A Study of Genetic Fuzzy Trading Modeling, Intraday Prediction and Modeling

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Abstract of thesis entitled:
A Study of Genetic Fuzzy Trading Modeling, Intraday Prediction and Modeling
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This thesis consists of three parts: a genetic fuzzy trading model for stock trading, incremental intraday information for financial time series forecasting, and intraday effects in conditional variance estimation. Part A investigates a genetic fuzzy trading model for stock trading. This part contributes to use a fuzzy trading model to eliminate undesirable discontinuities, incorporate vague trading rules into the trading model and use genetic algorithm to select an optimal trading ruleset. Technical indicators are used to monitor the stock price movement and assist practitioners to set up trading rules to make buy-sell decision. Although some trading rules have a clear buy-sell signal, the signals are always detected with 'hard' logical. These trigger the undesirable discontinuities due to the jumps of the Boolean variables that may occur for small changes of the technical indicator. Some trading rules are vague and conflicting. They are difficult to incorporate into the trading system while they possess significant market information. Various performance comparisons such as total return, maximum drawdown and profit-loss ratios among different trading strategies were examined. Genetic fuzzy trading model always gave moderate performance. Part B studies and contributes to the literature that focuses on the

forecasting of daily financial time series using intraday information. Conventional daily forecast always focuses on the use of lagged daily information up to the last market close while neglecting intraday information from the last market close to current time. Such intraday information are referred to incremental intraday information. They can improve prediction accuracy not only at a particular instant but also with the intraday time when an appropriate predictor is derived from such information. These are demonstrated in two forecasting examples, predictions of daily high and range-based volatility, using linear regression and Neural Network forecasters. Neural Network forecaster possesses a stronger causal effect of incremental intraday information on the predictand. Predictability can be estimated by a correlation without conducting any forecast.Part C explores intraday effects in conditional variance estimation. This contributes to the literature that focuses on conditional variance estimation with the intraday effects. Conventional GARCH volatility is formulated with an additive-error mean equation for daily return and an autoregressive moving-average specification for its conditional variance. However, the intra-daily information doesn't include in the conditional variance while it should has implication on the daily variance. Using Engle's multiplicative-error model formulation, range-based volatility is proposed as an intraday proxy for several GARCH frameworks. The impact of significant changes in intraday data is reflected in the MEM-GARCH variance. For some frameworks, it is possible to use lagged values of range-based volatility to delay the intraday effects in the conditional variance equation.

本論文的摘要：

這篇論文包含了三個部分：第一部份是爲股票交易而設計的遺傳模糊交易模式，第二部份是將日內增量信息(Incremental Intraday Information) 應用於金融時間序列預測上，第三部份是研究在估計條件變異數中的日內效應。

第一部份探討爲股票交易而設計的遺傳模糊交易模式。這部份的貢獻是使用模糊交易模式，去消除不理想的間斷，將含糊的交易法則用於交易模式，以及使用遺傳算法來選擇最佳的交易法則集。技術指標用於監測股價運動，幫助從業人員設立交易法則，以便作出買賣的決定。雖然有些交易法則集，擁有明確的買賣信號，可是這些信號的檢測，總是利用邏輯上的〔是〕和〔非〕，當投資決定由這些交易法則集和布爾變數(Boolean variables)組成時，只要其中一個技術指標出現微小轉變，就引發了意想不到的間斷。另外，有些交易法則含糊和矛盾，很難納入現存的交易系統內，可是他們亦擁有有效的市場信息，能夠幫助交易系統作出準確的決定。同時，爲了更廣泛研究交易模式的各項性能，我亦探討和比較不同交易系統的總回報，最大跌幅，以及損失和盈利率。總括而言，遺傳模糊交易模式的表現是最平穩。

第二部部份的研究和貢獻，側重利用日內信息於每日財務時間序列預測上。傳統的每日預測常常著眼於如何使用滯後的每日信息(Lagged Daily Information)，而忽略了日內信息的使用。這種日內信息被稱日內增量信息。它們不但可以提高某個特定時間的預測準確性，而且預測準確性亦跟隨日內時間向前而增加。從兩個預測例子中，可探之一二，第一個是每日最高值的預測，第二個是极差波動(Range-based Volatility)的預測，在預測時，分別使用了線性回歸和神經網絡的模式。結果發現，神經網絡預測具有較強的因果增量日內信息效應。同時，可預測性(Predictability)是可以透過日內增量信息和預測者的相關値來估計。

第三部份，探討在估計條件變異數中的日內效應。這方面的貢獻，側重於如何將日內效應加於估計的條件變異數上。傳統非對稱一般化自我迴歸條件異質變異數（GARCH）的波動是由兩條方程式組成，第一條是每日回報相等於其平均值加誤差的方程式，第二條是自我迴歸移動平均規範 (autoregressive moving-average specification)的條件變異數所制定。然而，現存的條件變異數並沒有包含日常的日內信息，但是這些信息對每日的變異數是有影響的。 因此，這部份提出了利用恩格爾(Engle)乘法誤差模式(MEM)的方案，將极差變異數替代日內信息，加於不同的非對稱一般化自我迴歸條件異質變異數的框架上。對於日內數據的正面影響，亦同時反映在乘法誤差模式的非對稱一般化自我迴歸條件異質變異數

(MEM-GARCH)的變異數上。另外，亦可以使用滯後极差的波動，以拖延日內效應的形式加上有條件變異數方程。

Acknowledgement

There are a lot of people whom I would like to thank for their support and contributions to this research.

I started this study in Jan 2002. Without the continuous support from my research advisor, Prof. K. P. Lam, I couldn't start or continuous this part-time study up to this moment.

In July 2003, I received bad news from my best friend. He was accused of a crime since January 2003. At that time, I was extremely busy at preparing the qualifying examination in early July, a presentation in September in JCIS'2003 and a progress presentation in early October. I regretted that I couldn't help him or even accompany him to the court in his hardest time at that busy period. When he was judged to be guilty, I had taken the plane to USA to attend JCIS'2003. Finally, I never saw my best friend again. This friend always encouraged me in different aspect including this PhD study. I sincerely thanks his encourage in my past time.

In Mar 2004, I received another bad news from my father. He got a cancer. I still remembered that after he took four-hour surgery, my mother greatly depressed. She returned home but couldn't sleep for whole night. On the other hand, I was accompanied my father for a whole night. The salt bag was replaced one after one every 20 minutes. The color of the bag changed from red to pink and from pink to transparent. The time was passed very slowly. After this surgery, he was under monitoring. Every time I accompanied him to the hospital. He

pretended not to be afraid of the checking. I held his hand tightly. When he knew that he needed to conduct the second surgery, he was very threatened and lost his direction. I was his final support at that moment. At that time, I made a decision to quit the study while Prof. K.P. Lam supported me to defer the study. I understood that this option should not be the best option for the department. Thank you for his fully support up to this moment.

In April 2005, I started the study again. After passing a qualifying examination in July, I needed to prepare an oral defense for thesis proposal. Prof. K.P. Lam provided very useful guideline to write down the thesis proposal and conduct the oral defense within one month. Under this tight schedule, I passed the oral defense of thesis proposal. It seemed to be impossible to me. However, he helped me again.

In September 2007, I found that I lost my direction and couldn't continue my research work again. Owing to the heavy loading day time work, I couldn't return to CUHK regularly on weekday. Prof. K.P. Lam returned to CUHK to provide comments on my research on Saturday every two weeks or one week. Until May 2008, the workload for my daytime work was very heavy and I got cough again. My doctor tried different medicine to cure my cough but the result was negative. (I still remembered that the symptoms were close to those in 2002 and 2003 summers. In those years, I cough blood after completing three research papers in a short period. I had tried different cough medicine but failed. Finally, I minimized my research work to let myself to recover it by myself.) I thought that if I wanted to carry on this study, I had no way but need to take rest. Thank you for Prof. Lam's tolerance on my one-month break in July. I would like to express my sincere gratitude to my research advisor, Prof. K.P. Lam, to accompany me to fight for this war.

Next, I would like to thank my older brother, Mr. Ng Hoi Tak. After I resumed my study in April 2005, he took up the family matters and accompanied my father to conduct regular health checking in hospital. Thus, I could concentrate on the study.

In addition, I would like to thank Prof. Wai Lam and Prof. Jreffey Yu for their helpful suggestions and comments on improving the quality of my research work. I was sorry that I was not a good presenter. However, they were patient to listen to my presentation. Furthermore, I would like to thank Prof. Chen Shu-heng's to provide valuable time to attend my oral defence during the seminar. He also provided very useful comments on my thesis so as to increase the quality of the thesis.

Thanks must go to my friends, Dr. Franklin Lam, Prof. Peter Zhang, Dr. Fung Wai Keung Prof. Jiming Liu and Mrs Linda Callaway to provide insight to my research. Dr. Joe Law, Miss Angel Tse, Lee Wai Hung, Kenneth Tang, Joseph Chung, Terrence Mak, Ms Bella Kong and Leung Chi Keung Bono always give me encouragement. Ms Ada Tse, Mrs Rita Lau, Keith Chan and Eric Kwok approved of my vacation leave to conduct this study.

Lastly, I would like to thank my fiancée, Miss Lam Kin Ha. In 2008 and 2009, they were the most difficult years. The lengthy PhD study caused me to break down. I not only couldn't concentrate on the reseach work but also lost interest in the research. I always enforced myself to sit in front of notebook but failed to work on the thesis. I even found that the cough problem was happened. In Mar 2009, overwhelming workloads from full time job brought me to sick. I understood that I had no way but needed to forfeit something. During that period, she gave me the most valuable support and encouragement in my life. Owing to this study, we deferred our marriage again and again.

I would also like to thank those who I have not mentioned in this acknowledgement, for their support or comments at the past eight years.

"Life was like a box of chocolate. You never know what you're gonna get ..." extracted from the novel of Forest Gump. To complete a PhD study is difficult. To complete a Part-time PhD study is extremely difficult because your brain are always swapped in different areas and works in a long period of time everyday, every month and every year. I am not sure whether I finally pass this study. However, this study has helped me to broaden my horizon. This thesis must be kept in my bookshelf as my life's reference even though I will not continue the research work in the future.

This work is dedicated to my parents, my brother, my fiancée and my best friend.

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Chapter 1

Introduction

1.1 Motivation

This thesis consists of three parts. Their motivations are described in the following three paragraphs.

Genetic Programming is recently applied to the trading system to select the optimal technical trading rules. Its structure is reducdant and complex. The indicator-based trading rules are combined with Boolean operators to form a profitable two-way trading strategy. However, the Boolean operations perform with a 'hard' logic. Any small change of technical indicator may result in unexpected jumps of Boolean variables. This triggers the undesirable discontinuities due to the jumps. Furthermore, vague trading rules are difficult to embrace in the trading system while they contain useful information for a trading decision. These motivate to extend the existing work.

Most of daily financial time series forecasts rely on the information set including and up to day $t-1$. Normally, these forecast problems are formulated by a forecast model given the past information($\mathcal{F}_{t-1}$). By uncovering the dynamic path of a daily time series, the predictable components of the series can be extrapolated into the future and it thus improves forecasts [17]. Recently, the availability of high frequency data initiates some active researches in finance [10]. Significant intraday information is very useful in the modelling of daily information ($y(t)$) such as realized volatility [3] and stochastic jump [55]. Conventional forecast of $\hat{y}(t)$ often focuses on the use of lagged daily information while neglecting intraday information between $t-1$ and t. This motivates to use such intraday information in the prediction. Such intraday information is referred to as "incremental intraday information" and has been largely neglected in current forecasting research.

Volatility has very important implications or a wide range of applications in financial forecasting and risk management [2]. There is no consensus on its "true" or "best" measure [19]. It only classify volatility either latent such as implied volatility [41] [7] or historical like realized volatility [3]. The simplest volatility measure is probably the squared daily return. This unbiased estimator is highly inefficient as a measure capturing the intra-daily price variation in the trading day [23]. When all daily close prices are shifted to same reference value, its volatility is zero but the intra-daily prices may have variation. There exists a risk to measure the volatility solely on the close price. Conventional daily conditional variance is formulated with an additive-error mean equation for daily return and an autoregressive moving-average specification for its conditional variance. However, the intra-daily information doesn't include in the conditional variance while it should has implication on the daily variance. This motivates to explore the possible method to include the intra-daily information to the conditional variance.

1.2 Thesis Contributions

This thesis introduces genetic fuzzy trading modeling, a daily prediction, and intraday modeling. The first model is a trading model which models the relationship between a market state and an action using a trading strategy. The daily prediction is conducted using incremental intraday information and daily past information. The second model is to embed the intraday fluctration in a daily conditional variance.

For the genetic fuzzy trading modeling, a fuzzy expert trading model is derived to map the market state to action. Owing to the natural of fuzzy, a vague trading rule like other trading rules can be easily embraced in the trading model as one of fuzzy rules in the trading system. As the trading action is determined based on an aggregated output, it minimizes the impact of any small change of a single technical indicator on the action. Subsequently, the action becomes less volatile. An undesirable and sudden discontinuity due to the jump of the Boolean variables will vanish. This trading model also identifies the optimal trading ruleset by genetic algorithm and eliminate the conflicting information from different trading rules by fuzzy system.

For the incremental intraday prediction, incremental intraday information is applied to the daily forecast problem. Various incremental intraday measures are derived to extract useful information from incremental intraday information. Such useful information acts as a predictor in the prediction and is very useful to improve the prediction accuracy. By modifying the error correction model, I apply its forecast equation in the incremental intraday prediction. Selection of an appropriate incremental measure is crucial to the prediction. When the formulation of incremental measure is close to the formulation of predictand, the prediction accuracy will gradually increase with intraday time. It is further discovered that the prediction accuracy can be estimated by the correlation between the predictand and the predictor.

For the intraday modeling, conventional GARCH modeling formulates an additive-error mean equation for daily return and an autoregressive moving-average specification for its conditional variance, without much consideration on the effects of intra-daily data. Using Engles multiplicative-error model formulation, range-based volatility is proposed as an intraday proxy for several GARCH frameworks. To evaluate the intra-daily effect on the conditional variance, different approaches for two 8-year market data sets: the S&P 500 and the NASDAQ composite index, are studied and compared. The impact of significant changes in intraday data has been found to reflect in the MEM-GARCH volatility. Besides, it is also possible to use lagged values of range-based volatility to delay the intraday effects in the conditional variance estimation for some frameworks.

1.3 Thesis Organization

This thesis is organized as follows: Chapter 2 gives the related work for the Genetic Fuzzy Expert Trading System, Intraday Prediction and Modelling. Chapter 3 defines the stock trading problem, describes the use of fuzzy trading system in trading and explains the selection the optimal fuzzy trading rules by genetic algorithm. Two training approaches for performance improvement are further evaluated. Chapter 4 defines the incremental intraday prediction problem and describes the use of incremental intraday information for different daily predictions. Chapter 5 revises the GARCH models and studies the intra-daily effect on the conditional variance. The conclusions and the future directions are presented in Chapter 6. For the ease of reference, the formula of technical indicators is included in Appendix A. 36 trading rules are listed in Appendix B.

1.4 List of Papers

This thesis is based on theoretical and experimental research which has previously been written up in 10 papers. They have been passed the peer-review process and have been accepted for publication in the proceedings of various international conferences and journal with high academic standards. Much of the same work is currently being written up or under review for archival publication in journals.

On problem with basing on a doctoral thesis on 10 papers is that the amount of research to describe threatens to make the thesis too long and lose focus. I have therefore selected 5 best papers to form the central arguments of this thesis. They are extensively discussed in this thesis. This means that the experiments in those papers may be described in rather more details in the thesis. The rest will be not be discussed in details. However, they may share same theory or related work and these will be included in the background chapter. The following are the ten papers:

- H.S. Ng and K.P. Lam (2006): "Incremental Intraday Prediction of Extreme Values and Range-based Volatility", In Proceedings of The Third IASTED International Conference on Financial Engineering and Applications. [46]

- H.S. Ng and K.P. Lam (2006): "How does Sample Size affect GARCH model?", In Proceedings of 5th International Conference on Computational Intelligence in Economics and Finance in conjunction with 9th JCIS. [47]

- H.S. Ng, S.S. Lam and K.P. Lam (2003): "Incremental Genetic Fuzzy Expert Trading System for stock market timing", In Proceedings of 2003 IEEE International Conference on CIFEr, pp.421-428. [49]

- H.S. Ng and K.P. Lam (2001): "Stock prediction using NASDAQ-GEM model", In Proceedings of the 5th World Multi-Conference on Systemics, Cybernetics and Informatics (SCI2001). [53]

- H. S. Ng and K. P. Lam (2000): "Modeling of NASDAQ-GEM Stock Price Relationship using Neural Network", In Proceedings of the 2000 IEEE International Conference on Management of Innovation and Technology. [54]

- K.P.Lam and H.S. Ng (2006):"Intra-daily information of Range-based Volatility in MEM-GARCH", To appear in Mathematics and Computers in Simulation. [31]

- K.P.Lam and H.S. Ng (2006): "Intra-daily information of Range-based Volatility in MEM-GARCH", In Proc. of Int. Conf. on Time Series Econometrics, Finance and Risk, Perth. [32]

- K.P. Lam and H.S. Ng (2001): "Non-linear News modeling of NASDAQ indices", In Proceedings of the 5th World Multi-Conference on Systemics, Cybernetics and Informatics (SCI2001). [34]

- S.S. Lam, H.S. Ng and K.P. Lam (2003): " Application of Dynamic GFETS in a Declining Stock Market", In Proceedings of FEA'2003, pp.327-30, Cary, North Carolina. [36]

- S.S. Lam, H.S. Ng and K.P. Lam (2002): "Genetic Fuzzy Expert Trading System for NASDAQ Stock Market Timing", Contributed a book chapter to Genetic Algorithms and Genetic Programming in Computation Finance. [37]

In addition, the following papers were published during my PhD but not included in this thesis.

- H.S. Ng and K.P. Lam (2003): "Analog and FPGA Implementation of BRIN for optimization problems", IEEE Transactions on Neural Network, Vol. 14, No. 5, pp.1413-25. [50]

- H.S. Ng, S.T. Mak and K.P.Lam (2003): "Field Programmable Gates Arrays and Analog Implementation of BRIN for Optimization Problems", In Proc. of IEEE ISCAS'03, Vol. V, pp73-76. [51]

- H.S. Ng and K.P. Lam (2002): "Analog Implementation of BRIN for optimization problems", In Proc. of IEEE TENCON'03, vol. 1, pp. 637 - 640. [52]

- Y.T. Yan, H.S. Ng, K. P. Lam (2003): "Advanced Trading Strategy Using Neuro-Candlestick", In Proc. of CIEF'2003, pp.1120-1123. [67]

- Terrence Mak, K.P. Lam, H.S. Ng, C.S. Poon, G. Rachmuth (2007): "A Current-Mode Analog Circuit for Reinforcement Learning Problems", In Proceedings of 2007 ISCAS. [40]

- P.Y. Mok, K.P. Lam and H.S. Ng (2004): "An ICA Design of Intraday Stock Prediction Models with Automatic Variable Selection", In Proceedings of IJCNN'04. [42]

- P.Y. Mok, K.P. Lam and H.S. Ng (2004): " Correlation-Predictability Analysis for Intraday Predictions", In Proc. of the 2nd IASTED Int. Conf. on FEA 2004. [43]

□ **End of chapter.**

Chapter 2

Literature Review

This chapter presents a brief review on the related work for Genetic Fuzzy Expert Trading System, Intraday Prediction and Modelling.

2.1 Related Work on Genetic Fuzzy Expert Trading System

Technical analysis is originated with the work of Mr. Charles Dow in the late 1800s. Mr. Dow is the founder and the first editor of the Wall Street Journal. Technical analysis is now widely used by investments professionals as input for trading decisions. Technical analysts argue that their approach can assist them to profit from changes in the psychology of the market. This view is clearly expressed in Pring's statement (in page 2-4 of [58]):

The technical approach to investment is essentially a reflection of the idea that prices move in trends which are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces. ... Since the technical approach is based on the theory that the price is a reflection of mass psychology ("the crowd") in action, it attempts to forecast future price movements on the assumption that crowd psychology moves between panic, fear, and pessimism *on one hand and confidence, excessive optimism, and greed on the other.*

Technical indicators are used in technical analysis. They do not analyze any part of the fundamental business such as earning, revenue or profit margins. Most of technical indicators are derived from price. They look at the price from different aspects such as price trend and movements. Practitioners believe that the technical trading rules, which are derived from the technical indicators, can generate substantial profit while some researchers swear only by the efficient market hypothesis. Subsequently, these researchers believe that the technical trading rule can't beat the market only referring to the historical price information.

Over the years, there has been a large literature on the effectiveness of different technical trading rules. However, there are a lot of significant results on the application of technical trading rules in stock trading system. In 1992, Brock et al. [8] considered the performance of various simple moving average rules for Dow Jones Industrial Average Index in the absence of transaction costs. They identified periods to be in the market when returns were high and volatility was low and out when the reverse was true. They also found that the simple technical trading rules had predictive power and suggested that the conclusions of earlier studies, that technical trading rules didn't have such power, were "pre-mature".

In 1997, Neely [44] used genetic programming to find technical trading rules in different foreign exchanges. They selected the trading rules based on the price and simple functions like maximum, minimum, average, greater-than, addition, subtraction, multiplication and etc. They discovered a profitable trading rule in the context of investment.

In 1999, Allen and Karjalainen [1] used genetic programming to learn the best technical trading rules for the daily S&P 500 index. Similar to Neely's work, they selected the trading rules based on the stock price and the simple functions. The trading rules didn't earn excess returns over simple buy-and-hold strategy after transaction costs and using out-of-sample data.

In 2001, Dempster et. al [12] [11] developed a trading system using genetic programming and technical indicators. They aim to construct a trading system based on the overall performance. They allowed genetic programming to construct strategies from a selection of indicators instead of a simple function. These indicator-based trading rules can be combined with boolean operators to form profitable two-way trading strategies.

Genetic Programming (GP) [30] is an evolutionary optimization algorithm. They resolve the problems by mimicking the process of evolution. GP considers the solution as non-recombining decision tree with non-terminal nodes as functions and the root as the funciton of output. It provides flexibility on the size of tree. On the other hand, some tree structures are highly redundant and complex due to the recursive operation. They are hard to understand by human although they can be simplified manually [1]. Dempster adopted GP to construct a buy/sell trading rule by combining the indicator-based trading rules with the boolean variables. The boolean operations work in 'hard' logic. Any small changes of indicator may change the buy/sell decision. Thus, these trigger undesirable discontinuities due to the jumps of the boolean variables.

