行情即將反轉。

'如果 10 日 ADX 趨勢是上升，而且價格在 8MA 之上，K 棒就顯示黃色；

' 如果 10 日 ADX 趨勢是上升，而且價格在 8MA 之下，K 棒就顯示藍色。

' 這樣顯示在 K 線圖中，就可以很清楚的知道趨勢的強度，也可以告訴我們價格跟短期均線的位置關係，如果顏色消失了，可能代表一個價格趨勢轉折的開始。

```
Cells(1, m + 24).Value = "ADX index"      'm+24

For i = 1 To k ' Check if Sp> 5-d Weighted moving average(m+1)

    ' Mono direction + 5 日線和 10 日線作過濾
    If Cells(i + 1, 2).Value >= Cells(i + 1, m - 1).Value And Cells(i + 1, 2).Value >= Cells(i + 1, m - 2).Value And Cells(i + 1, m + 23).Value >= 30 Then
        Cells(i + 1, m + 24).Value = 1
```

```
' +DI 表示上升方向指標，為最近 N 日內實際上漲的動量百分比；

        ElseIf Cells(i + 1, 21).Value = 1 And Cells(i + 1, 2).Value >= Cells(i + 1, m - 2).Value And Cells(i + 1, m + 23).Value >= 30 Then
            Cells(i + 1, m + 24).Value = 1

        ElseIf Cells(i + 1, 2).Value < Cells(i + 1, m - 1).Value And Cells(i + 1, 2).Value < Cells(i + 1, m - 2).Value And Cells(i + 1, m + 23).Value >= 30 Then
            Cells(i + 1, m + 24).Value = -1

         ' 以 - DI 表示下跌方向指標，為最近 N 日內實際下跌的動量百分比
        ElseIf Cells(i + 1, 21).Value = -1 And Cells(i + 1, 2).Value <= Cells(i + 1, m - 2).Value And Cells(i + 1, m + 23).Value >= 30 Then
            Cells(i + 1, m + 24).Value = -1

        Else
            Cells(i + 1, m + 24).Value = 0
        End If

    Next i

    '==========================================================

    ' KD index

      '當 K 值大於 D 值，顯示目前是向上漲升的趨勢，此時，若 K 線由下往上突破 D 線，則表示行情看漲，是為買進時機。當 D 值偏低(通常指 20%以下)表示股市處於超賣狀態，是為買進時機。
      ' 當 D 值大於 K 值，顯示目前的趨勢是向下跌落, 此時, 若 K 線由上往下跌破 D 線，則表示行情可能下跌，是賣出時機。當 D 值偏高(通常指 80%以上)表示股市處於超買狀態，是為賣出時機。
      ' 當 K 線傾斜角度趨於平緩時是警告訊號，表示行情可能回軟或止跌, 而當股價走趨創新高或創新低價時，KD 線未能創新高或創新低, 可能是股價走勢即將反轉的徵兆，為買進或賣出的時機。

    Cells(1, m + 25).Value = "RSV-9D"
```

```
    For i = 1 To k - 8 ' Check Min -8, max -7

        Set myRange = Range(Cells(i + 1, 8), Cells(i + 9, 8))
        Call minND(myRange, minD)

        Set myRange = Range(Cells(i + 1, 7), Cells(i + 9, 7))
        Call maxND(myRange, maxD)

        ' Raw Stochastic Value
        Cells(i + 1, m + 25).Value = 100 * (Cells(i + 1, 2) - minD) / (maxD - minD) 'RSV9D
100*(B2-MIN(H2:H10))/(MAX(G2:G10)-MIN(H2:H10))

    Next i

    ' ‘◎震盪指標
    ' ‘日ＫＤ－短線震盪指標，Ｋ＞Ｄ為短線震盪向上亮紅色，Ｋ＜Ｄ為短線震盪向下亮綠色。
    ' ‘週ＫＤ－中線震盪指標，Ｋ＞Ｄ為中線震盪向上亮紅色，Ｋ＜Ｄ為中線震盪向下亮綠色。
    ' ‘月ＫＤ－長線震盪指標，Ｋ＞Ｄ為長線震盪向上亮紅色，Ｋ＜Ｄ為長線震盪向下亮綠色

    Cells(1, m + 26).Value = "K9"

    Cells(2 + k, m + 26).Value = Cells(k + 1, m + 25).Value

    For i = 1 To k ' Check Min -8, max -7

        Cells(k - i + 2, m + 26).Value = Cells(k - i + 2, m + 25).Value / 3 + Cells(k - i + 3, m + 26).Value * 2 / 3   '
=(AJ2/3+AK3*2/3)

    Next i
```

```
Cells(1, m + 27).Value = "D9"

Cells(2 + k, m + 27).Value = Cells(k + 1, m + 25).Value

For i = 1 To k ' Check Min -8, max -7

    Cells(k - i + 2, m + 27).Value = Cells(k - i + 2, m + 26).Value / 3 + Cells(k - i + 3, m + 27).Value * 2 / 3

Next i
```