In 2007, P. Lin and J. Chen [9] further enhanced the GP model. They discovered that a subtree crossover operator usually destroys building blocks due to the random and blindly choosing crossover points. Many researchers proposed different crossover methods to obtain more effective building blocks by reserving crucial schemata. However, These crossover operators only exchanged constant schemata for all individuals in the population. No new genotype was generated even when swapping partial trees in the dedicated population. It initialized the exploration of a new crossover operator in fuzzy genetic programming. FuzzyTree crossover is more effective than a subtree crossover in terms of complexity and run time. In 2001, Tay and Linn [64] expressed that the actual financial market environment was usually much more ill-defined. Under the ill-defined environment, it was impossible for practitioners to form precise and objective price expectation. The participants thus should rely on some alternative form of reasoning to guide their decision making. An inductive reasoning model at best relied on fuzzy decision making rules under ill-defined environment. The study of fuzzy system in evolutionary algorithm becomes a new direction for the study of the ill-defined environment.

In this thesis, I extend Dempster's study on the application of the technical indicator and evoluationary algorithm to the trading system. However, the other evoluationary algorithm, Genetic Algorithm (GA) [26], is used as GA's solution has a simple structure and GA only considers a fixed solution length. The introduction of fuzzy trading system can reduce the discontinuities by considering the weight average of the output signal of each indicator-based trading rules. The output signal is a degree of signal instead of one or zero. By taking the advantage of fuzzy system, some vague trading rules can also be embeded in the trading system. These trading rules are always come from the ill-defined market environment. Thus, the genetic fuzzy trading model is proposed.

It is well-known that the stock market is dynamic. Without any re-learning approach, the same set of fuzzy trading rules are unable to time the market. The importance of time horizons in models of learning in finance has been discussed in 2001 by LeBaron [38]. He also explored the convergence properties of learning with heterogeneous horizons. In 1999, Lanquillon [35] also examined the learning in irregular intervals. These research work demonstrated the importance of re-training approach during a dynamic stock market. It also provides the ground to further extend the genetic fuzzy trading model using two different training approaches to tackle with the dynamic stock market.

2.2 Related Work on Incremental Intraday Information for Time Series Forecasting

Most of daily financial time series forecasts ($y(t)$, t is the day index) rely on the information set including and up to day $t-1$ ($\mathcal{F}_{t-1}$). Normally, these forecast problems are formulated by a forecast model given the past information($\mathcal{F}_{t-1}$). By uncovering the dynamic path of a series, the predictable components of the series can be extrapolated into the future and it thus improves forecasts [17]. Recently, the availability of high frequency data initiates some active researches in finance [10]. Significant intraday information is very useful in the modelling of daily information ($y(t)$) such as realized volatility [3] and stochastic jump [55]. Conventional forecast of $\hat{y}(t)$ often focuses on the use of lagged daily information while neglecting intraday information between $t-1$ and t. In this thesis, I focus on the use of such intraday information, referred to as "incremental intraday information", which have been largely neglected in current forecasting research.

Suppose that a daily predictand is determined only at the time of the market close. Incremental intraday information varies with current time. The current time refers to a time point when a daily forecast is required to be just conducted. In an extreme case, when the forecast event occurs at the time of market close, the predictand can be calculated directly from all intraday data on current day. The prediction error variance is zero. The prediction problem doesn't exist. Furthermore, incremental intraday information contains all intraday data on current day. Suppose the forecast event occurs within a time period between market open and close. The incremental intraday information refers to the group of intraday data from the time of market open to current time. Given incremental intraday information at current time and the past information set up to former day. There exists a unique prediction problem. I called it an incremental intraday prediction problem. The number of intraday prediction problem depends on the number of forecast events. In another extreme case, the forecast event occurs before the time of market open. Only the past information set up to former day is available. The incremental intraday prediction problem reduces to conventional forecast problem. The use of incremental intraday information is crucial to the incremental intraday prediction. If it is used effectively, it will reduce the prediction error variance gradually with intraday time.

The incremental intraday predictions of daily high, range-based volatility and realized volatility are studied using Nasdaq Composition Index. The daily high is the highest price on a trading day. Different forecasters can be extracted from incremental intraday information by an incremental intraday measure. The most effective forecaster should give the lowest prediction error variances at different events. The similar approach is used to select the effective forecaster for the prediction of range-based volatility. The range-based volatility have a long history and it estimates historical volatility from intraday data. In 1980, Parkinson [56] developed a daily volatility estimator based on daily extreme values, open and close which followed a Brownian motion process. At the same period, Garman and Klass defined an efficiency ratio to evaluate the efficiency of volatility estimators and further proposed a number of more efficient volatility estimators [23]. The range-based volatility is further modified by Beckers [6], Roger and Satchell [59] and Yang and Zhang[68]. Nowadays, the extreme values, open and close are reported in many business newspapers in form of candlestick, which is a popular indicator [16]. The most representative range-based volatility estimator, which is derived in Garman and Klass [23], is used to evaluate the causal effect of forecaster on the predictand.

2.3 Related Work on Intra-daily Effect on Conditional Variance

The volatility has very important implications for a wide range of financial applications such as financial forecasting and risk management [2]. However, there is no consensus on its "true" or "best" measure [19]. Generally, the volatility is classified as latent or historical. The latent volatility refers to non-measurable and model-based volatility like implied volatility [28]. The historical volatility is measurable and can be determined empirically like realized volatility [3]. The most simple volatility measure should be the squared daily return ($r^2 = p(t) - p(t-1)$) where $p(t)$ refers to the logarithmic close price of day t. This estimator is highly inefficient as a measure for capturing the intra-daily price variation in the trading day [23]. Consider an illustrative example in Fig. 2.1a. The intra-daily data (referenced against the open price of each day) show significant variations. These variations remain unchange when the daily close are all shifted to the same fixed reference. However, the squared daily return equals to zero. Although it is unlikely for real financial data to resemble Fig. 2.1b, it demonstrates the risk in relying solely on close prices to measure volatility.

Range-based volatility based on extreme values have been proposed and proved to be more efficient than the squared daily return. Its historical have been briefed in Section 2.2. Among the various range-based volatility estimators, the two representative ones derived by Garman and Klass are used for my further investigation. The first relied on the daily high, low and close

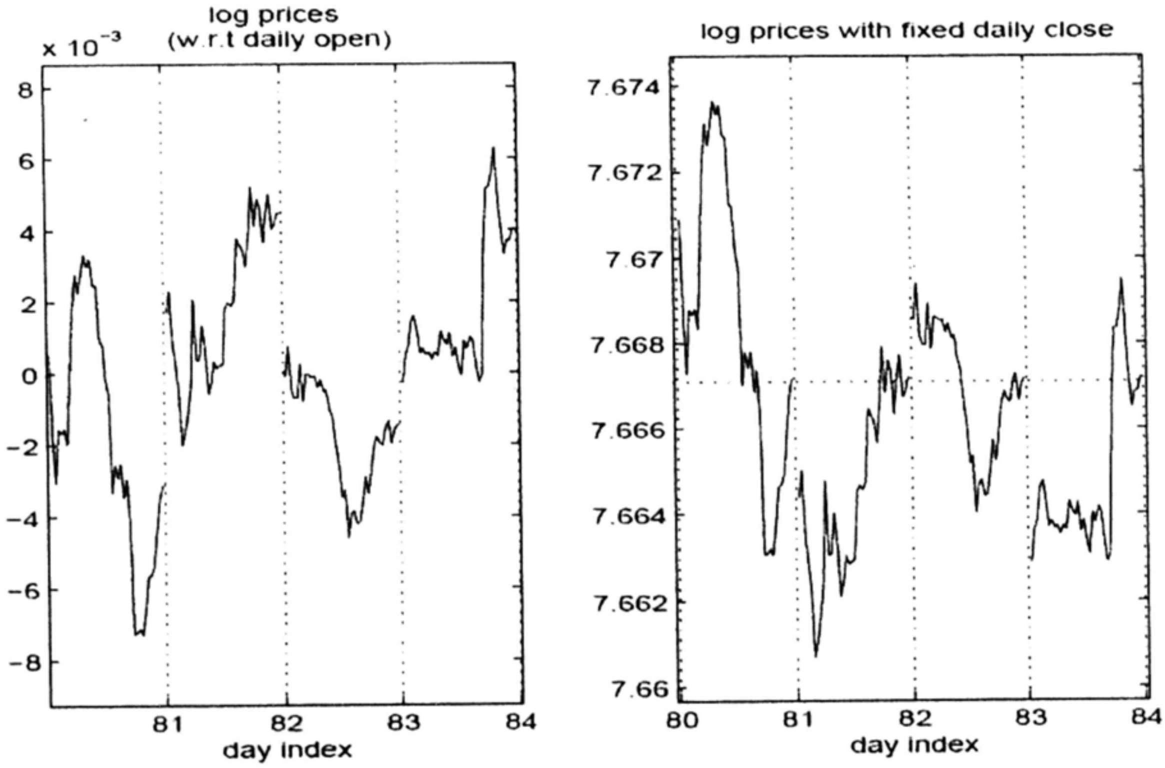


Figure 2.1: (a) Intra-daily data with reference to open(left), (b) Shifted data to a fixed close price(right)

with reference to the open. The second considers a more complete form using a weighting factors to accomodate the variation between the previous close and the present day open.

In this thesis, I consider the use of both types of range-based volatility estimator as intraday proxies for conditional volatilities derived from GARCH modeling. Several interesting issues motivate this research: (i) The highly succesfully GARCH(1,1) provides good estimates for conditional volatilities using only daily close price, but it is not clear how additional intraday information should be embedded and their effects on these estimates; (ii) the recently proposed multiplicative-error model (MEM) provides very effective means for including intraday data within the GARCH framework; and (iii) knowing the effects of readily available but limited intraday data {open, high, low, and close } on GARCH should help in understanding the use of more extensive and precise intraday information, such as realized volatility, in the future work.

□ **End of chapter.**

Chapter 3

Genetic Fuzzy Expect Trading Model for Stock Trading

This chapter starts with a description of the stock trading problem in Section 3.1. A Genetic Fuzzy Expert Trading (GFET) Model is proposed to resolve the stock trading problem in Section 3.2. To tackle with a time-evolving market, two training approaches, an incremental and a dynamic approaches, are introduced in Section 3.4. Empirical results for a GFET system and both approaches are presented in Section 3.5.

3.1 Stock Trading Problem

The stock trading problem is to find the optimal trading strategy among various trading strategies. Suppose that a trading strategy ϖ (like Fig. 3.1) is a function $\varpi : \mathcal{T} \times \mathcal{A} \rightarrow \mathcal{A}$, $(tr_t, a_{t-1}) \rightarrow a_t$. $tr_t \in \mathcal{T}$ is a market state on day t. It represents all output signals of i trading rules. The state space ($\mathcal{T} = (0,1)^i$) is defined as the set of all possible market states. $a \in \mathcal{A}$ is an action. The value of a is equal to 0 (i.e. holding 'CASH') or 1 (holding 'ASSET'). $\varpi(tr_t, a_{t-1})$ tells us whether we should hold CASH or ASSET. Various trading strategies are formed by considering different combinations of trading rules. The optimal trading strategy is a trading strategy with the maximum return

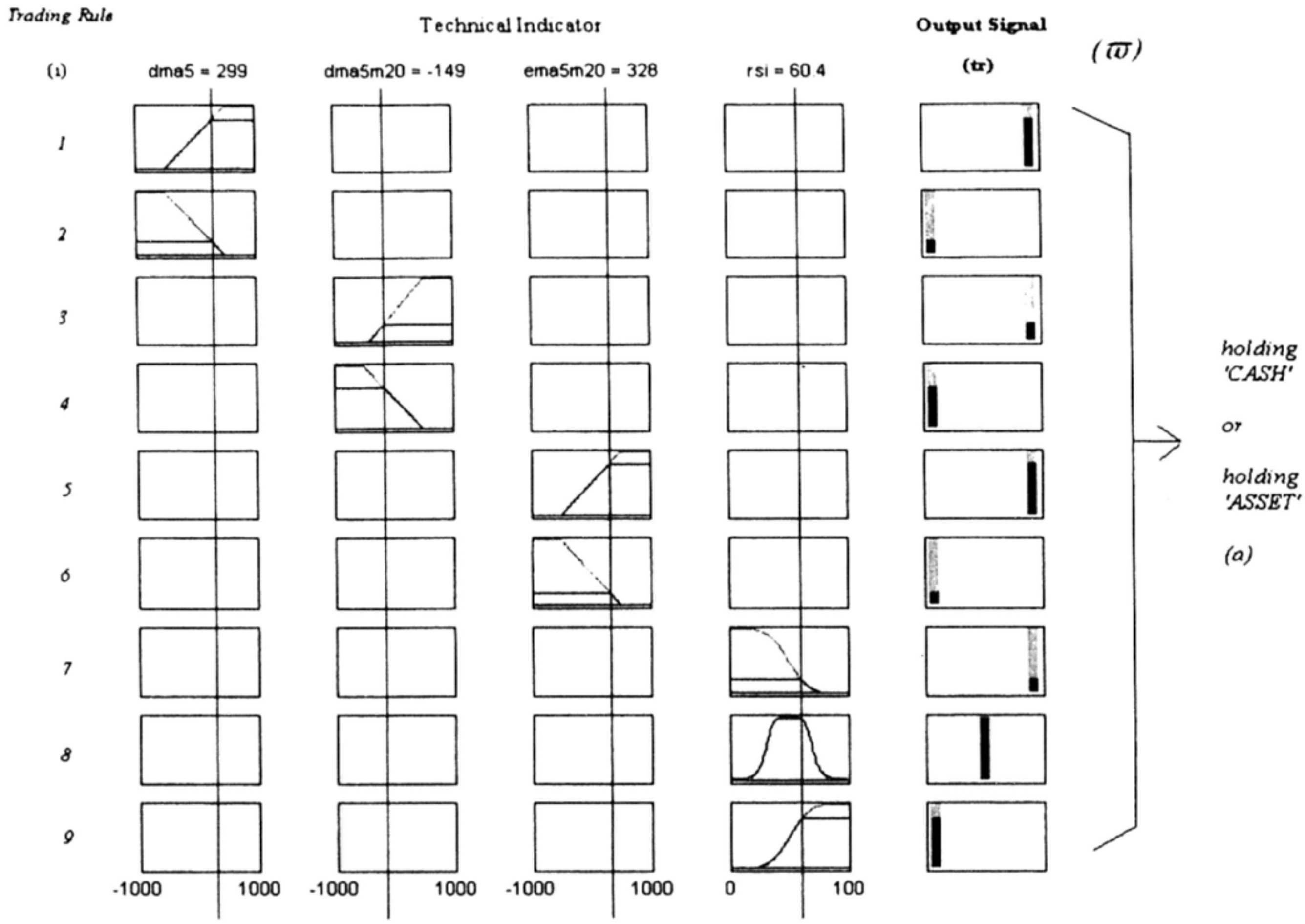


Figure 3.1: An Example of Trading Strategy

after transaction costs to some horizon t_f.

$$r(t_f) = \prod_{t=1}^{t_f-1} \frac{p(t+1)}{p(t)}^{\varpi(tr_t)} (1-\xi_t)^{|\varpi(tr_t)-\varpi(tr_{t-1})|} \tag{3.1}$$

where ξ_t is a proportional transaction cost.

3.1.1 Trading Strategy (ϖ)

Each trading strategy is used to determine an action under different market states. Suppose that an action on day $t-1$ and a trading recommendation on day t are known, and short selling is forbidden. The action on day t is easy to determine and is

Action on day $t-1$	Trading Recommendation on day t	Action on day t
Asset	Buy	Asset
Asset	Hold	Asset
Asset	Sell	Cash
Cash	Buy	Asset
Cash	Hold	Cash
Cash	Sell	Cash

Table 3.1: Next Action

depicted in Table 3.1.1. For the ease of representation, Eq. 3.2 is formulated to represent the the relationship in Table 3.1.1.

$$a_t = f(R_t + a_{t-1}, 0) \tag{3.2}$$

where $f(x,y)$ is a step function. If x ¿ y, $f(.) = 1$. Otherwise, $f(.) = 0$. a_{t-1} is the action on day $t-1$. $R_t \; \epsilon \; \{-1, 0, 1\}$ is the trading recomendation on day t. -1, 0 and 1 represent sell, hold and buy actions respectively.

In reality, the trading recommendation R_t is unknown but can be derived from the current market state tr_t. For example, Eq. 3.3 is formulated to classify an aggregate signal into buy, sell and hold recommendations based on the aggregate signal and threshold value τ. The aggregate signal (in Eq. 3.3) is the weighted average of market state (i.e. tr_t).

$$R_t = f(|\bar{w}|, \tau) * sign(\bar{w}) \tag{3.3}$$

$$\bar{w} = \frac{\sum w_i * 1 + \sum w_j * (-1) + \sum w_k * 0}{\sum w_i + \sum w_j + \sum w_k} \tag{3.4}$$

where $sign(x)$ is the sign of x. w_i, w_j and w_k refer to the buy, sell and hold signal strengths of these trading rules respectively. w_i, w_j or w_k is rated on a scale of 0 to 1. $\{w_i, ..., w_j, ..., w_k\}$ is the market state.

3.1.2 Optimal Trading Strategy

The optimal trading strategy under the time horizon t_f is a trading strategy ϖ which maximizes the return $r(t_f)$ after transaction cost in Eq. 3.1. Suppose that only n trading rules are considered as the whole ruleset. Each trading rule has a significant impact on the return. If a subset of these trading rules is used to construct a trading strategy ϖ_i, it will give another return $r_i(t_f)$. Totally, there are 2^n trading strategies. The optimal trading strategy refers to one of them and defined by

$$\varpi = \{\varpi_i | \max_{\forall i} r_i(t_f)\} \tag{3.5}$$

When n is small, all trading strategies can be tested to identify the optimal trading strategy. On the other hand, when n is large, it is impossible to test all trading strategies. Therefore, an efficient searching alogrithm is necessary.

3.1.3 Performance Measures

The return in Eq. 3.1 is of our great interest in the trading problem. On the other hand, maximum drawdown (in Eq. 3.8) and a profit-and-lose ratio (in Eqs. 3.9 and 3.10) are commonly used to measure the performance of different trading strategies. They are defined as follows.

Maximum DrawDown

The Maximum Drawdown (MDD) measures the maximum potential loss during the trading period (t_0, t_f). It is calculated by

$$M(t) = \max_{i \epsilon (t_0, t)} log[r(i)] \tag{3.6}$$

$$D(t) = M(t) - log[r(t)] \tag{3.7}$$

$$mdd(t_f) = \max_{i \epsilon (t_0, t_f)} [0, D(i)] \tag{3.8}$$

Profit and Loss Ratios

The profit and loss ratios measure the pecentage of positive and negative transactions respectively. Suppose the number of positive or negative return up to the current day t_f is $p_{ret}(t_0, t_f)$ or $n_{ret}(t_0, t_f)$ respectively. The total number of transaction is tr ($\neq p_{ret} + n_{ret}$). The profit and loss ratios are calculated by

$$PosR = \frac{p_{ret}}{tr} \quad (3.9)$$

$$NegR = \frac{n_{ret}}{tr} \quad (3.10)$$

If $PosR$ ($NegR$) is greater than 0.5, it will imply that profitable transactions are more (smaller) than loss transactions.

3.2 Genetic Fuzzy Expert Trading Model

A genetic fuzzy exxpert trading (GFET) model is proposed to resolve the stock trading problem. This model consists of two major parts - formulation of various trading strategies and search for an optimal trading strategy. Each trading strategy is formed by a fuzzy expert trading system. Various trading strategies are constructed with different trading rulesets. The optimal trading strategy is found by a genetic algorithm (GA).

3.2.1 Fuzzy Expert Trading System

A fuzzy expert trading system is a fuzzy expert system which performs approximate reasoning. It applies a set of if-then rules in the canonical form to map the input space to output space [14]. The input space is specified as fuzzy concept or linguistic variable and is defined by a membership function. The membership function is a curve that maps each point in the input space to a degree of membership function with the scale of 0 to 1 (i.e. fuzzification). Interpreting an if-then involves evaluating the antecedent using the fuzzification and applying that result to the consequent (i.e. Implication). The outputs of all rules are combined to give a crisp value (i.e. Aggregation and defuzzification). If the antecedent has several parts, fuzzy operators are applied to obtain a single number. The process of formulating the mapping from an input to an output using fuzzy logic is called fuzzy inference.

The fuzzy expert trading system adopts Sugeno-type inference method [61]. This method uses a constant or linear output membership function. The constant output membership function matches the crisp nature of the buy, sell or hold signal of fuzzy trading rules. For example, a zero-order Sugeno fuzzy trading system is depicted in Fig. 3.2.

Suppose that each trading rule has the following form.

$$\textit{If input } A = x_i, \textit{ then Output is } z_i = c_i.$$

where c_i refers to the buy, hold or sell signal (i.e. 1, 0 and -1 respectively). The output level z_i of each trading rule is weighted by the firing strength w_i of the trading rule. The firing strength is measured by a membership function in Eq.3.11.

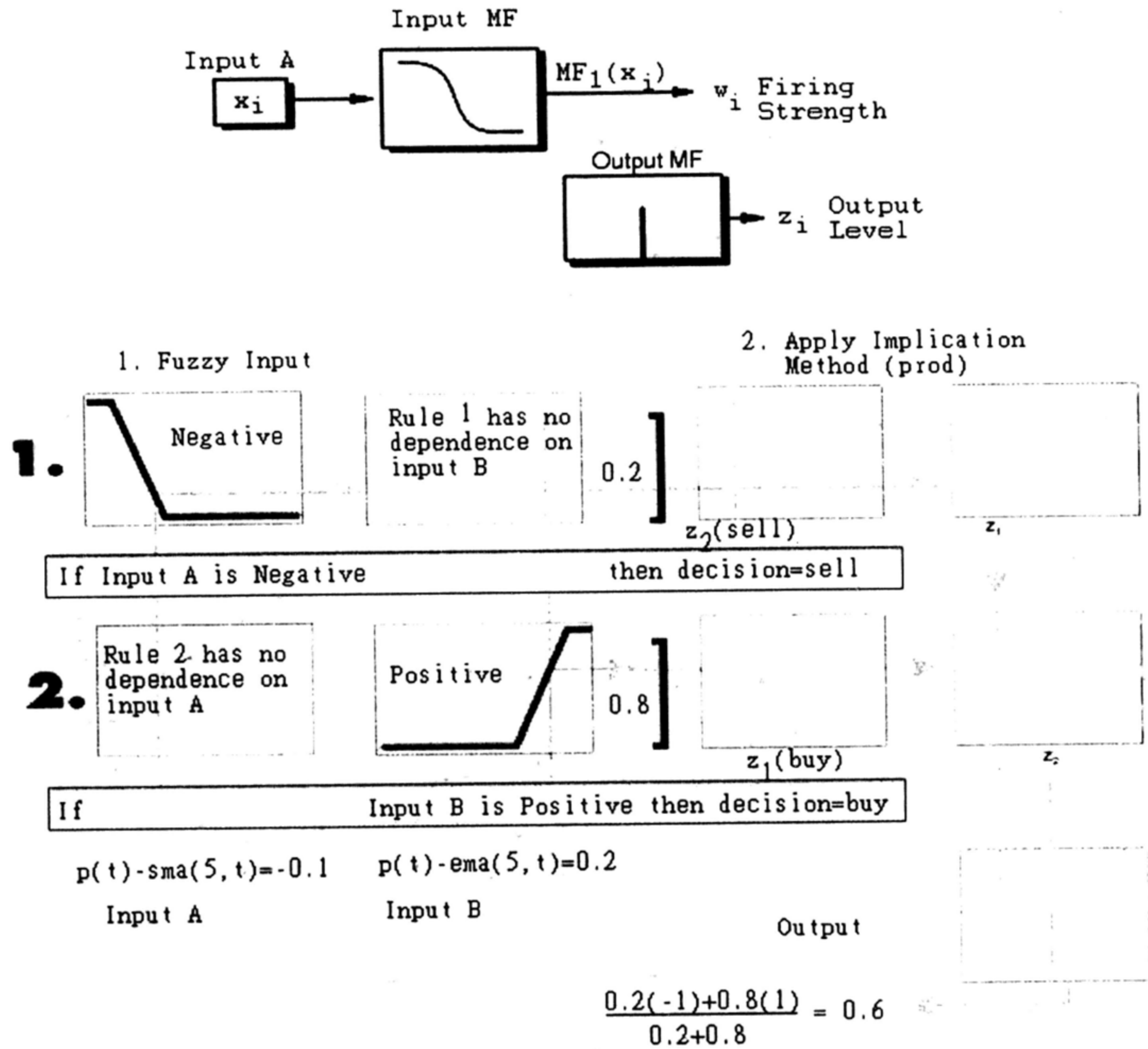
$$w_i = MF(x_i) \tag{3.11}$$

On the other hand, the antecedent of the trading rule has several parts as follows:

$$\textit{If input 1} = x_i \textit{ AND input 2} = y_i, \textit{ then Output is } z_i = c_i.$$

The fuzzy operator is AND and the firing strength of the fuzzy trading rule will be $w_i = min[MF_1(x_i), MF_2(y_i)]$ as in Fig. 3.3.

The final output of fuzzy trading system is the weighted average



Rule 1: If closing price crosses below 5-day simple moving average, decision is sell.

Rule 2: If closing price crosses above 5-day exponential moving average, decision is buy.

Figure 3.2: Sugeno-Type Fuzzy Trading Rule

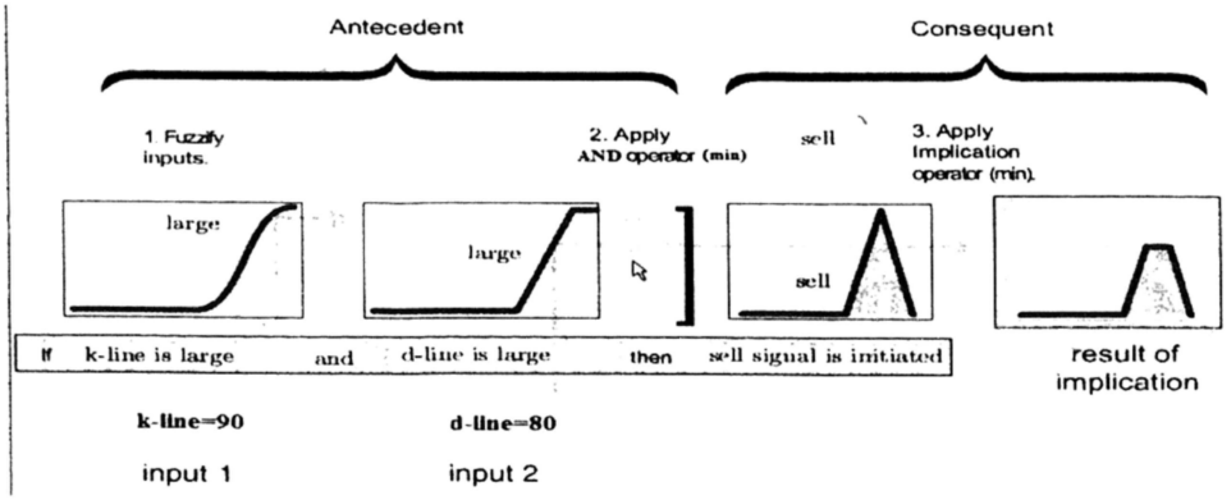


Figure 3.3: Fuzzy AND Operation

of all outputs as follows:

$$Output = \frac{\sum_{i=1}^{n} w_i z_i}{\sum_{i=1}^{n} w_i} \tag{3.12}$$

If the rules are re-grouped with the similar output signal, Eq. 3.12 is reformated as

$$Output = \frac{\sum w_i(1) + \sum w_j(-1) + \sum w_k(0)}{\sum w_i + \sum w_j + \sum w_k} \tag{3.13}$$

It is the same as $\bar{w}$ in Eq. 3.4. The firing strength is considered to be the same as the signal strength.

A simple example can be found in Fig.3.2. Suppose there are two trading rules as follows.

Rule 1: If closing price crosses below 5-day simple moving average, decision is sell *Rule 2: If closing price crosses above 5-day exponential moving average, decision is buy*

We can rewrite the above trading rule to the fuzzy trading rules with the linguistic term $NEGATIVE$ and $POSITIVE$. The input of the membership function $NEGATIVE$ is the closing price minus the 5-day simple moving average while the input of the membership function $POSITIVE$ is the closing price minus the 5-day exponential moving average. The fuzzy trading rules are formed like the following.

Rule 1: If input $A = NEGATIVE$*, then output is decision* $=$ *sell* *If input* $B = POSITIVE$*, then Output is decision* $=$ *buy*.

For the first trading rule, if the value of A is equal to -0.1, the firing strength is 0.2 and the output level of sell is 0.2. For the second trading rule, if the value is equal to 0.2, the firing strength is 0.8 and the output level of buy is 0.8. Then, the final output is equal to the weight average of all outputs as follows:

$$\frac{0.2 * (-1) + 0.8(1)}{0.2 + 0.8} = 0.6 \tag{3.14}$$

Based on the final output of fuzzy system (i.e aggregate signal), the threshold and Eq. 3.3, the series of action during the time horizon t_f is determined. The corresponding return can be found with the series of action.

3.2.2 Optimal Trading Strategy by Genetic Algorithm

Genetic Algorithms (GAs) are a well-known efficient searching algorithm. A GA performs population initialization, selection, crossover, mutation and replacement until the goal or the maximum number of generation is reached. The objective of GA is to maximize the return. The fitness function thus is the return in Eq. 3.1.

Population Initialization

The initial population contains u chromosomes or individuals. Each chromosome consists of n genes and represents a trading

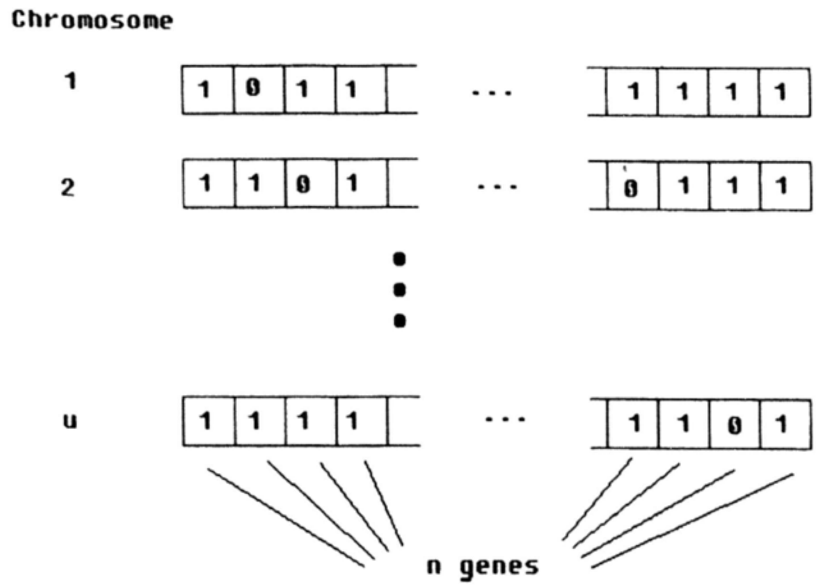


Figure 3.4: Initial Population

strategy ϖ_i such as Fig. 3.4 or 3.5. The value of each genes, being either 1 or 0, is randomly generated. Citing an example of Fig. 3.5, the value of 2^{nd} and 4^{th} genes are zero. It represents that the trading strategy doesn't use these fuzzy trading rules. A fuzzy trading system is built using the selected fuzzy trading rules. The fitness value is thus determined by this fuzzy trading system.

Selection

The selection of trading strategies (i.e. chromsomes) to produce successive generations plays an important role in the GA. A probabilitistic selection is performed based on the return of trading strategy. The better trading strategies have a higher chance to be selected. A ranking model is adopted to assign the probabilities to each trading strategy i. Each trading strategy is ranked in order of fitness value. A probability (P_i in Eq. 3.15)

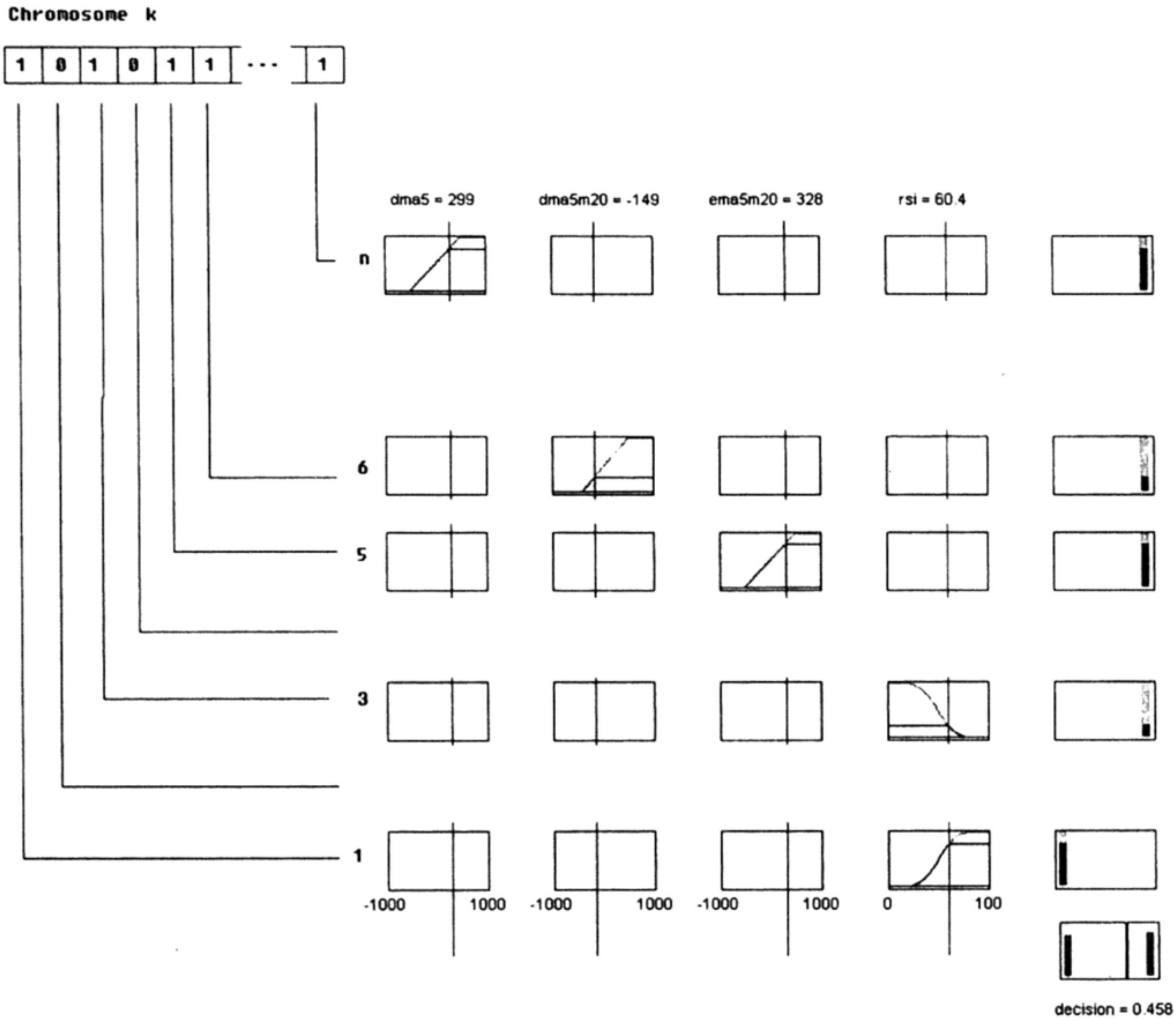


Figure 3.5: Trading Strategy with Selected Fuzzy Trading Rules

is defined by normalized geometric ranking [29] and is assigned to each trading strategy.

$$P_i = s(1-q)^{i-1} \qquad (3.15)$$

where q is the probability of selecting the best , i is the ranking of trading strategy, s is $\frac{q}{1-(1-q)^u}$. The cumulative probability of trading strategy i is calculated by $C_i = \sum_{j<i} P_i$. u generated random numbers are sorted and compared against the cumulative probability. If the cumulative probability of trading strategy i is greater than the random number, it will be selected. Then, the cumulative probability is again compared with the next random number. Otherwise, the cumulative probability of next trading strategy is compared with the current random number. Some trading strategy can be selected more than one and reproduce into the next generation.

Crossover

The reproduced population is used to conduct crossover. Crossover takes two trading strategies and produces two new trading strategies. Suppose trading strategies U and V are randomly selected from the population with the probability of 0.8. They are represented by a n-bit string. Simple crossover generates n random numbers (k_i) from a uniform distribution and creates two new trading strategies U' and V' by

$$u_i' = \begin{cases} u_i, & : \quad k_i \leq 0.5 \\ v_i, & : \quad otherwise \end{cases}$$

$$v_i' = \begin{cases} v_i, & : \quad k_i \leq 0.5 \\ u_i, & : \quad otherwise \end{cases}$$

The new trading strategies replace the original trading strategies in the population.

Mutation

The generated population is further processed by binary mutation. Binary mutation flips each bit in every trading strategies in the population with probability 0.1 according to the following equation.

$$u_i' = \begin{cases} 1 - u_i, & : \quad l_i \leq 0.1 \\ u_i, & : \quad otherwise \end{cases}$$

where l_i is a random number $U(0,1)$. The fitness value of each trading strategies in the mutated population is re-calculated again.

Replacement

In order to ensure the profitable trading strategy is not lost due to the stochastic character of the genetic operators, we have selected the Elitist strategy. The best trading strategy from the current population will pass to the next generation without any modification.

Termination Condition

For each generation, the above process, excluding the population initialization stage, is repeated until a chosen maximum number of generations is reached.

3.3 36-Rule Genetic Fuzzy Expert Trading System

A 36-rule genetic fuzzy expert trading system (GFETS) was built using the GFET model. Totally 68719476736 trading strategies can be formed with these 36 trading rules. These rules are listed in Appendix B. The GA is used to select the optimal trading rulset to build various trading strategies and find the optimal trading strategy among them. Each trading strategy is built with the fuzzy expert trading system (FETS). This system provides the trading decisions for each trading strategy. It consists of five parts: fuzzification of technical indicators, application of the fuzzy operator in the antecedant, implication from the antecedent to the consequent, aggregation of consequences across the rules and determination of trading decision. Their details are given in the following subsections.

3.3.1 Fuzzification of Technical Indicators

Fuzzification involves the conversion of the technical indicator to the degree of membership in the qualifying linguistic set. All technical indicators and their corresponding linguistic terms are described in the following paragraphs.

Technical indicators can be classified into trend, momentum and volatility analyses. Trend analysis indicates whether a new trend has appeared in the data or an existing trend has finished. Momentum analysis measures the rate of change of data as opposed to the actual levels. Volatility analysis measures the rate of random change in market prices. For the completeness of the universal fuzzy ruleset, technical indicators in each analysis can be found in the universal ruleset. Totally, 11 technical indicators have been used to built 36 fuzzy trading rules. They are listed according to these analyses.

Trend Analysis : Daily Moving Average (DMA), Weighted Moving Average (WMA), Exponential Moving Average (EMA), and Directional Movement Index (DMI)

Momentum Analysis : Relative Strength Index (RSI), Moving Average Convergence-Divergence (MACD), Fast and Slow Stochastic (KD-line), Oscillator (OSC), Rate of Change (ROC), and Percent R (P-R)

Their mathematical formulations are given in Section A.

To fuzzify the inputs of fuzzy trading rules, it is necessary to define their linguistic terms. Some conventional trading rules are vague in natural. By the definition of linguistic terms, these trading rules can also be converted to fuzzy trading rule and embed in the fuzzy trading system. Table 3.3.1 summarized the linguistic terms of each trading rule. For the ease of reference, "cross-above" and "cross-below" are replaced with "NEGATIVE" and "POSITIVE" respectively. The membership functions of "SMALL" in RSI, %K or %D are different although they refer to the linguistic term "SMALL". For RSI, the small value always refers to the value smaller than 50 while the small value of %K or %D refers to the value smaller than 15. It is similar to the membership functions of "LARGE", "HIGH" and "LOW". To eliminate the duplicated definition of linguistic variables, the linguistic varaibles are grouped into NEGATIVE, POSITIVE, $SMALL_1$, MODERATE, $LARGE_1$, LESS-THAN-35, GREATER-THAN-65, SMALLER-THAN, GREATER-THAN, ZERO, $SMALL_2$, $LARGE_2$, LOW_1, $HIGH_2$, DECLINE, INCLINE, LOW_2, $HIGH_2$, SHORT and LONG. They are depicted in the following diagrams.

3.3.2 Application of Fuzzy Operator in the antecedent

In 36 trading rules, only rules 16 and 17 have mutliple parts. Both rules use the AND operation.

3.3.3 Aggregation of Consequences

After the truth values of antecedent of all trading rules are known, the output fuzzy set for buy, sell or hold is truncated using the minimum function (i.e. implication). The final output is the weight average of all rule outputs.

Item	Variable	Type	Min	Max	Linguistic variable
1	sma(5,.) - p(.)				
2	sma(20,.) - sma(5,.)				
3	wma(5,.) - p(.)	input	-1000	1000	NEGATIVE or POSITIVE
4	wma(20,.) - wma(5,.)				
5	ema(5,.) - p(.)				
6	ema(20,.) - ema(5,.)				
7	rsi(5,.)	input	0	100	$SMALL_1$, MODERATE or $LARGE_1$
8	rsi(14,.)	input	0	100	FEWER-THAN-35 or GREATER-THAN-65
9	rsi(t,.) - marsi(5,5.)	input	-100	100	SMALLER-THAN or GREATER-THAN
10	macd(39,9,2)	input	-1000	1000	NEGATIVE, ZERO or POSITIVE
11	%K(5,.)	input	0	100	$SMALL_2$ or $LARGE_2$
12	%D(5,.)	input	0	100	$SMALL_2$ or $LARGE_2$
13	%K(5,.) -%D(5,.)	input	-100	100	NEGATIVE or POSITIVE
14	osc(20,5,.)	input	-1000	1000	NEGATIVE or POSITIVE
15	roc(5,.)	input	-1000	1000	LOW_1 or $HIGH_1$
16	mom(5,.)	input	-1000	1000	DECLINE or INCLINE
17	%R(4,.)	input	0	100	LOW_2 or $HIGH_2$
18	pdi(5,.) - ndi(5,.)	input	-1000	1000	NEGATIVE or POSITIVE
19	vi(.)	input	-1	1	SHORT or LONG