' 如果行情是一個明顯的漲勢，會帶動 K 線與 D 線向上升。如漲勢開始遲緩，則會反應到 K 值與 D 值，使得 K 值跌破 D 值，此時中短期跌勢確立。

' 當 K 值大於 D 值，顯示目前是向上漲升的趨勢，因此在圖形上 K 線向上突破 D 線時，即為買進訊號。

' 當 D 值大於 K 值，顯示目前是向下跌落，因此在圖形上 K 線向下跌破 D 線，此即為賣出訊號。

'上述 K 線與 D 線的交叉，須在 80 以上，20 以下(一說 70、30；視市場投機程度而彈性擴大範圍)，訊號才正確。

' 當 K 值大於 80，D 值大於 70 時，表示當日收盤價處於偏高之價格區域，即為超買狀態；

' 當 K 值小於 20，D 值小於 30 時，表示當日收盤價處於偏低之價格區域，即為超賣狀態。

' 當 D 值跌至 15 以下時，意味市場為嚴重之超賣，其為買入訊號；當 D 值超過 85 以上時，意味市場為嚴重之超買，其為賣出訊號。

' 價格創新高或新低，而 KD 未有此現象, 此為背離現象, 亦即為可能反轉的重要前兆。

```
Cells(1, m + 28).Value = "KD index" 'm+28

 For i = k To 1 Step -1 ' K -D index

    If Cells(i + 1, m + 26).Value > Cells(i + 1, m + 27).Value And Cells(i + 2, m + 28).Value >= 0.5 Then
        Cells(i + 1, m + 28).Value = 1

    ElseIf Cells(i + 1, m + 26).Value <= 30 And Cells(i + 1, m + 27).Value <= 30 And Cells(i + 2, m + 26).Value < Cells(i + 2, m + 27).Value And Cells(i + 1, m + 26).Value > Cells(i + 1, m + 27).Value Then            'K-D Golden
```

```
index
                Cells(i + 1, m + 28).Value = 0.5

           ElseIf Cells(i + 1, m + 26).Value < Cells(i + 1, m + 27).Value And Cells(i + 2, m + 28).Value <= -0.5 Then
'K-D death index
                Cells(i + 1, m + 28).Value = -1

            ElseIf Cells(i + 1, m + 26).Value >= 70 And Cells(i + 1, m + 27).Value >= 70 And Cells(i + 2, m + 26).Value
> Cells(i + 2, m + 27).Value And Cells(i + 1, m + 26).Value < Cells(i + 1, m + 27).Value Then        'K-D death index
                Cells(i + 1, m + 28).Value = -0.5

           Else
                Cells(i + 1, m + 28).Value = 0
           End If

      Next i

      '*****************************************************************

       Cells(1, m + 29).Value = "WillamR%"

       '=100*(MAX(G20:G24)-B20)/(MAX(G20:G24)-MIN(H20:H24))

       For i = 1 To k ' Check

           Cells(i + 1, m + 29).Value = 100 - Cells(i + 1, m + 25).Value   ' 100-RSV 9D

       Next i

       '=================================================================

       ' 一般而言，當 PSY 大於 75 時，代表上漲出現的頻率已高到多數樂觀人的水準，也就是股價到達買超
```