Table 3.2: Linguistic Variables of Fuzzy Trading Rules

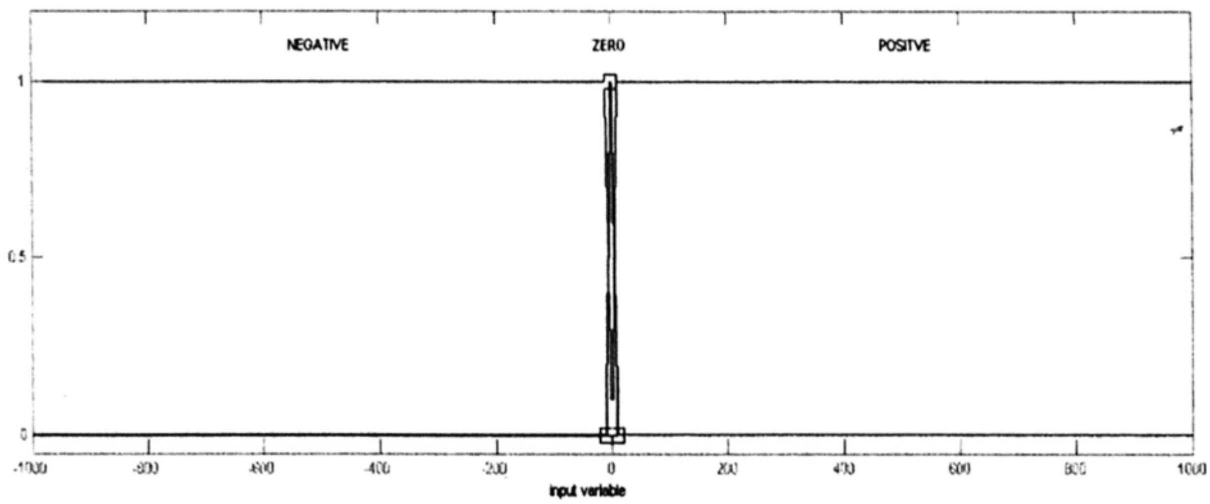


Figure 3.6: Membership Function of NEGATIVE, ZERO and POSITIVE

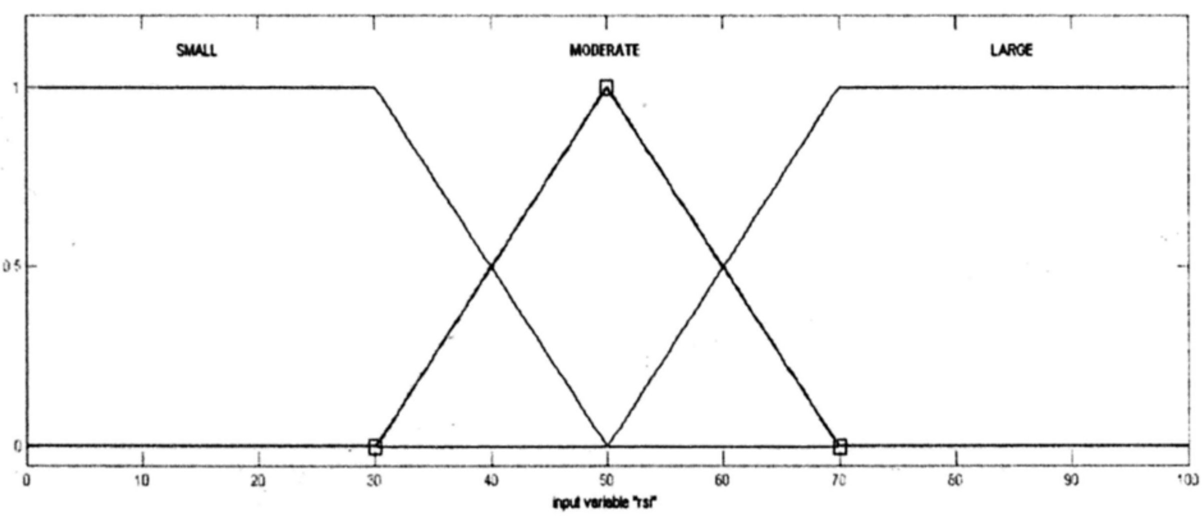


Figure 3.7: Membership Function of $SMALL_1$, MODERATE and $LARGE_1$

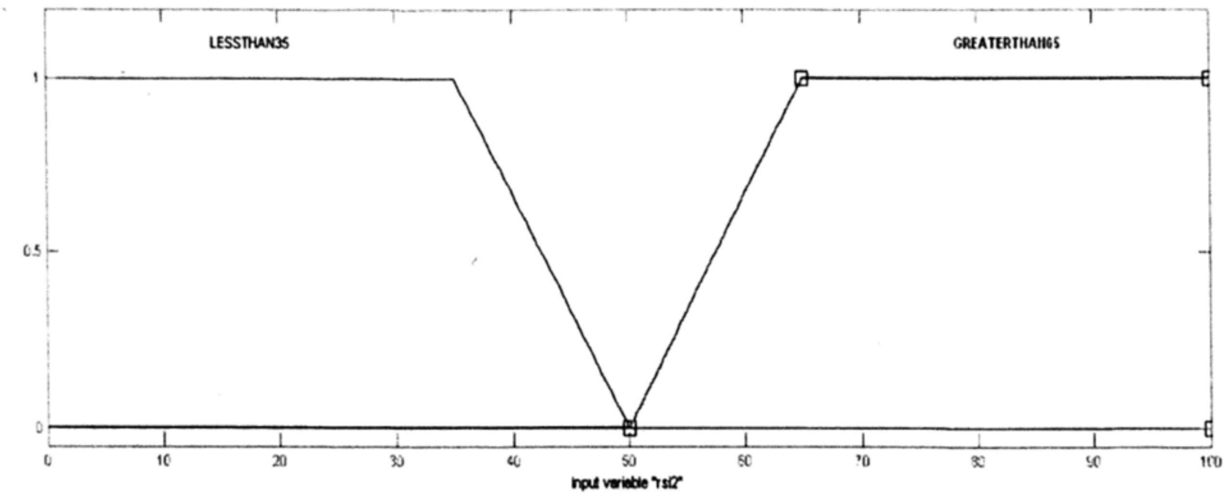


Figure 3.8: Membership Function of > 35 and < 65

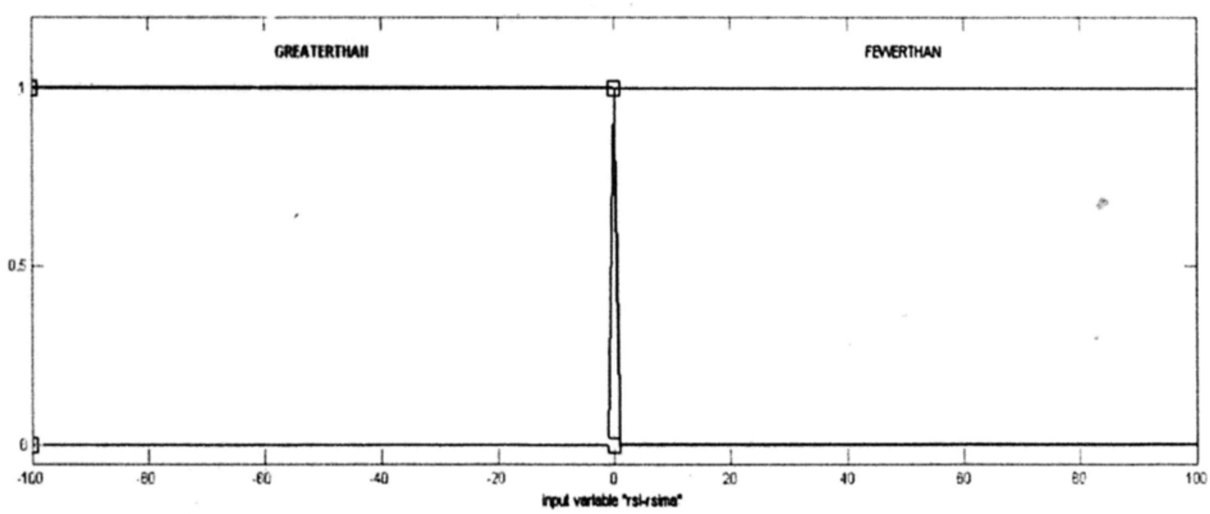


Figure 3.9: Membership Function of SMALLER-THAN and GREATER-THAN

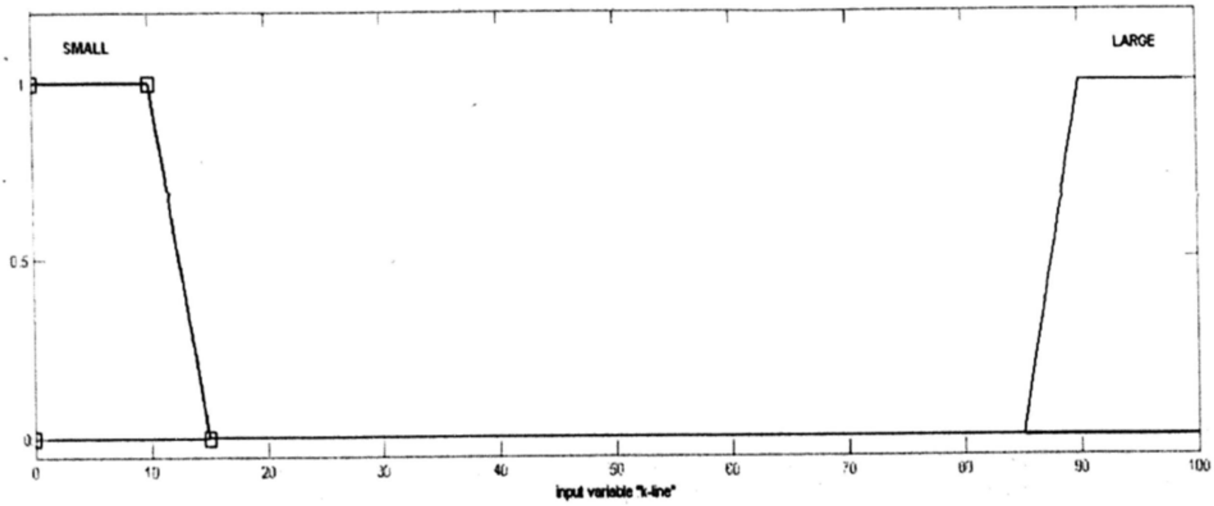


Figure 3.10: Membership Functions of $SMALL_2$ and $LARGE_2$

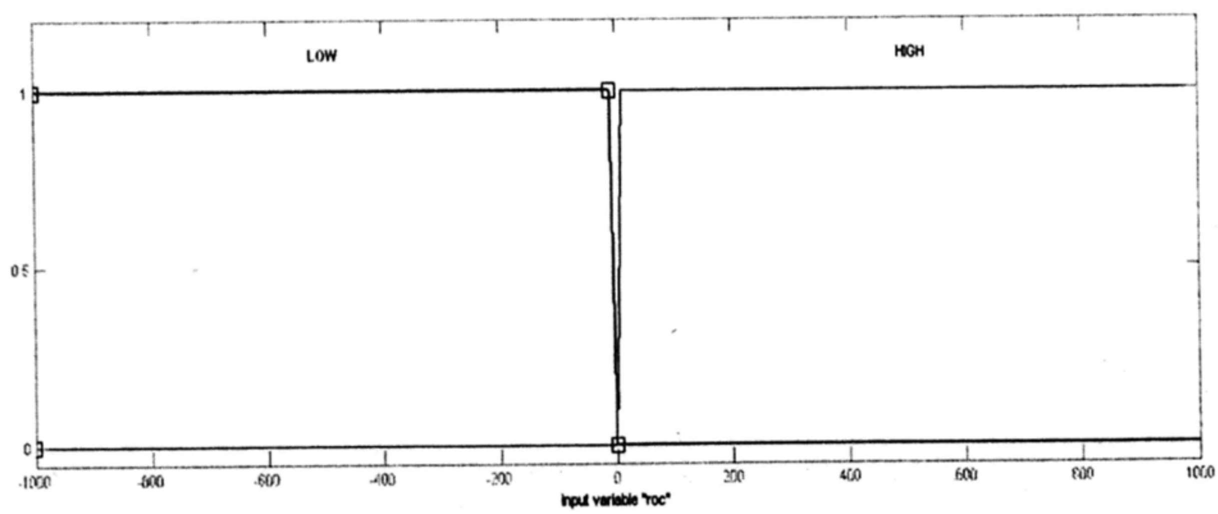


Figure 3.11: Membership Functions of LOW_1 and $HIGH_1$

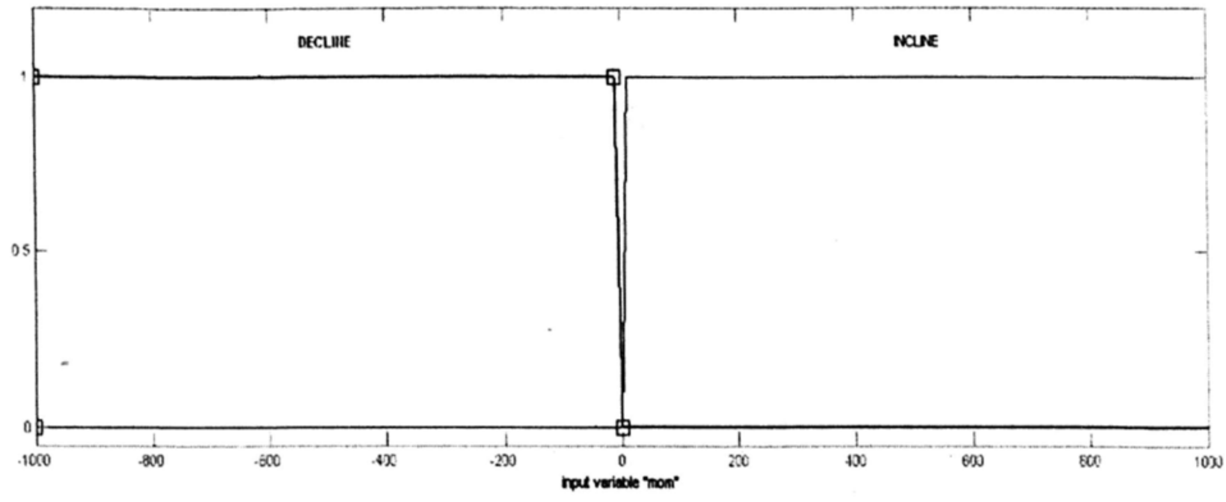


Figure 3.12: Membership Functions of DECLINE and INCLINE

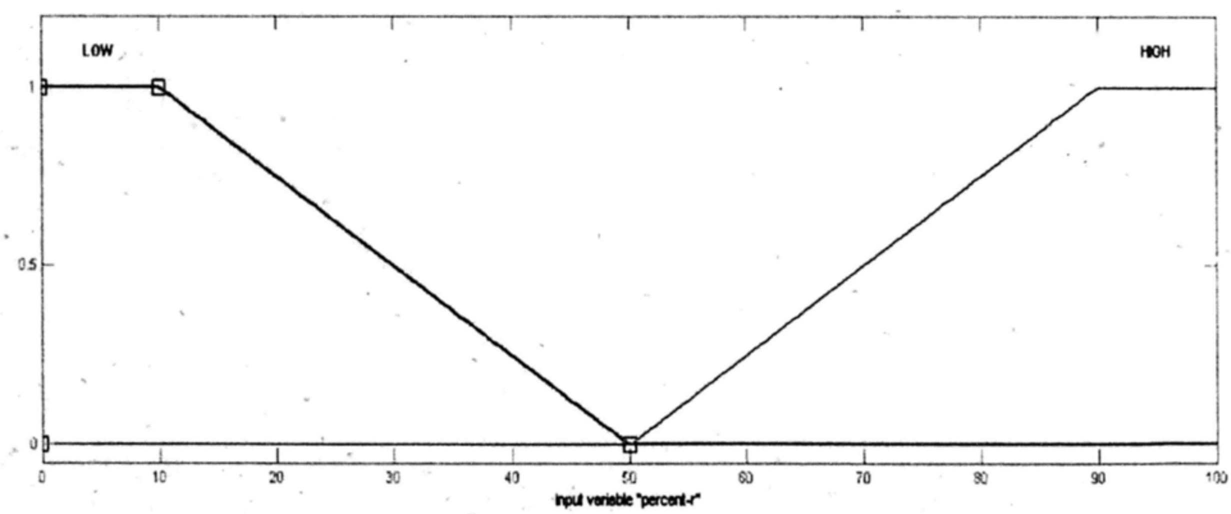


Figure 3.13: Membership Functions of LOW_2 and $HIGH_2$

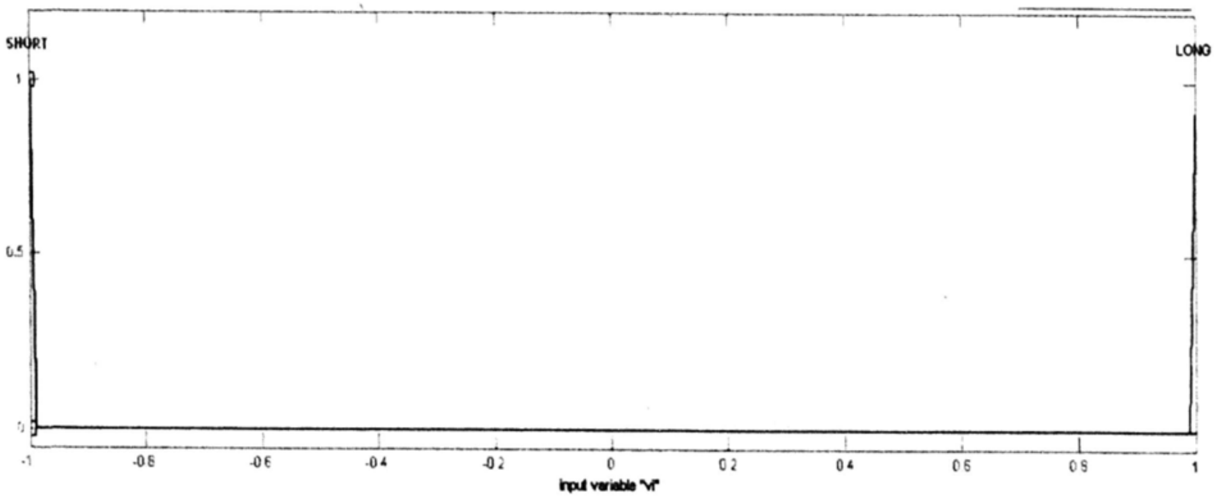


Figure 3.14: Membership Function of SHORT and LONG

3.3.4 Determination of Trading Decision

The threshold value τ is assigned to be 0.1. When the aggregated signal is higher than $+\tau$, a buy recommendation is triggered. If the aggregated signal is smaller than $-\tau$, a sell recommendation is triggered. Otherwise, the system suggests to hold the current status. The trading decision is made by Eq. 3.2.

3.4 Training Approaches

Two type of training approaches, incremental and dynamic, are introduced to tackle with time evolving market. The market is dynamic and changing rapidly with time. A trading strategy works very well in the past but may perform poor in the future. A trading system is necessary to be re-optimized from time-to-time so that it maintains its performance.

Both approaches are similar. They use the latest price information to train the trading system to ensure that the new fuzzy trading ruleset reflects the current market change. Each approach is briefly discussed in the following subsections.

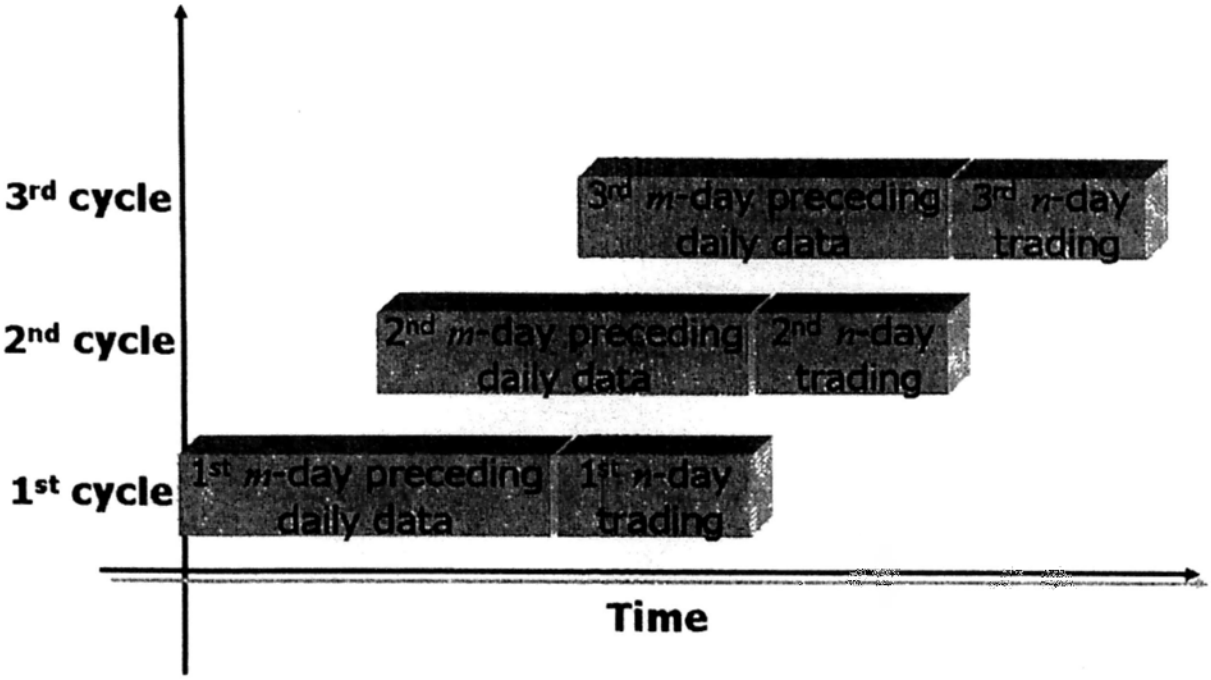


Figure 3.15: Incremental Training Approach

3.4.1 Incremental Training Approach

The GFETS is trained with m daily data and then re-trained once n trading days as in Fig. 3.15. The GA is used to select an optimal fuzzy trading ruleset from the fuzzy trading rules knowledge base using the first m preceding training data. The trading ruleset is used to trade for the first n trading days. The trading system is then re-initialized and is re-trained with the second m preceding daily data. The re-trained data set includes the first n daily data and the last $m - n$ receding training data. The new fuzzy trading ruleset is used to trade for the second n trading days. This process is repeated again and again until the end of trading.

The period of the training data and the interval to re-train the system are determined by the parameters (m, n). Generally, the value of the (m, n) pair directly affects the sensitivity and the responsiveness of GFETS to the market fluctuation.

Sensitivity (m)

When m was small and the historical data is insufficient for the GFETS to select a good fuzzy trading rules. The selection process is ineffective. As m increases and the training data increases, the selection process is more and more effective. Then, the larger the value of m, the more the historical data will be used for selecting the good fuzzy trading rules. This reduces the effect of short-term market fluctuation on the selection process and thus makes the GFETS less sensitive to the short-term fluctuation.

Responsiveness (n)

When n is small and the trading system is re-trained frequently, the fuzzy trading rules will change accordingly. The GFETS always makes adjustment in the system. The adjustment is ineffective. As n increase, the adjustment becomes more and more effective. When n is large, increase of the value of n results in increase of the re-training interval. It thus reduces the chance of making appropriate adjustment in the system in the evolving market. The responsiveness of GFETS will be reduced.

Thus, the selection of paramters (m, n) is very important so that the selected fuzzy trading rules give a good performance.

3.4.2 Dynamic Training Approach

The GFETS is first trained using m preceding daily data. The selected fuzzy trading rules are used for trading. If the current return is dropped below a return threshold level, the GFETS will be re-trained. Citing an example in Fig. 3.16, the system is trained with the first m preceding daily data. At the end of each trading day, the optimal trading ruleset is assessed with m current daily data. The current m daily data includes the most current daily data(e.g i) and the last $m - i$ preceding training

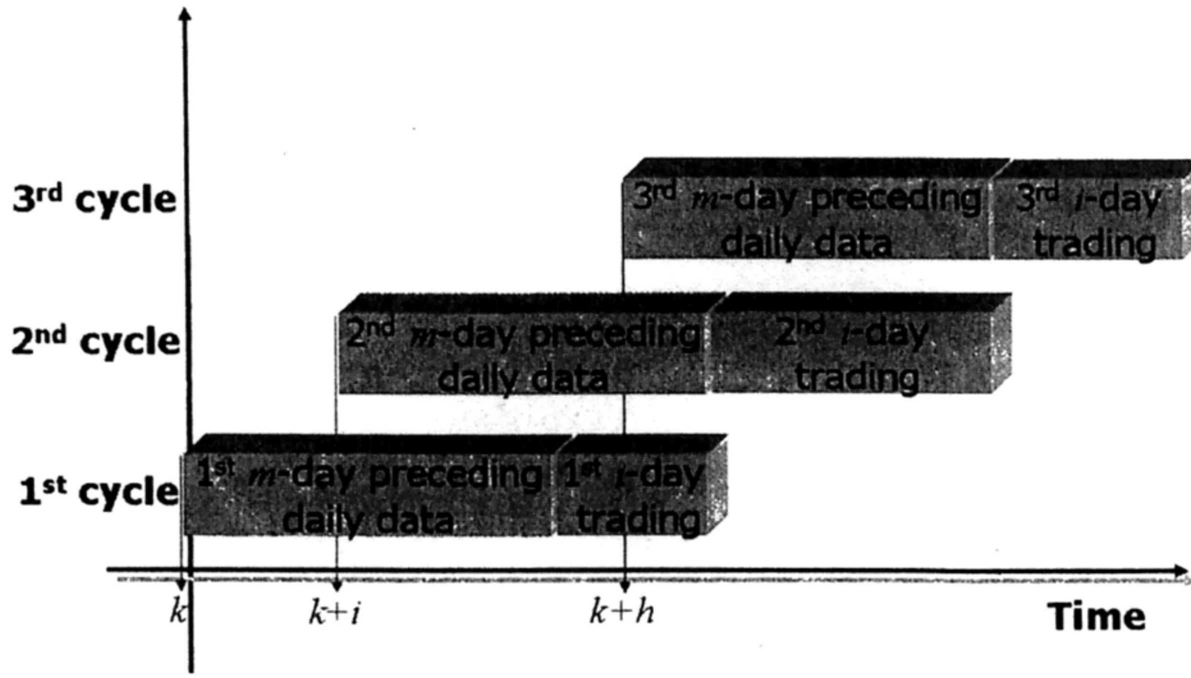


Figure 3.16: Dynamic Training Approach

data. If the current profitable return is greater than the return threshold level (R_τ), the current trading ruleset will be kept for trading. Otherwise, the trading system is re-trained again to select a new fuzzy trading rules. The assessment is repeated every trading day until the end of trading.

The period of the training data and the return threshold level are determined by the parameters (m, R_τ). Similar to the incremental training approach, the value of m affects the sensitivity of GFETS and the value of R_τ affects the responsiveness of GFETS.

Sensitivity (m)

It is similar to the sensitivity of incremental training approach.

Responsiveness (R_τ)

When R_τ is small, all tests of assessments are passed. The dynamic GFETS will not make any adjustment to the evolving market. The increase of R_τ increases the chance of making appropriate adjustment in the system in the evolving market. The responsiveness of GFETS will be higher. When the value of R_τ is large, the selected trading rules will be changed frequently.

Therefore, the parameters (m, R_τ) must be selected carefully in order to have good performance.

3.5 Empirical Results

Four sets of experiments were conducted. The first set of experiments focused on the problem of four fuzzy trading rules. The second set of experiments examined a 36-rule GFETS. The third set of experiments studied the incremental training approach and the fourth set of experiments explored the dynamic training approach.

3.5.1 Four Fuzzy Trading Rules

You may argue that why a 36-rule trading system is built. Before I examine this question, it needs to know whether a trading strategy built by a single technical indicator is good enough to obtain a profitable return. If yes, we don't need to proceed to the study of 36-rule trading system. If not, it means that the best trading strategy always embraces different technical indicator. In this part, it demonstrate a good trading strategy needs different indicator-based fuzzy trading rules. For the ease of explanation, trading strategies built by different combination of four fuzzy trading rules were examined to answer the above query.

For the four fuzzy trading rule, we can evaluate all possible trading strategies. When the number of trading rules increases, it is impossible to examine all trading stratgies. The second question is arised. Would an efficient searching algorithm is necessary to find the optimal trading strategy?

Stock Data and Fuzzy Trading Rules

Each trading strategy was tested with the daily Hang Seng Index from 10 April 2006 to 7 April 2008. Totally, there were 487 daily close, high, low or open index data. For the ease of reference, four fuzzy trading rules are listed as below.

1. If (a close price minus a 5-day simple moving average is NEGATIVE), (a sell signal is initiated).
2. If (a close price minus a 5-day simple moving average is POSITIVE), (a buy signal is initiated).
3. If (a close price minus a 20-day simple moving average is NEGATIVE), (a sell signal is initiated).
4. If (a close price minus a 20-day simple moving average is POSITIVE), (a buy signal is initiated).

Implementation

To implement these fuzzy trading rules, Matlab Fuzzy Logic Toolbox was used. Two input variables and two linguistic variables were defined. The input variables included "a close price minus a 5-day SMA", and "a close price minus a 20-day SMA". The linguistic terms included NEGATIVE and POSITIVE. The output was either a buy or sell signal. In Matlab Fuzzy Logic Toolbox, each rule was associated with a flag. It indicated the corresponding rule was selected or not. All trading strategies could be implemented easily by turning on or off the corresponding flag. For the four trading rules, there are totally $16(= 2^4 - 2 * (2^2 - 1))$ trading strategies. After eliminating the trading strategy with buy or sell rules only, there are only 10 strategies.

Results

The overall performances of 10 trading strategies were tabulated in tables 3.3 and 3.3. The 1^{st} column is used to represent the trading strategy. The 2^{nd} to 5^{th} column represented the four trading rules. If the value of these columns was one, that rule would be selected. Otherwise, it would not.

Good Trading Strategy Containing Different Technical Indicators

Empirical results showed that the good trading strategy always consisted of different technical indicators. In table 3.3, based on the profitable return, the best trading strategy was strategy 1, which included the advice from all trading rules. The second was trading strategy 6 and used the sell rule of 5-day simple moving average and the buy rule of 20-day simple moving average. Based on the positive transactions, both strategies 1 and 6 were the highest. Although their maximum drawdown was not the smallest, their values were moderate. After inclusion of transaction costs, the results as shown in table 3.3 were similar to those without. On the other hand, the return of the worst strategy dropped to the negative return as they had high transaction volumns. Its maximum drawdown also dropped.

The best strategy could reduce the loss under a fluctrated market. In Figs. 3.17 and 3.18, the combined output signal of the strategy 1 suggested to sell stock on day 243. Although the combined signal raised to zero in the following day, it was smaller than the threshold value τ. Thus, the strategy suggested to hold CASH until day 290. It avoided trading in the declining market during day 260 to 290. However, strategy 4 was failed to do it. It trigged a lot of buy and sell signal in this period and caused a great loss. The trading strategy 9 suggested holding CASH during day 243 to 285. However, this strategy issued a

Strategy	1(S)	2 (B)	3 (S)	4 (B)	Profit Return (pr)	mdd	PosR	Trans.
1	1	1	1	1	0.27	0.23	0.57	7
2	1	1	1	0	0.24	0.10	0.50	20
3	1	1	0	1	0.08	0.43	0.25	20
4	1	1	0	0	0.09	0.30	0.36	33
5	1	0	1	1	0.22	0.23	0.56	9
6	1	0	0	1	0.27	0.23	0.57	7
7	0	1	1	1	0.26	0.23	0.50	8
8	0	1	1	0	0.24	0.23	0.50	8
9	0	0	1	1	0.21	0.24	0.50	10
10	Buy and Hold				0.20	0.16	1	1

Table 3.3: Performances of Ten Trading Strategies Without Transaction Cost

	Cost = 0.1%			Cost = 0.2%			Cost= 0.5%		
	pr	mdd	PosR	pr	mdd	PosR	pr	mdd	PosR
1	0.25	0.23	0.57	0.23	0.24	0.57	0.23	0.24	0.57
2	0.19	0.10	0.50	0.15	0.11	0.50	0.15	0.11	0.50
3	0.04	0.46	0.25	0.00	0.49	0.25	0.00	0.49	0.25
4	0.02	0.33	0.36	-0.05	0.35	0.36	-0.05	0.35	0.36
5	0.20	0.24	0.44	0.18	0.24	0.44	0.18	0.24	0.44
6	0.25	0.23	0.57	0.23	0.24	0.57	0.23	0.24	0.57
7	0.24	0.24	0.50	0.22	0.25	0.50	0.22	0.25	0.50
8	0.23	0.24	0.50	0.21	0.24	0.50	0.21	0.24	0.50
9	0.19	0.25	0.40	0.17	0.25	0.40	0.17	0.25	0.40
10	0.19	0.16	1	0.19	0.16	1	0.18	0.16	1

Table 3.4: Performance of Ten Trading Strategies With Different Transaction Cost

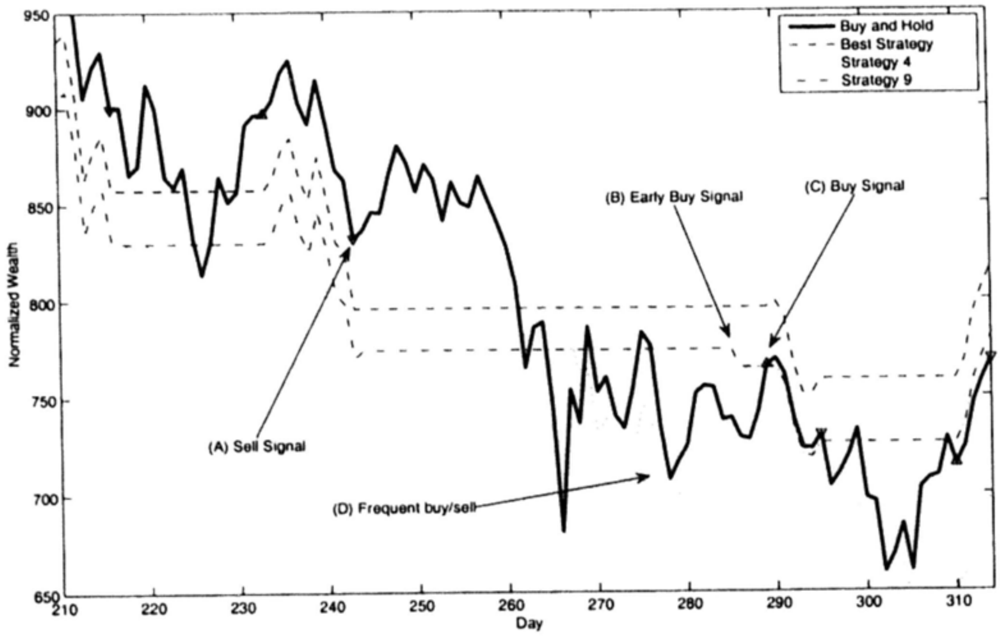


Figure 3.17: Wealth of Different Trading Strategy during 210 to 310

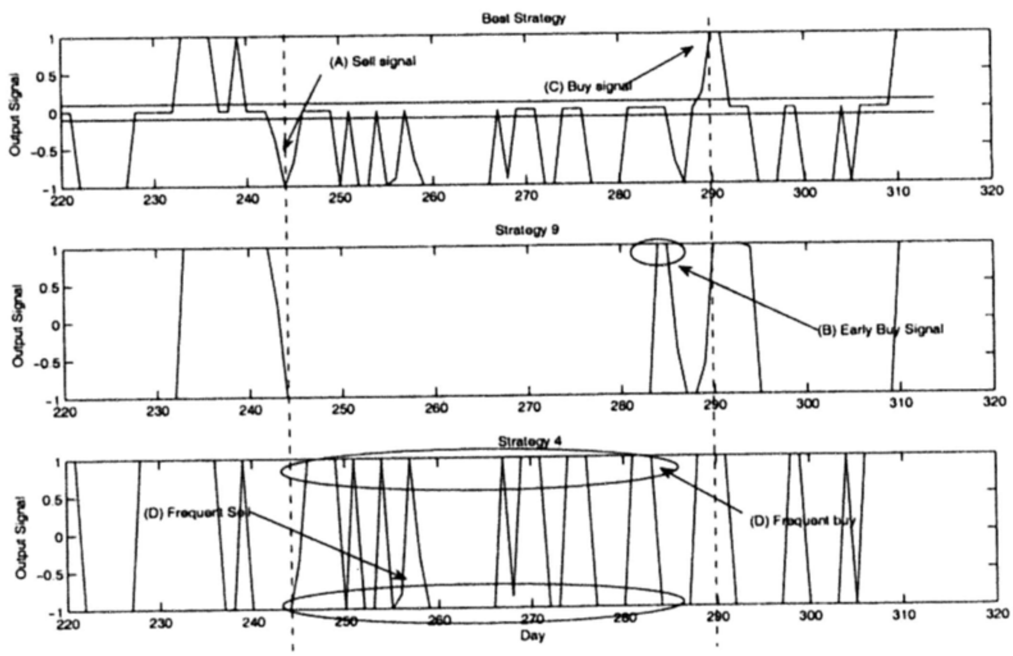


Figure 3.18: Output Signal of Best Strategy, Strategies 4 and 9

early buy signal on day 285 and got a loss immediately. As the strategy 1 consider the aggregate signal, it could avoid the loss. Thus, it provided good advice among these strategies.

Need for Efficient Searching Algorithm?

A trading system doesn't need an efficient searching algorithm when the number of trading rules is small. Citing 4 fuzzy trading rules as an example, after eliminating the trading strategies with buy or sell rule only, there are 10 trading strategies. The optimal trading strategy can be easily identified after evaluating these strategies. However, the same method might not be applicable to the large number of trading rules. In Section 3.1.2, the number of trading strategies for n trading rules is n^2. Therefore, it is impossible to eliminate the trading strategies with only sell or buy rule and evaluate the remaining trading strategies. An efficient algorithm is definitely useful to identify the optimal trading strategy.

3.5.2 36 Fuzzy Trading Rules

Three experiments were conducted to evaluate a 36-rule GFETS with different data sets.

The first experiment focused on the use of daily Hang Seng Index from 10 April 2006 to 7 April 2008 for training. The GA was used to select the optimal trading strategy. The overall performance between the GFETS strategy and other strategies are evaluated.

The second and third experiments focused on the training of GFETS using two different data sets. As the market evolves with time, the optimal training strategy is changed accordingly. By examining the optimal trading rule during different period, it might discover the evolving market. The former data set was splitted into in-sample data set and out-of-sample data set. The second experiment used only the in-sample data set for training and the out-of-sample data set for testing. The third experiment swapped these data sets for training and testing.

Full Data Set

The GFETS was trained and tested using the full set of data. Empirical results showed that the GFETS could learn a profitable trading strategy. In Fig. 3.19, the dark black line was a cumulative return using the buy and hold strategy but the top curve was the cumulative return of the GFETS strategy. The dot lines and dash lines were the trading strategies which was built by a single technical indicator. The cumulative return for dash lines were higher than that of the buy and hold strategy but not for the dot lines. It implied that the GFETS strategy always performed better than the other trading strategies. However, the trading strategies with a single technical indicator had only a moderate performance.

The other performance measures were tabulated in Table 3.5.2. The profitable return of most trading strategies with a single technical indicator was worst then that of the buy and hold strategy. However, they generally had lower maximum drawdown than the buy and hold strategy's. The profitable return of GFETS strategy was much higher than the other strategies. Its maximum drawdown was the smallest and its positive transaction rate was high. It was hard to say that these trading strategy performed better than the buy and hold strategy.

The GFETS could select a good fuzzy trading rules. In order to explore the selected fuzzy trading rules more in depth, these rules are listed in the following.

- If 5-days exponential moving average crosses above 20-day exponential moving average, buy signal is initiated.
- If 5-days exponential moving average crosses below the 20-

Stra.	Rule #	Variables	*pr*	mdd	PosR
i	1-2	p(.) & SMA(5,.)	0.01	0.30	0.43
ii	3-4	SMA(5,.) & SMA(20,.)	0.19	0.24	0.40
iii	5-6	p(.) & WMA(5,.)	-0.04	0.33	0.42
iv	7-8	WMA(5,.) & WMA(20,.)	0.15	0.31	0.33
v	9-10	p(.) & EMA(5,.)	0.02	0.33	0.37
vi	11-12	EMA(5,.) & EMA(20,.)	0.31	0.19	0.44
vii	13-15	rsi(5,.)	0.09	0.25	0.68
viii	16-17	rsi(14,.) & marsi(5,5,.)	0.02	0.25	0.86
xi	18-20	MACD(5,5,.)	0.10	0.26	0.50
x	21-22	k-line	-0.00	0.29	0.67
xi	23-24	%K(5,.)-%D(5,.)	0.31	0.20	0.51
xii	25-26	oscillator	0.00	0.26	0.67
xiii	27-28	RoC(5,.)	0.20	0.39	0.67
xiv	29-30	mom(5,.)	0.14	0.28	0.74
xv	31-32	%R	0.13	0.26	0.72
xvi	33-34	pdi(5,.)-ndi(5,.)	0.21	0.31	0.50
xvii	35-36	vi	0.13	0.34	0.36
	11,12,14,15,17,23, 25,27-30,32,34-36	GFETS	0.97	0.15	0.63
	Benchmark Strategy	Buy and Hold	0.20	0.34	1.00

Table 3.5: Performance of Trading Strategy using a Single Technical Indicator, GFETS and Benchmark Strategy

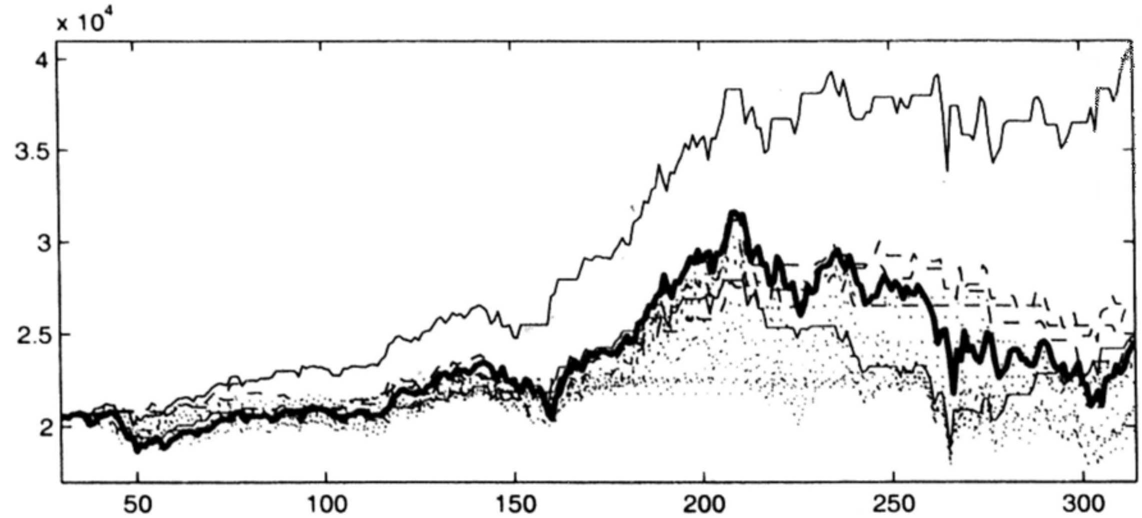


Figure 3.19: Cumulative return using the GFETS and individual technical indicators

days exponential moving average, sell signal is initiated.

- If 5-day rsi is moderate, hold signal is initiated.
- If 5-day rsi is large, sell signal is initiated.
- If 14-day rsi is larger than 65 and 5-day rsi is smaller than 5-day moving average of 5-day rsi, sell signal is initiated.
- If kd-line is negative, sell signal is initiated.
- If oscillator is negative, buy signal is initiated.
- If rate of change is high, sell signal is initiated.
- If rate of change is low, buy signal is initiated.
- If momentum is declining, buy signal is initiated.
- If momentum is inceasing, sell signal is initiated.
- If %R is high, buy signal is initiated.
- If pdi crosses above ndi, buy signal is initiated.

- If vi is long, buy signal is initiated.
- If vi is short, sell signal is initiated.

The fuzzy trading ruleset, which was selected by the GFETS, was consisted of different technical indicators. It was noted that the GFETS only selected some but not all trading rules from the same technical indicators. The trading rules of these technical indicators could form different strategies. They were strategies *vi*, *xi*, *xiii* and *xvi* in table 3.5.2. The GFETS's strategy produced a higher profitable return and minimized the risk of potential loss (i.e. low maximum drawdown). However, if all trading rules of strategies *vi*, *xi*, *xiii* and *xvi* were used to build a trading strategy, would this strategy also perform good? this trading strategy was used to trade during the same period. Its profit return, maximum drawdown and positive return were 0.25, 0.23 and 0.46. Although this strategy performed worst than the GFETS's strategy, its return performance was better than most trading strategies and it had a low maximum drawdown.

In-sample and Out-of-sample data

The GFETS strategy had a good overall performance while it was limited to the in-sample data. In this experiment, the out-of-sample data was tested. The input data was splitted into two datasets. The first was in-sample data for training the GFETS. The second was out-of-sample data for testing the GFETS. The cumulative wealth was plotted in Fig. 3.20. The top solid line was the cumulative wealth of the GFETS's strategy. The second top solid line was the cumulative wealth of a simple buy and hold strategy. The dot lines were the cumulative wealth of strategy using a single technical indicator. In the in-sample period, the GFETS strategy performed better than the buy and hold strategy. However, it performed worst than some trading strategies

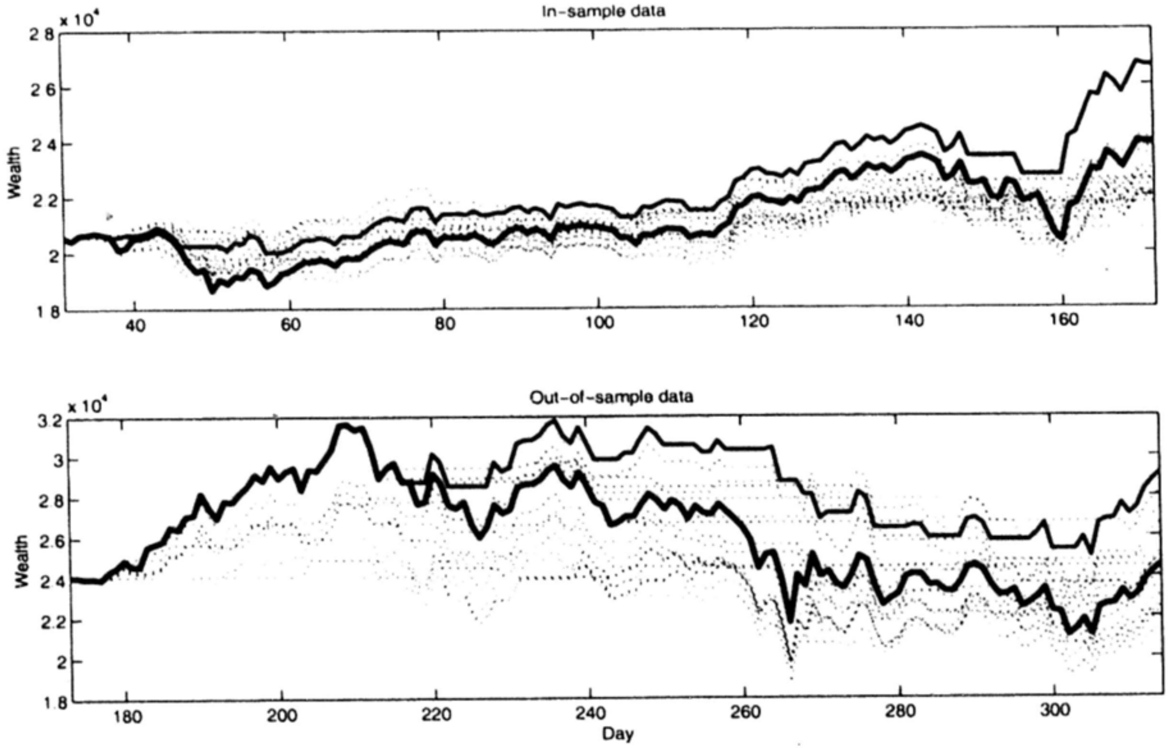


Figure 3.20: First Half Dataset for In-sample Training and Second Half Dataset for Out-of-sample Testing

using a single technical indicator in early stage. After that, it performed better than all strategies. In out-of-sample period, the performance of GFETS strategy was similar to in-sample period. However, some strategies using a single technical indicator performed moderate in early stage but their performance was improved then.