區，這個時候盤勢反轉向下的可能性大增

' 當 PSY 小於 25 時，代表下跌發生的頻率已高到多數悲觀者的預期程度，也就是股價到達了賣超區，此時應留意盤勢將反轉向上。

```
Cells(1, m + 31).Value = "PSY-12D"

Cells(1, m + 32).Value = "PSY index"
Pi = m + 32

For i = 1 To k   ' PSY index M+32
    Cells(i + 1, m + 31).Value = 0
    For j = 1 To 12 ' 12- day up counts

        If Cells(i + j, 3).Value > 0 Then 's/p up or down rate
            Cells(i + 1, m + 31).Value = Cells(i + 1, m + 31).Value + 1

        End If

    Next j
    Cells(i + 1, m + 31).Value = 100 * Cells(i + 1, m + 31).Value / 12

Next i

For i = k To 1 Step -1 ' PSY check M+32


    ' PSy check
    If Cells(i + 1, m + 31).Value >= 75 And Cells(i + 2, m + 32).Value <= -0.5 Then
        Cells(i + 1, m + 32).Value = -1

    ElseIf Cells(i + 1, m + 31).Value >= 75 Then
```

```
            Cells(i + 1, m + 32).Value = -0.5

        ElseIf Cells(i + 1, m + 31).Value <= 25 And Cells(i + 2, m + 32).Value >= 0.5 Then

                    Cells(i + 1, m + 32).Value = 1

        ElseIf Cells(i + 1, m + 31).Value <= 25 Then

                    Cells(i + 1, m + 32).Value = 0.5

        Else
             Cells(i + 1, m + 32).Value = 0

        End If

    Next i
'===========================================================================
 ' William index
```

　' 當 12 日%R 值大於 80，代表股市呈現超賣現象，為買進時機。反之，當 12 日%R 值小於 20 時，股市呈現超買現象時，為賣出時機。

　' 當 12 日%R 由超賣區向上升，代表行情將上跌回穩。若 12 日%R 突破中軸線(50)時，代表行情漲勢轉強，可追漲買進。

　' 反之，當 12 日%R 由超買區向下滑落，且跌破中軸線(50)時，便是行情跌勢轉強，可追跌殺出。

　' 當股價跌深，12 日%R 值落至 80 ~ 100 之間，且反彈時一次突破 80 ~ 100 之區域，而落於 20 ~ 80 時，則為買進時機。

　' 反之，當股價位於高檔，12 日%R 值介於 0 ~ 20 之間，且回檔時一次跌破 0 ~ 20 之區域，而落於 20 ~ 80 時，則為賣出時機。

```
    Cells(1, m + 30).Value = "WillamR%"

    For i = k To 1 Step -1 ' Willam index M+30
```

```
If Cells(i + 1, m + 29).Value >= 80 And Cells(i + 2, m + 30).Value >= 0.5 Then
    Cells(i + 1, m + 30).Value = 1

ElseIf Cells(i + 1, m + 29).Value >= 80 Then
    Cells(i + 1, m + 30).Value = 0.5

 ElseIf Cells(i + 1, m + 29).Value <= 20 And Cells(i + 2, m + 30).Value <= -0.5 Then
     Cells(i + 1, m + 30).Value = -1

   ElseIf Cells(i + 1, m + 29).Value <= 20 Then
     Cells(i + 1, m + 30).Value = -0.5

Else
     Cells(i + 1, m + 30).Value = 0

End If

Next i
End Sub
'===================================================================
```