Exchange Training and Testing samples

As the trend of in-sample data was different from that of out-of-sample data, the GFETS could be further test by exchanging these samples. Empirical results showed that the maximum drawdown of GFETS strategy was much smaller than that of other strategies using a single indicator in both in-sample and out-of-sample periods. In Fig. 3.21, although the cumulative

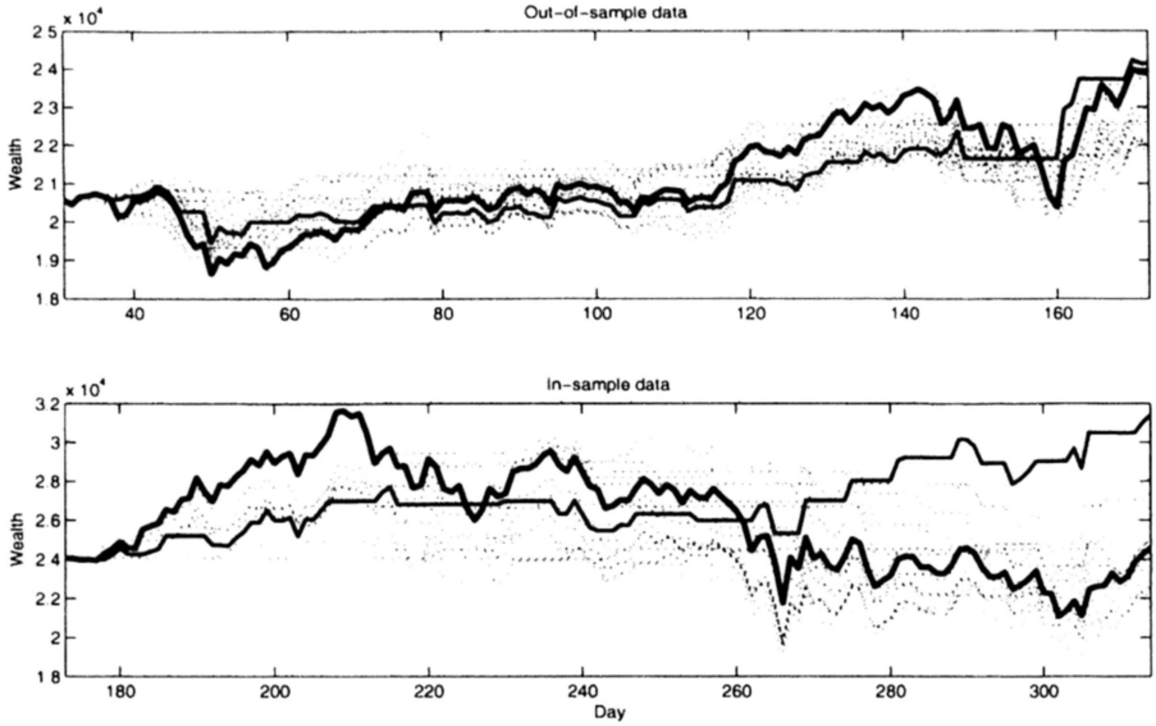


Figure 3.21: Second Half Dataset for In-sample Training and First Half Dataset for Out-of-sample Testing

wealth of GFETS strategy was lower than the buy and hold strategy in early stage, the cumulative wealth in later stage was higher than the buy and hold strategy. Also, it was higher than the other trading strategy. This was mainly due to the low maximum drawdown. The similar observation was reported during in-sample period.

Although the GFETS strategy finally gave the highest profitable return in both training and testing periods, the performance in experiment two was much better than that in experiment three. This was mainly due to the difference between the in-sample market and the out-of-sample market. This demonstrated that the market was evolving with time.

3.5.3 Incremental Training Approach

Two sets of experiments were conducted. The first set of experiments examined the effect of different input parameters (m, n) on the performance of incremental training approach. The second set of experiments looked at the performance of incremental GFETS (i.e. The GFETS with incremental training approach) in H-share stocks.

Different Input Parameters (m, n)

Different input parameters had been tested with 487 Hang Seng Daily Indexes. Owing to the limited sample size, the sensitivity and the response of GFETS were difficult to observe. Therefore, the sample size increased from 487 to 2482. Ten years daily Hang Seng Indexes from 2 November 1998 to 29 October 2008 were used.

Suppose that all incremental GFETSs started to trade on day 240. Their cumulative wealth was depicted in Fig. 3.22. Their performances were ranked as follows: the Buy-and-Hold strategy (i.e. dclose) and the incremental GFETSs using the input parameters (240, 90), (240, 360), (240, 120) and (240, 240). When n increased, the incremental GFETS could respond to the evolving market more promptly. The performance became better and better. However, as n became very larger (i.e 360), the trained GFETS was used for long long time for each trading period but the market had evolved. The GFETS couldn't response to the market quickly in the later time of each trading period. Subsequently, the performance couldn't be maintained. Therefore, the performance for (240, 360) was dropped.

On the other hand, the value of n was kept constant. The performance of each input pair was depicted in Fig. 3.23. m affects the sensitivity of GFETS. The performances of each input parameters were ranked as follows: the buy-and-hold strategy

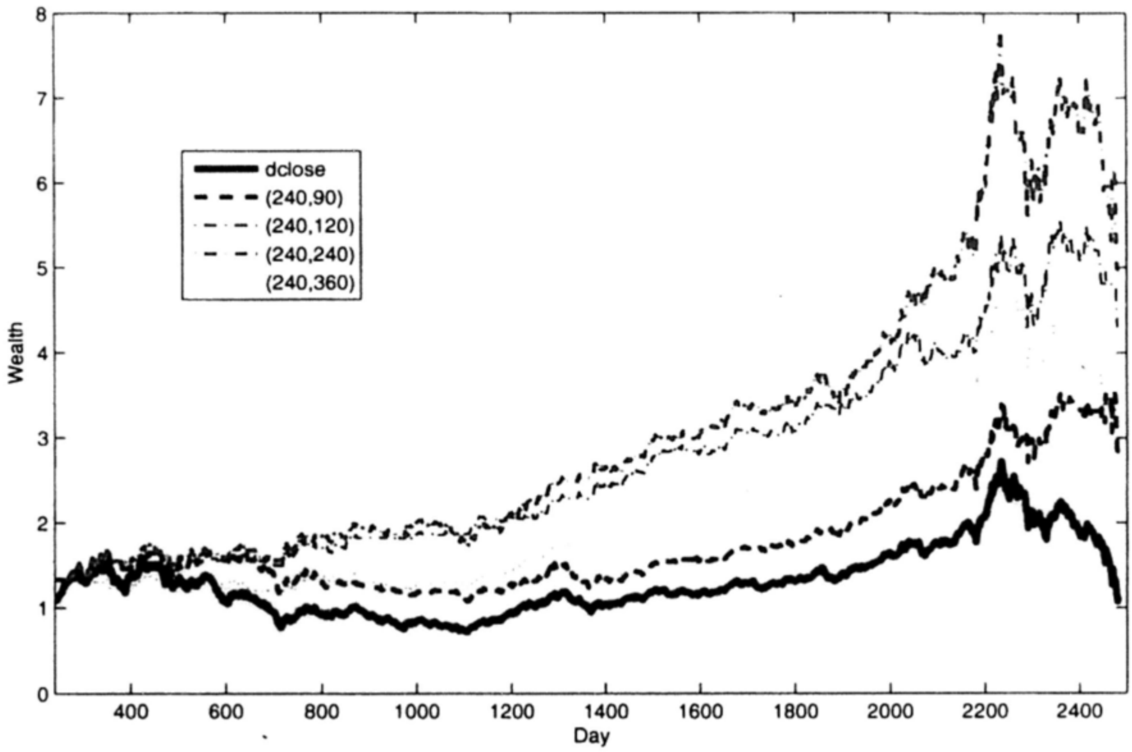


Figure 3.22: m is fixed at 240 and n is changing

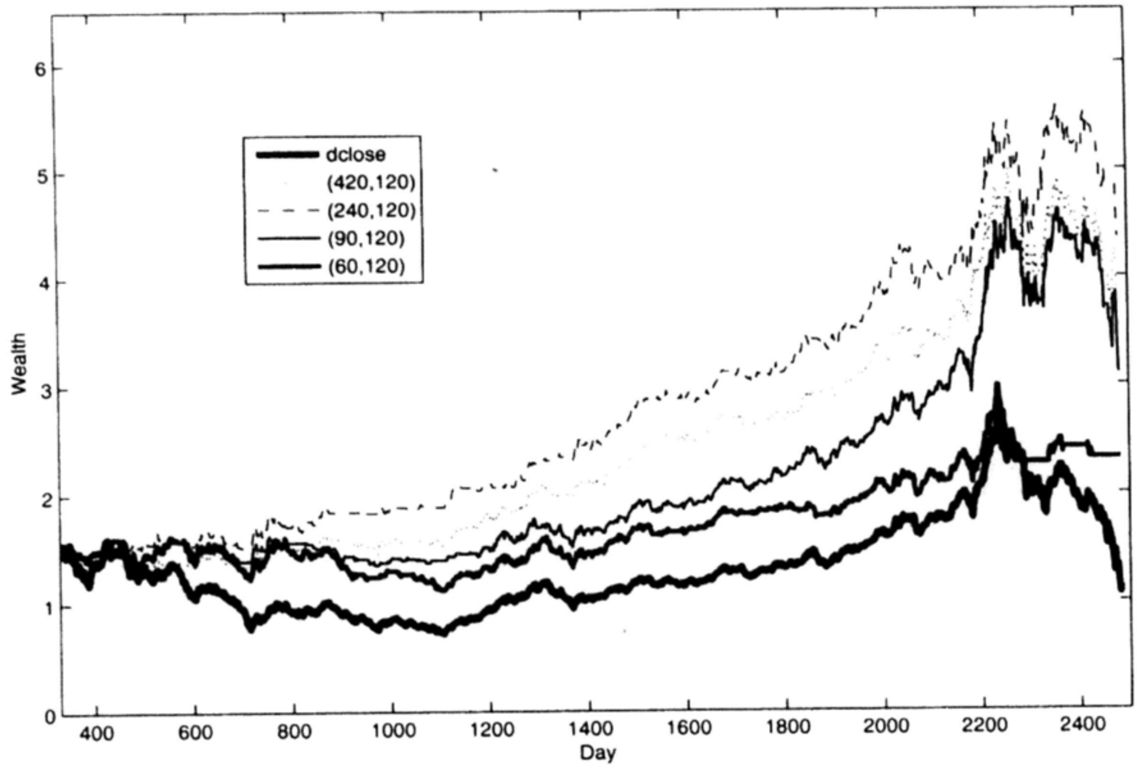


Figure 3.23: m is changing and n is fixed at 120

(i.e. dclose), and the incremental GFETSs using the input parameters (60, 120), (90, 120), (420, 120) and (240, 120). As m increased, more historical data would be used to select the optimal trading strategy. The selected trading strategy for input parameters (420,120) became less sensitive to the evolving market. The performance was dropped.

Both empirical results implied that the selection of appropriate input parameter (m, n) was also crucial to the performance of incremental GFETS.

Application of Incremental GFETS to H-Share Stocks

HSCEI are also called H-shares Index. It tracks the performance of mainland China enterprises with H-share listings in Hong Kong. H-share companies tend to specialize in a single activity,

Stock	% Return					
code	250/100	100/60	100/90	90/60	60/30	30/10
1055	120	136	151	139	75	100
1071	122	104	121	92	78	86
1122	88	85	43	60	85	80
1128	146	98	56	76	75	60
1171	92	70	77	88	103	19
Average	114	99	90	91	83	69

Table 3.6: Percentage Return of GFETS with different (m, n) values

usually heavy industry or a major infrastructure project. Although most countries reported a negative GDP growth following the hi-tech bubble burst in 2000, China maintained around 7% growth annually. Therefore, I used these stock data to evaluate the incremental GFETS.

The stock prices from 27 May 1999 to 27 May 2002 of 25 HSCEI stocks are used for the evaluation of the incremental GFETS (i.e., GFETS under the incremental training approach). Totally three different experiments were conducted.

The first experiment was to find the best (m,n) values. Six pairs of values including (250, 100), (100, 60), (100,90), (90, 60), (60,30), and (30,10) were considered. These values were selected such that the system was varying from a low to a highly sensitive and responsive to the market fluctuation and changes. The results for five representative HSCEI stocks were selected and tabulated in Table 3.5.3. The results demonstrated that the ranking of the (m,n) values by their average percentage return were (250,100), (100,60), (90,60), (100,90), (60,30), and (30,10). (250,100) always gave the best profitable return. The average annual return using (250,100) for 25 stocks was 89%.

The second experiment was to find the highest percentage of positive transactions and the lowest risk of trading. Suppose

(m,n)	No. of trans.	% of -ve trans.	% of +ve trans.	Risk
(250,100)	42.52	27.04	63.44	31.61
(100,90)	51.92	30.58	58.45	40.01
(100,60)	53.00	30.54	57.76	38.82
(90,60)	53.62	30.15	56.90	39.99
(60,30)	60.58	35.77	59.04	40.69
(30,10)	64.73	35.92	55.52	44.29
Average	54.39	31.67	58.52	39.23

Table 3.7: Positive Transaction Rate and Risk

that the risk of trading is defined by the proportional to the investment time as follows.

$$Risk = \frac{No.of Trading Days Holding Stock}{Total No.of Trading Days}, \quad (3.16)$$

If the value of risk is 1, the devaluation of investment will be affected by the market fluctuation. If the value of risk is 0, the devaluation of investment will not be affected by the market fluctuation. For example, the risk of a simple buy-and-hold strategy is 1 while the risk of holding money strategy is 0.

The same input parameters were used in this experiment. The average values of the respective performance measures were tabulated in Table 3.5.3. More than 50% of transactions were positive. The best (m,n) values was once again (250,100). Its average risk was about 31.63%. It always gave the lowest risk as 31.61%.

The third experiment was to compare the performance of the incremental GFETS with the regular investment and the buy-and-hold strategy. The input parameters (250,100) gave the best results and thus this experiment used this parameters. The regular investment assumed the investors bought the stocks every 20 trading days. The buy-and-hold strategy assumed the investors bought the stocks at the first day of trading. 25 HKCEI stocks were tested. The results of five representative stocks were

Code	GFETS	Regular Investment	Buy and Hold
323	118	20	66
325	108	23	-6
358	129	10	71
576	180	19	54
1128	146	35	22
All stocks	89	13	36

Table 3.8: Percentage of Profit Return using Incremental GFETS, Regular Investment and Benchmark Strategy

tabulated in Table 3.5.3. The results demonstrated that the incremental GFETS performed much better than both strategies. Without the transaction cost, the incremental GFETS had 89% profit return. Its profitable return was 6.3 times and 2.5 times higher than those of regular investment strategy and the buy-and-hold strategy respectively. If the transaction cost was 0.3%, the average percentage of profitable return reduced by 3% to 86%. This profitable return was much better than that of the common Great China funds. For instance, the best Great China Stock funds for last 3 years could only obtain 94.97%. The average return of common Great China Stock funds for last three years was -3.04% [15].

3.5.4 Dynamic Training Approach

Similar to the incremental training approach, two sets of experiments were conducted. The first set of experiments examined the effect of different input parameters (m, R_τ) on the GFETS. The second set of experiments focused on the use of dynamic training approach to GFETS in China B shares stocks.

Different Parameters (m, R_T)

Different input parameters had been tested with 487 Hang Seng Daily Indexes. Owing to the limited samples, the result was distorted. Therefore, ten years daily Hang Seng Indexes from 2 November 1998 to 29 October 2008 were used. The sample size increased to 2482.

To examine the effect of the return threshold level, I set $m = 120$. The cumulative wealth was depicted in Fig. 3.24. Their performances were ranked as follows: the Buy-and-Hold strategy (i.e. dclose) and the dynamic GFETSs using the input parameters (120, 0.04), (120, 0.05), (120, 0.03), (120, 0.02), (120, 0.01) and (120, 0.00). When R_T increased from 0.01 to 0.04, the time between two successive training periods decreased. The GFETS responded to the evolving market more and more promptly. Therefore, the performance was improved. When R_T was large (i.e. 0.05), the dynamic GFETS over-responded to the evolving market. The performance was dropped then.

To examine the effect of m, the value of R_T was kept at 0.01. The cumulative wealth of each dynamic GFETS was depicted in Fig. 3.23. Their performance was summarized as follows: the buy-and-hold strategy (i.e. dclose) and the dynamic GFETSs using the input parameters (30, 0.01), (90, 0.01), (250, 0.01) and (120, 0.01). When m increased from 30 to 120, the dynamic GFETS could time the market fluctuation more accurately. Therefore, the performance was improved. However, when m was large (i.e. 250), the dynamic GFETS became less sensitive to the short-term fluctration. The performance was dropped.

Application of Dynamic GFETS to China B Shares Stocks

China B shares market was established in 1991. B shares are shares issued by China companies for investors outside China.

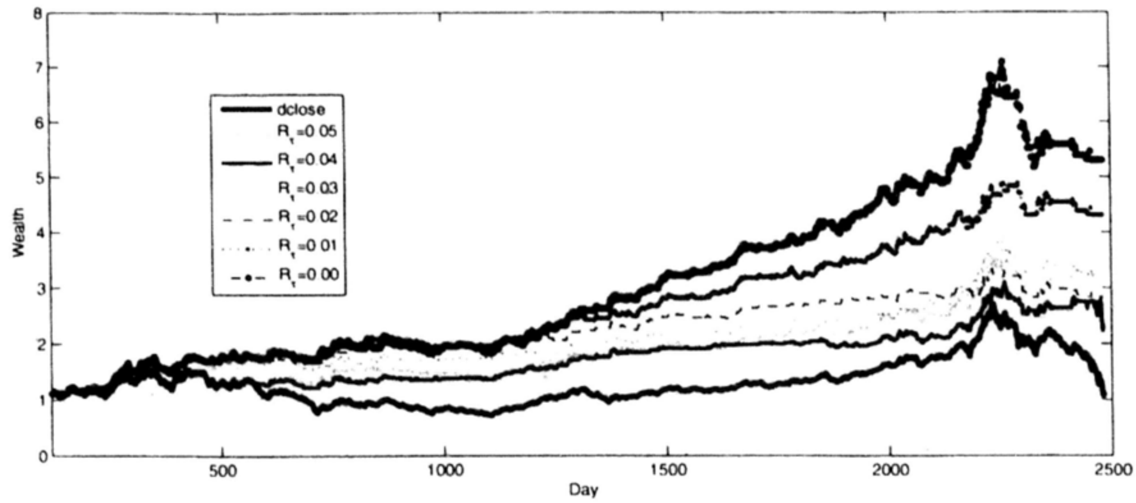


Figure 3.24: $m = 120$

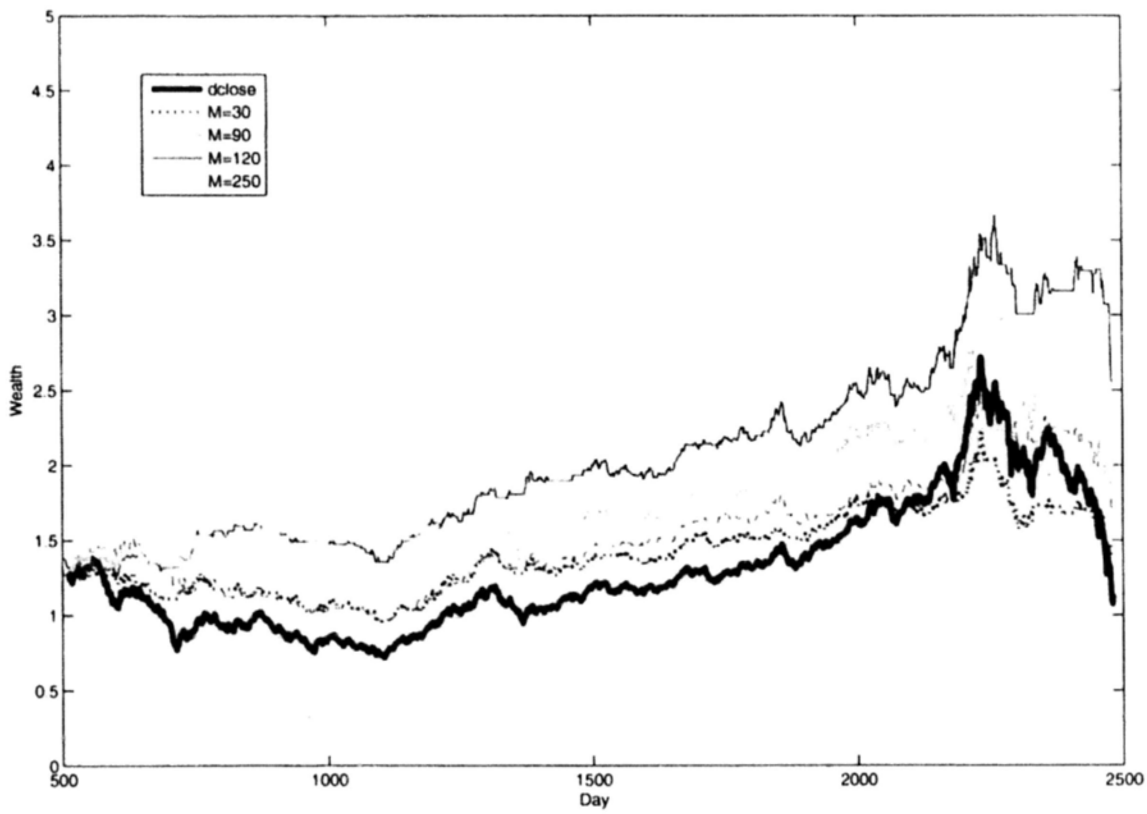


Figure 3.25: $R_\tau = 0.01$

B shares was first listed and traded on the Shanghai and Shenzhen Stock Exchanges in 1992. They are subscribed and traded in foreign currencies and are one of the major markets for foreign investors to play a role in the evolvement of China's securities market. In the first few years, B shares market was in general well received by investors but many of the growth were attributed to illegal speculation by Chinese investors. But due to the lack of uniform guidelines, this enthusiasm had soon turned soared that led to price plummet. During 2001 to 2002, Shenzhen B share sub-index had plummeted by about 22.37% from 265.67 to 206.25 [60]. Investing in the Shenzhen B share using the simply buy-and-hold strategy would result in a great lose in the capital.

To evaluate the performance of the dynamic GFETS, 46 Shenzhen B shares stocks for 1 year ended on 4 June 2002 was used. The system was trained with 90 trading days of market data (i.e., m=90). The return threshold level R_τ for re-training was 0.1. A regular investment strategy at the interval of 20 trading days and a buy-and-hold strategy were used for performance comparison.

The empirical result showed that the profitable return of the dynamic GFETS ranged from -43.1% to 84.9% and was 17.8% on average. The 95% confidence interval of the average profitable return was equal to $[13.0, 22.6]$. So, it was very likely that the average profitable return was more than 13.0%. However, the average return of regular investment and buy-and-hold strategies was -26.7% and -49.9% respectively. The performance of the dynamic GFETS is much better than both strategies.

To better understand the performance of the dynamic GFETS, we plotted buy-sell signals generated by the dynamic GFETS for the best and the worst stock in Fig 3.26 and 3.27, respectively. The figures showed that most of the transactions occurred during the short-term rebound. The dynamic GFETS could pick

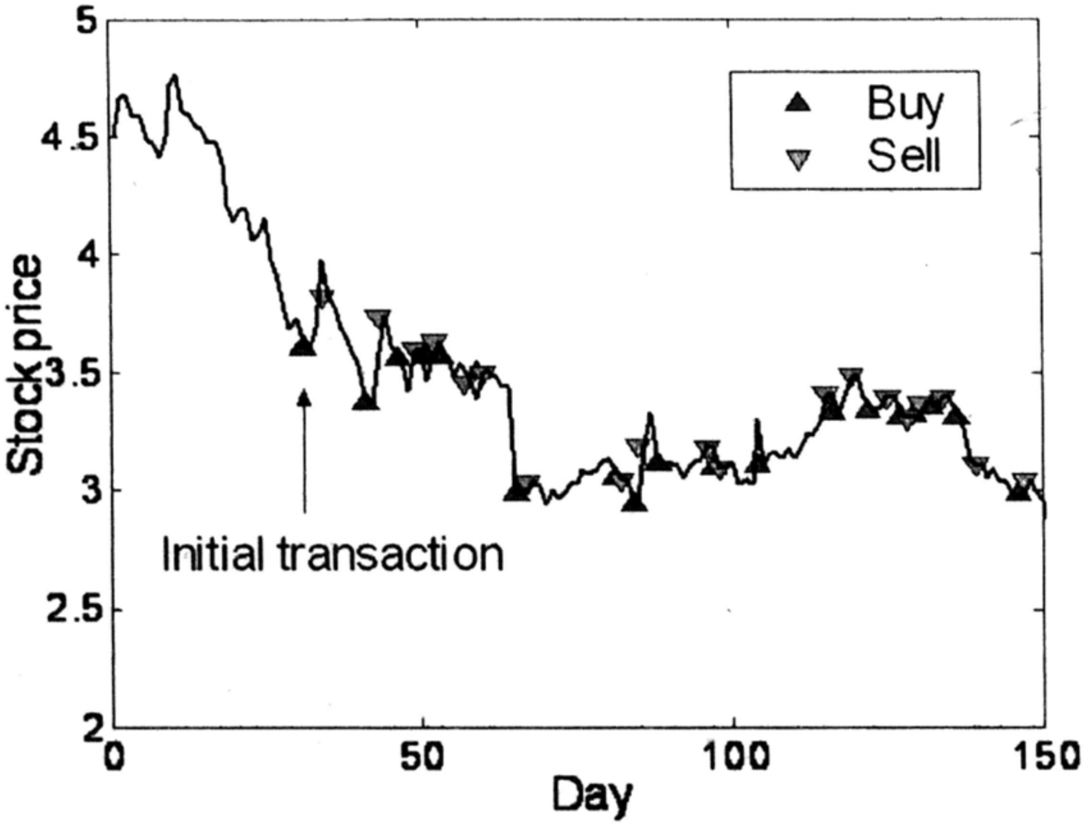


Figure 3.26: Buy and Sell of Dynamic GFETS in stock 761

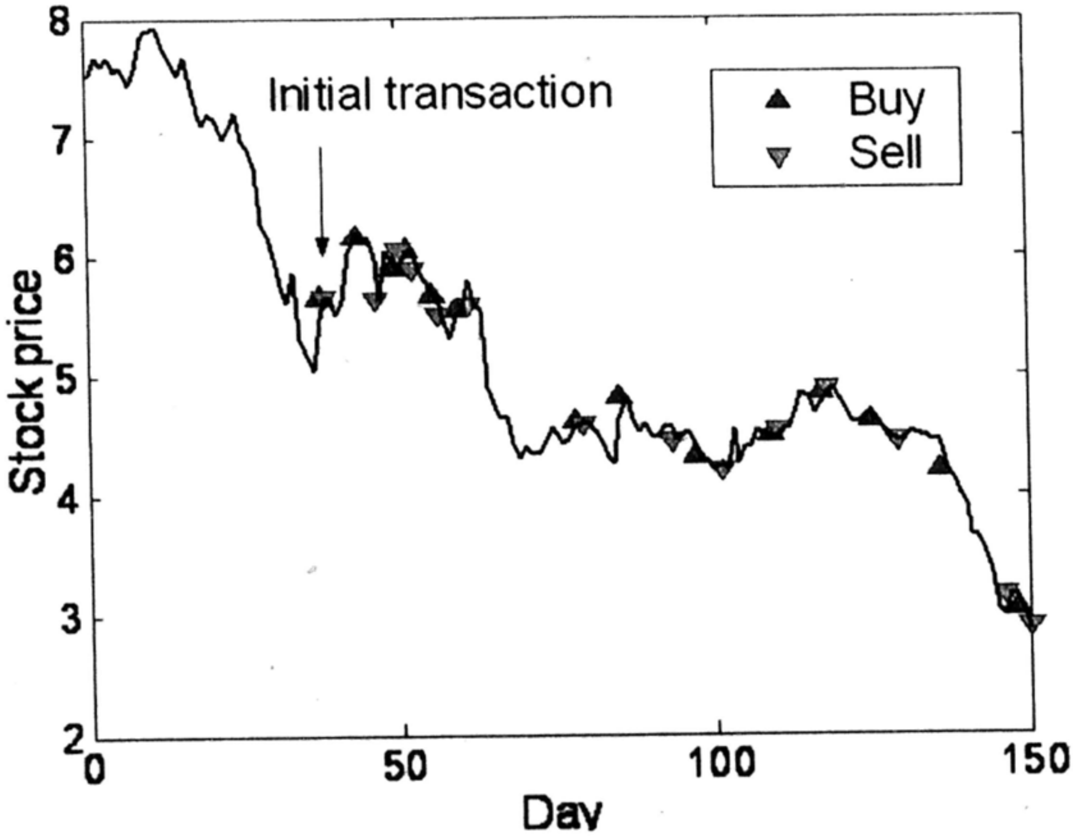


Figure 3.27: Buy and Sell of Dynamic GFETS in stock code 570

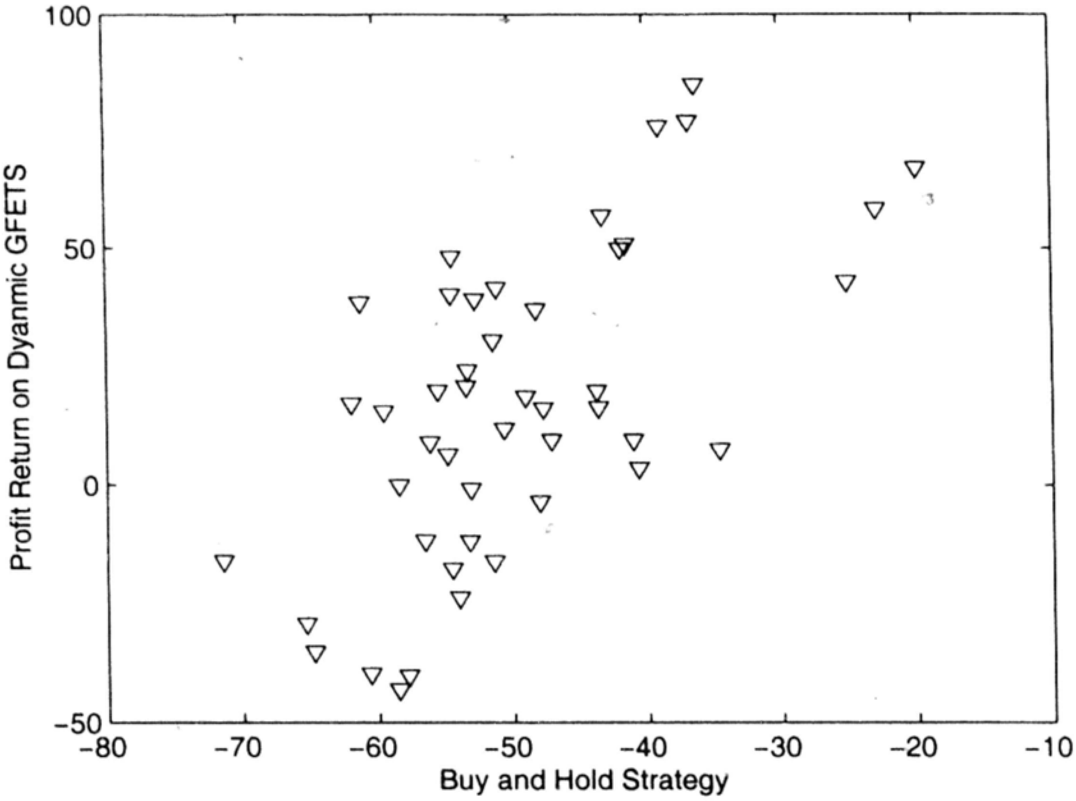


Figure 3.28: Profit of Dynamic GFETS against Profit of Buy and Hold Strategy

the right time to buy low and then sell high in the former but fail to do the same in the later. The stock price of stock code 570 was decreasing rapid than that of stock code 761 making it hard to produce good market timing. Without exception, the performance of the dynamic GFETS would be constrained by the market situation. The dynamic GFETS could not guarantee making profit in a poorly performed market but it could reduce lose. The coefficient of correlation between the profit of the dynamic GFETS and the profit of buy-and-hold strategy is 0.61. From Fig 3.28, we note that the dynamic GFETS has a very high resistance to lose even in a very poor market.

If we assumed the transaction cost was about 0.3% per transaction, the average profit would be reduced by about 5.5% to

12.3%. The 95% confidence interval is equal to [7.6%, 16.9%]. Hence, the dynamic GFETS could give more than 7.6% profit in one year in Shenzhen B share market even though the market value had declined by almost 50%. In fact, the performance of the dynamic GFETS probably outperformed many stock funds in the same period [15].

3.5.5 Comparison of Stock Trading System between Genetic Algorithm and Genetic Programming

Genetic Programming (GP) is close to Genetic Algorithm (GA) but operates on a population of computer programming of varying sizes and shapes [30]. Since they are evolutionary algorithms (EAs), it is also interesting to compare the trading system built by them. Table 3.5.5 lists out the configuration of three EA trading systems. Three trading systems were tested and were compared using HangSeng Index from 2 Nov 1998 to 22 Dec 2003. Totally, there were 1271 samples. The empirical results was tabulated in Table 3.5.5. In addition, the result of simple buy and hold stratgy was also tabulated in the same table for reference.

The first EA trading system is similar to Allen's or Neely's trading systems. It adopted GP to search the optimal trading strategy. The trading strategy contains only one trading rule. The terminal nodes include the close, high, low and open prices, constants and random variables. The function nodes contain "MAXIMUM", "MINIMUM", "AND", "OR", "NOT", "GREATERTHAN", "EQUAL", "LESSOREQUALTHAN", "ADD", "MINUS" and "PRODUCT". The output of the trading rule represents the suggestion to hold "CASH" or "ASSET". As the constant of terminal nodes is assigned before conducting the experiment, the selection of constants is crucial. To provide more options for the constant terminal nodes, a random number is

Trading Systems	One	Two	Three
Inputs	Stock Prices, Random Variable and Constants	Indicator	
EA	GP		GA
Individual	Trading rule (Tree Structure with maximum 28 nodes)		Group of Fuzzy Trading Rules (Binary String with 36 genes)
Sampling	Roulette		
Genetic Operator	Crossover and Mutation		
function(s)	arithmetic, maximum and minimum	Boolean Operators	N/A
Survival	elitism and fixed population size		
Fitness Value	Profit Return in Eq. 3.1		
Output signal	Discrete		Continuous

Table 3.9: Comparison among GP's stock trading and GFETS

adopted.

The second EA trading system is closed to Dempster's model. It uses Genetic Programming to search the optimal trading strategy. Similar to the first trading system, its optimal trading strategy has only one trading rule. Similar to Dempster's input, the terminal node contains the indicators only. The output signal of each indicator is either 1 or 0. The function nodes contains the Boolean operators (i.e. "AND", "OR", "NOT", "XOR" or "NAND"). The output of the trading rule represents the suggestion to hold "CASH" or "ASSET". A trading rule is formed by the Boolean variables and different indicators. As this trading rule involves the Boolean operators, any small change of indicator will direct the change of decision. It is also called an undesirable jump. For example, when the strength of a particular indicator has a small change in a certain level, the indicator for that terminal note will change from 1 to 0.

It subsequently triggers the change of final output of the trading from holding "CASH" to "ASSET" after going through the Boolean operation. If that indicator fluctuates around the level, the final output will be volatile. The number of transaction will increase. Empirical result showed that the percentage of transactions,which holding "ASSET" for 1-day, were 24.8% and 23.1% for in-sample and out-of-sample data. When comparing them with GFETS, GP was 5% higher than GFETS.

The third EA trading system is the 36 trading rules' GFETS in Section 3.5.2. It uses the indicator as the input. The signal strength of each indicator is measured by the degree of membership. The averaging strength of selected trading rules against the threshold level is used to determine the action (i.e. holding "CASH" or "ASSET"). As the aggregate signal is used, the trading decision won't mainly depend solely on a single indicator.

Owing to the difference of the chromosome, GP and GA have some unique features. For GP, some trees have redundant structure like Fig. 3.29 but this structure can be simplified to Fig. 3.30 manually. On the other hand, the individual of GA doesn't have this problem. As the GP tree is evaluated in a recusive manner, many individuals can be formed by extending its branch. GA uses a fixed length and binary string as a chromosome. The total number of individuals is 2^n, where n is the number of genes per chromosome. Thus, GP has infinite number of individuals while GA has a finite number of individuals.

Some empirical results also tabulated in Table 3.5.5. It showed that the optimal GA trading strategy was profitable than the GP trading Strategies. It was also better than the simple buy-and-hold strategy. By comparing their maximum drawn down, GA's trading strategy had a moderate value in both in-sample and out-of-sample data. GA's performance was consistent in both in-sample and out-of-sample data.

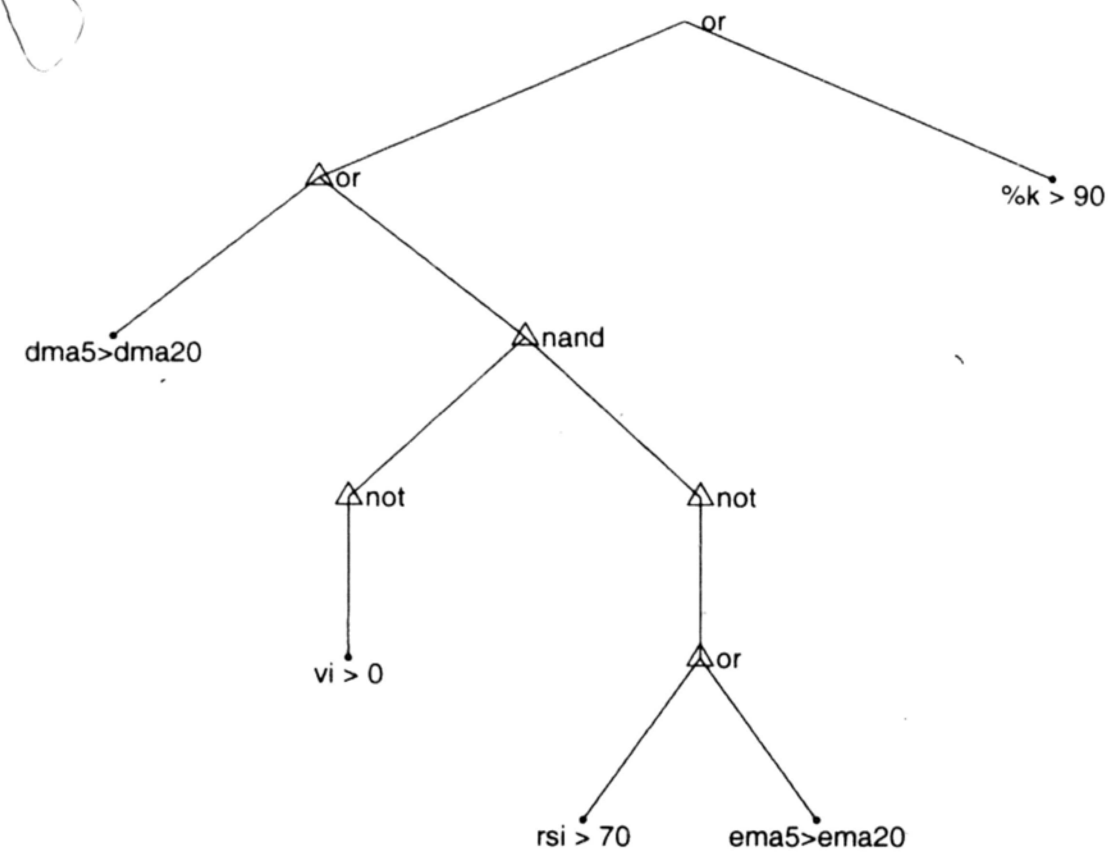


Figure 3.29: Redundant Tree for the First Trading System

	Trading Systems		
Items	One (GP+Stock Price)	Two (GP+indicator)	Three (GFE
	In-sample		
Wealth(System)/Wealth(GA)	0.9960	0.7500	1
MDD	0.0005	0.1002	0.1162
Profit Return	14,265	37,841	40,336
	Out-of-sample		
Wealth(System)/Wealth(GA)	0.9878	0.9878	1
MDD	0.0241	0.4114	0.2418
Profit Return	20,092	20,269	24,738
1-day Buy-Sell			

Table 3.10: Comparison among GP's stock trading and GFETS

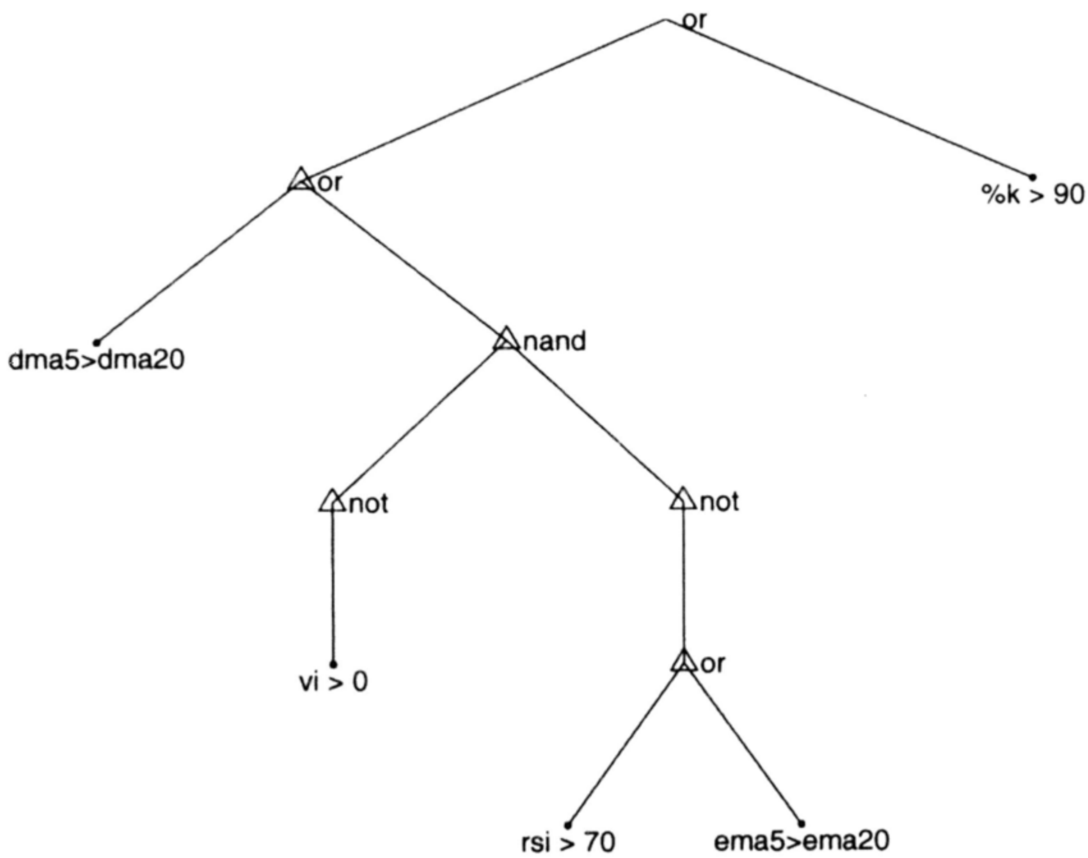


Figure 3.30: Simplified Tree for the Second Trading System

3.5.6 Chapter Summary

In summary, the genetic fuzzy expert trading system (GFETS) was proposed to resolve the trading problem. As it is a fuzzy expert system, it can embed the vague trading rules to the trading system. As this trading system used the aggregate signal as output, it didn't have the undesirable discontinuities due to the jump of Boolean variables that might occur for small changes of the technical indicator.

GFETS could identify the optimal trading strategy and map the market state to action. By comparing the performance of different trading strategy using single technical indicator and the buy and hold strategy, it found that the GFETS was able to select the best trading rules so as to give the best profitable return, a low risk of potential loss and the highest positive transaction.

By evaluating different samples with the GFETS, it found that the GFETS had to re-train to cope with the evolving market. Incremental and dynamic training approaches were examined. The sensitivity and the responsiveness of incremental/dynamic GFETS controled their overall performance. If an appropriate parameter is selected, both training approaches will have similar overall performance. Furthermore, the incremental GFETS were further examined by the HSCEI stocks. Empirical results showed that its profitable return, after eliminating the transaction cost, was even better than that for the common Great China stock funds. The dynamic GFETS was also tested with the Shenzhen B shares stocks. Empirical results showed that although the market had been declined by 50%, the system could effectively catch the short-term rebound in the market and produce significant profit. However, it couldn't refrain from lose if the market was declining too fast and only re-bound for a very short period.

By comparing the trading system using genetic programming and genetic algorithm, it found that the formulation of genetic algorithm's trading system was simpler than that of genetic programing's trading system. The trading system built by GA performed better than that by GP or simple buy-and-sell strategy.

□ **End of chapter.**

Chapter 4

Incremental Intraday Prediction

This section is organized as follows. An incremental intraday prediction problem is described in Section 4.1. The forecast equations are defined in Section 4.2. Data Samples are described in Section 4.3. Two models are examined for this prediction. The first is linear regression model and is presented in Section 4.4. The second is nonlinear forecast model and is discussed in Section 4.5. The concluding remarks are given in Section 4.6.

4.1 Incremental Intraday Prediction Problem

4.1.1 Problem Definition

An incremental intraday prediction problem is defined as follows:

Given incremental intraday information at current time and an information set up to and including day $t-1$, how can we conduct a prediction at current time?

This problem contains two major parts. The first part is to derive a forecast function using an incremental intraday in-

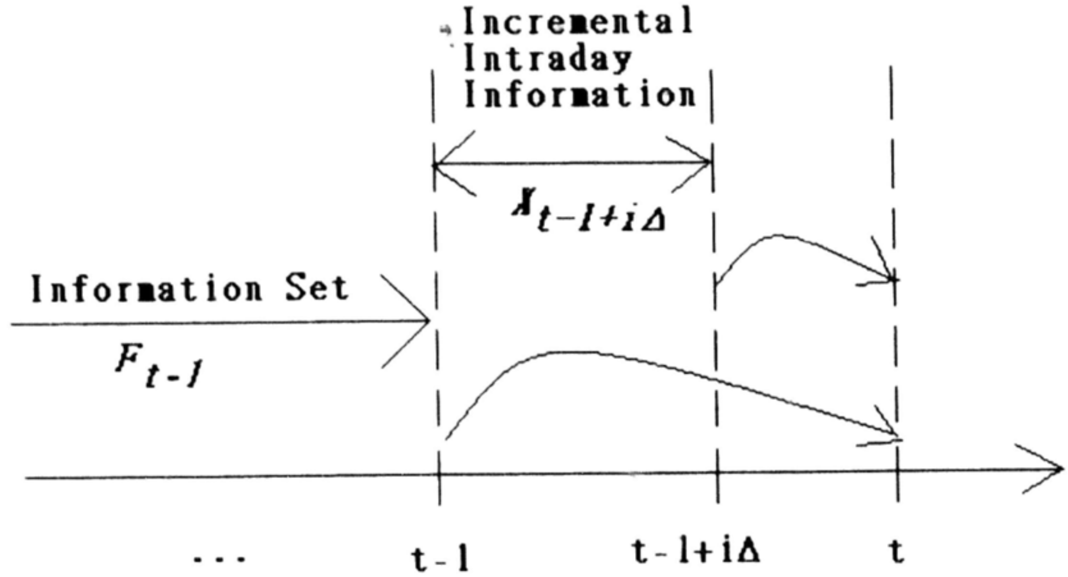


Figure 4.1: Conventional Forecast and Incremental Intraday Prediction

formation at current time. The second part is to examine the intraday trend of forecast accuracy. The intraday trend refers to the change of forecast accuracy with intraday time.

To start the study of this problem, we look at conventional daily forecast (f_1). f_1 always uses the information set up to and including day $t-1$ to forecast.

$$f_0 : \mathcal{F}_{t-1} \to \mathcal{Y}_t. \tag{4.1}$$

where $y(t)$ is the predictand and is belonged to $\mathcal{Y}_t$. The information set $\mathcal{F}_{t-1}$ includes $(y(t-1), y(t-2), \ldots)$. However, the incremental intraday information, which collect the intraday data from $t-1$ to $t-1+i\Delta$, as depicted in Fig. 4.1 are seldom to discuss in the daily forecast. This information $\mathcal{X}_{t-1+i\Delta}$ can be used with the information set $\mathcal{F}_{t-1}$ to conduct forecast (f_i). I called f_i an incremental intraday prediction.

$$f_i : \{\mathcal{F}_{t-1} \bigcup \mathcal{X}_{t-1+i\Delta}\} \to \mathcal{Y}_t \tag{4.2}$$

After $\mathcal{X}_{t-1+i\Delta}$ incorporates into the forecast function, you may find that this prediction has some properties. When $t-1+i\Delta = t-1$, $\mathcal{X}_{t-1+i\Delta}$ is null. f_i equals to f_0. When $t-1+i\Delta = t$, $\mathcal{F}_{t-1} \cup \mathcal{X}_{t-1+i\Delta} = \mathcal{F}_t$. The predictand can be obtained directly from the information set $\mathcal{F}_t$. The prediction shouldn't exist. During the period of day $t-1$ to t, the information of $\mathcal{X}_{t-1+i\Delta}$ becomes richer and richer with intraday time. The prediction should become more accurate over intraday time.

To realize the merit of the incremental intraday information in forecast, we need to assume that the incremental intraday information is causally affected the predictand. An incremental intraday predictor $x(t-1+i\Delta)$ at current time can be derived from this information. A unidirectional causal relationship between the predictand and the incremental intraday predictor in Eq. 4.3 is of particular interest. If the predictor is missing, it will reduce to conventional forecast in Eq. 4.4.

$$y(t) = f_i(x(t-1+i\Delta)|t-1) + e_i(t) \quad (4.3)$$

$$y(t) = f_0(t-1) + e_0(t) \quad (4.4)$$

where $e_0(t)$ and $e_i(t)$ are the the random noise process affecting $y(t)$. Suppose that both forecast functions are adequately modeled and estimated $y(t)$ as follows.

$$\hat{y}_0(t) = \hat{f}_0(t-1) \quad (4.5)$$

$$\hat{y}_i(t) = \hat{f}_i(x(t-1+i\Delta)|t-1) \quad (4.6)$$

The causal effect can be quantified by the reduction of error variances in Eq. 4.7. I called it **predictability measure**, $\beta(i)$.

$$\beta(i) = \frac{\sigma_y^2 - \varsigma_y(i)^2}{\sigma_y^2} \quad (4.7)$$

where σ_y^2 and $\varsigma_y(i)^2$ are the prediction error variance of $y_0(t)$ and $y_i(t)$ respectively. The predictability operates between 0 and 1.

When it equals to 0, the incremental intraday predictor has no causal effect on the predictand. When it equals to 1, an exact prediction fully considers the causal effect of the incremental intraday predictor. The predictability varies with intraday time $t-1+i\Delta$. The intraday trend of forecast accuracy can be obtained by plotting the predictability with intraday time.

Practically, a perfect model is not easy to find. An indicator without knowing the models f_1 and f_2 is very useful to study the causal relationship. The **correlation** ($\rho(i)$) between $y(t)$ and $x(t-1+i\Delta)$ is proposed as predictability indicator. It is proposed largely based on common sense. Under the hypothesis that "If the predictor correlates strongly with the predictand, it should affect the forecast value through a causal path". For an extreme case, if the predictor equals to the predictand,

$$\beta(i) = 1 \quad (4.8)$$

$$\rho(i) = 1 \quad (4.9)$$

For the other extreme case, if the predictor uncorrelates with the predictand, $\rho(i) = 0$. However, it is difficult to prove that $\beta(i) = 0$. If the correlation is a good predictability indicator, the forecast accuracy can be estimated by the correlation without knowing the forecast function. The relationship between the predictability and the correlation is also of particular interest.

As an example, the incremental intraday predictions of daily high and Garman and Klass (GK) range-based volatility are examined in this section. Their mathematical formulations are given in Eqs. 4.10 and 4.11 respectively.

$$max(P(t)) \quad (4.10)$$

$$\begin{aligned} & 0.511[U(t) - 0.383C(t)^2 - D(t)]^2 \\ & -0.019[C(t)[U(t) + D(t)] - 2U(t)D(t)] \end{aligned} \quad (4.11)$$

where $P(t)$ represents all stock prices, $U(t)$, $D(t)$ and $C(t)$ are the daily high, low and close with respective to the daily open.

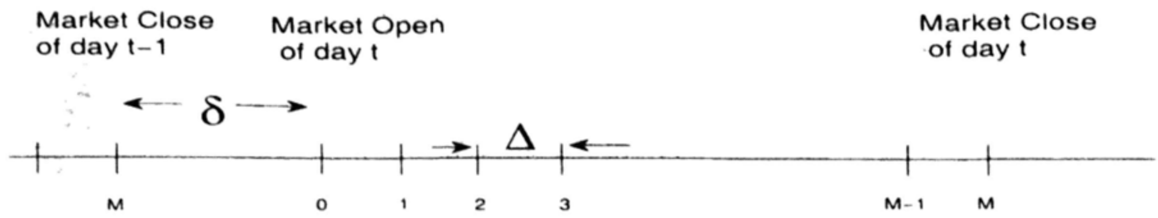


Figure 4.2: Intraday Time Index

Throughout this section,"price" means "logarithm of original price".

4.1.2 Notations

Suppose that intraday data are available after market open, at even-sampled time instants where Δ is the sampling interval. For simplicity of representation without loss of generality, we treat $t_0 = t - 1 + \delta(\delta \ = 0)$ (Fig. 4.2). $t_i = t - 1 + i\Delta)$ refers to the i-th interval after market open on day t. $t_M = t - 1 + M\Delta$ refers to t. The intraday index i refers to i-th interval after market open. The last interval is M and refers to the time of market close.

$y(t)$ is a predictand. It is calculated directly from the intraday prices on day t.

$p(t - 1 + i\Delta)$ (or $p(t_i)$) is the intraday stock price which is measured at intraday index i of day t.

Suppose that the forecast event occurs at t_i. An incremental intraday predictor $x(t_i)$ (or $x(t - 1 + i\Delta)$) at current time t_i is derived from the incremental intraday information $\mathcal{X}_{t-1+i\Delta}$ using an incremental intraday measure.

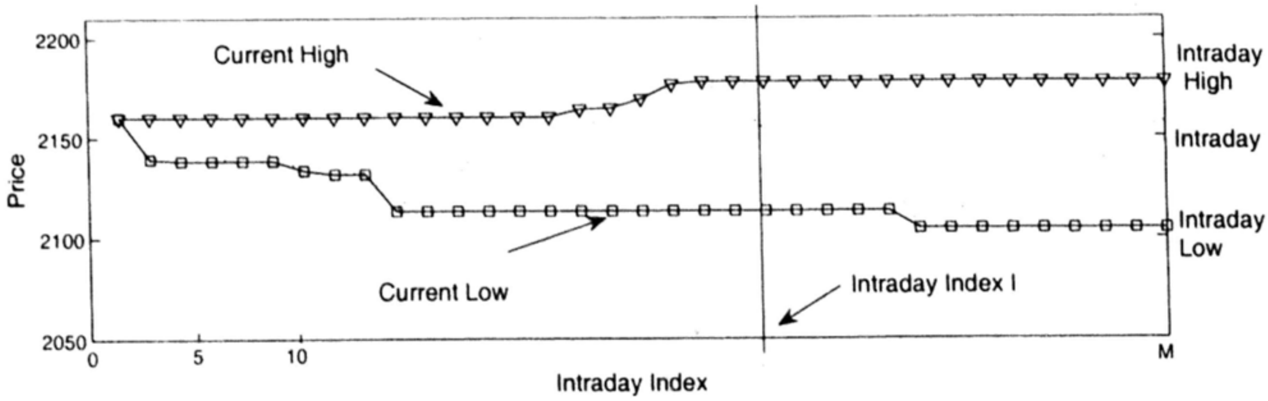


Figure 4.3: Incremental (High, Low) for Intraday Curves

4.1.3 Incremental Intraday Measure

Incremental intraday information refers to all intraday prices (or a group of intraday prices if sample available or a single price) collected from the time of market open to the current time t_i. When the current time refers to t, a full set of intraday prices $\mathcal{X}_t$ on that day are available. The predictand $y(t)$ on day t can be calculated directly from the information $\mathcal{X}_t$. When the current time refers to t_i, only the intraday prices up to the $i-th$ interval are available. Although $y(t)$ can't be calculated using the available information $\mathcal{X}_{t_i}$, it can still use the information with the mathematical formular to measure the value of this information $x(t_i)$ at current time. We call it an incremental intraday measure. For example, in Fig. 4.3, incremental (i.e current) high or low in Fig. 4.3 measure the value of daily high or low at current time respectively. When $t_i = t_M$ or $t_i = t$, incremental high or low are equal to daily high and low. The following are a list of incremental intraday measures.

Incremental Close

$$p(t_i) \tag{4.12}$$

Incremental High

$$max[P(t,i)] \tag{4.13}$$

Incremental Low

$$min[P(t,i)] \tag{4.14}$$

where $P(t,i)$ refers to a group of intraday prices $(p(t-1), p(t_1), p(t_2), ..., p(t_i)$ up to t_i.

Following the same vein, more complex incremental intraday measures can be defined. They include incremental range, incremental Parkinson (PK) range-based volatility, incremental GK range-based volatility and incremental realized volatility.

Incremental Range

$$hl(t_i) = u(t_i) - d(t_i) \tag{4.15}$$

Incremental PK Range-based Volatility

$$\frac{[u(t_i) - d(t_i)]^2}{4log_e 2} \tag{4.16}$$

Incremental GK Range-based Volatility

$$\begin{aligned} &0.511[hl(t_i)]^2 - 0.383c(t_i)^2 \\ &-0.019\{c(t_i)[u(t_i) + d(t_i)] - 2u(t_i)d(t_i)\} \end{aligned} \tag{4.17}$$

Incremental Realized Volatility

$$\sum_{k=1}^{i} r(t,k)^2 \tag{4.18}$$

where $u(t_i)$, $d(t_i)$ and $c(t_i)$ are the incremental high, low and close with reference to the open, and $r(t,k)$ is the intraday return (i.e. $p(t_i) - p(t_{i-1})$).

These incremental intraday measures can be used as an incremental intraday predictor $x(t_i)$ to forecast the predictand $y(t)$.

4.2 Forecast Functions

Co-integration and error correction models are widely applied to many financial time series where a linear equilibrium relationship exists among non-stationary variables [17]. Suppose that $y(t)$ and $x(t_i)$ are non-stationary variables and a linear equilibrium relationship exists between them. The long-run relationship between $y(t)$ and $x(t_i)$ can be expressed as

$$y(t) = a_0 + b_0 x(t_i) + e_{t_i} \tag{4.19}$$

where e_{t_i} is a zero-mean innovation process.

When regression analysis is conducted on the differences of the non-stationary variables, the error correction term is omitted. The error correction term in Eq. 4.20 usually refers to the residual estimates at $t-1$.

$$\hat{e}_{t-1} = y(t-1) - a_0 - b_0 x(t-1_i) \tag{4.20}$$

Engle and Granger [21] derived an equivalent error correction formulation to avoid the misspecification error. It also contributes to the regression analysis of the difference equation as follows.

$$Dy(t) = \alpha_1 + \alpha_2 \hat{e}_{t-1} + \sum_{j=1}^{m} \alpha_3(j) Dy(t-j) + \sum_{j=1}^{n} \alpha_4(j) Dx(t-j_i) + \epsilon_{t_i} \tag{4.21}$$

where ϵ_{t_i} is a white noise disturbance, D is the first-difference operator and α are the constant to be determined.

When this model is used in our causal relationship between $y(t)$ and $x(t_i)$, several useful interpretations based on Eqs. 4.19 and 4.21 should be considered. First of all, a long-run linear equilibrium relationship between $y(t)$ and $x(t_i)$ implies that they are highly correlated. Secondly, if $y(t)$ and $x(t_i)$ have unit roots and a non-stationary model estimation problem can reduce to a stationary model in Eq. 4.21, $y(t)$ and $x(t_i)$ are co-integrated. Thirdly, $x(t_i)$ is known shortly in advance of $y(t)$. The error correction term can be interpreted by considering it as the causal effect of $x(t_i)$ on $y(t)$. By summarizing the above interpretation, the following linear and nonlinear forecast equations are derived.

$$Dy(t) = \alpha_1 + \alpha_2 s(t_i) + \sum_{j=1}^{m} \alpha_3(j) Dy(t-j) + \sum_{j=1}^{n} \alpha_4(j) s(t-j_i) + \epsilon_{t_i} \tag{4.22}$$

where $s(t_i)$ is the first-difference of $x(t_i)$. Similarly, the nonlinear equation is

$$Dy(t) = G_i(Dy(t-1), Dy(t-2), ..., s(t), s(t_i), s(t-1_i), s(t-2_i), ...) \tag{4.23}$$

where $G_i(.)$ is a nonlinear function to be determined.

For simplicity, a three-order autoregressive model (i.e $m = 1$) is adopted and α_1 and α_4 are taken as zero. Eq. 4.21 reduces to

$$Dy(t) = \alpha_2 s(t_i) + \sum_{j=1}^{3} \alpha_3(j) Dy(t-j) + \epsilon_{t_i} \tag{4.24}$$

A third-order nonlinear model becomes

$$Dy(t) = G_i(Dy(t-1), Dy(t-2), Dy(t-3), s(t)) \tag{4.25}$$

The forecast functions f_1 and f_2 refer to Eqs. 4.24 and 4.25 with and without $s(t,i)$ respectively. $\hat{y}(t)$ can be recovered by $Dy(t) + y(t-1)$.

4.3 Data Sample

10-minute NASDAQ composite intraday data, from 16 Aug 2005 to 9 Jul 2007, were used in experiments. The total number of trading minutes per trading day is 390 minutes. As the sampling interval is 10 minutes, $\Delta = \frac{10}{390}$ and $M = 39$. Totally, there are 474 daily close prices and 18,960 intraday prices.

4.4 Linear Forecast Model

In this section, it is demonstrated how the linear forecast function is used for the prediction of daily high and how the forecast accuracy varies with intraday time and incremental intraday measures.

4.4.1 Testing of Conditions for Linear Forecast Equation

In Section 4.2, the forecast function has been derived based on the predictand $y(t)$ and the predictor $x(t_i)$. There are three important interpretations. They include that (i) $y(t)$ and $x(t_i)$ are highly correlated; (ii) $y(t)$ and $x(t_i)$ are co-integrated; and (iii) $x(t_i)$ is known shortly in advance of $y(t)$.

Suppose that a long-run equipment relationship between daily high and incremental high/close exists. Both incremental measures are known on the same day with daily high. To use this forecast function, we need to further check that both series $y(t)$ and $x(t_i)$ are unit root processes. The most common unit root test is the Dickey Fuller (DF) test [13].

$$Dy(t) = e_0 + e_1 y(t-1) + u'_t \tag{4.26}$$

The null hypothesis is that there is a unit root, $e_1 = 0$.

Under 5% significant level, the null hypothesis, that $y(t)$ has a unit root, is accepted. Regarding the incremental close and high, all series of $x(t_i)$ for $i = 1, ..., 40$ have a unit root under 5% significant level. The similar test is conducted on the difference of these series. The results show that under 5% significant level,

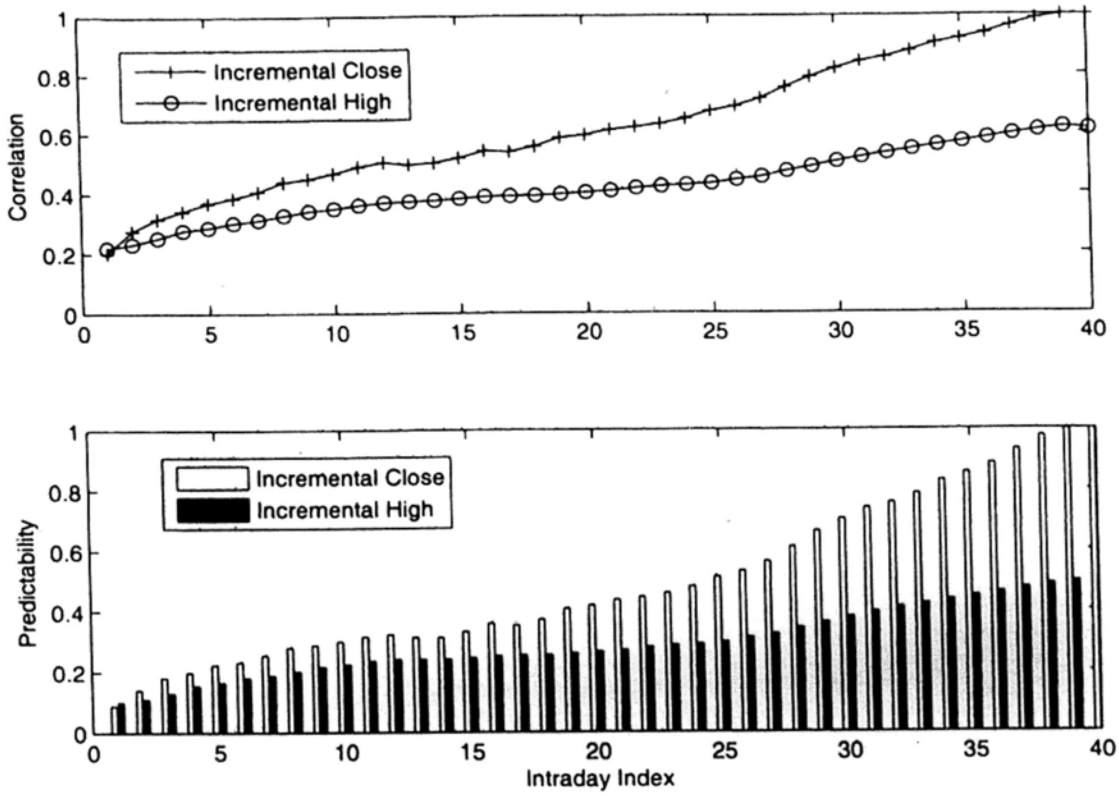


Figure 4.4: Correlation and Predictability using Incremental High and Incremental Close

the null hypothesis for a unit root is rejected. It implies that the series of $y(t)$ and $x(t_i)$ for $i = 1, ..., 40$ are integrated of order one. Thus, the forecast equation in Eq. 4.21 using the difference of series is also a stationary model. The spurious regression in the forecast equation using daily high and incremental high/close didn't exist.

4.4.2 Empirical Results of Prediction

In Fig. 4.4, the upper figure plotted the correlation $\rho(i)$ with intraday time t_i. All correlations were greater than 0.6. These supported the high correlation assumption. The lower figure plotted the predictability $\beta(i)$ with intraday time t_i. In general, the predictability was higher than 0.5. These implied that the incremental intraday predictor $x(t_i)$ had a positive causal effect on the predictand $y(t)$. The incremental intraday information was useful in the improvement of prediction accuracy.

At the same intraday index, the prediction accuracy using the incremental high as the predictor was different that using the incremental close although the same set of incremental intraday information was used. It indicates that the selection of incremental intraday measure plays an important role in the prediction. It directly affect the prediction accuracy at current time or with intraday time.

The prediction accuracy for the forecast functions using an incremental high has a general upward trend. Both the daily high and the incremental high have a similar formulation. It indicates that if the predictand and the incremental intraday measure have a similar formulation, the predictability will increase with intraday time.

By comparing the upper figure with the lower figure, you might find that the predictability and the correlation for incremental high or close have a similar trend. When I computed the correlation between them, a high linear relationship existed between them.

4.5 Nonlinar Forecast Model

In this section, it is demonstrated how the nonlinear forecast function is used for the prediction of Range-based Volatility and whether the same upward trend of predictability is observed in the incremental intraday prediction of Range-based volatility. Also, would the nonlinear model perform better than the linear model in this problem?

4.5.1 Testing of Conditions for Linear Forecast Equation

Similar to the prediction of daily high, testing on a unit root for the GK range-based volatility and incremental GK range-based volatility is necessary. Under 5% significant level, both range-based volatility and incremental GK range-based volatility $x(t_i)$ for $i = 1, 2, ..., M$ didn't have root unit. It implied that the series of range-based volatility and incremental GK range-based volatility were stationary.

Now, the question become whether the forecast model in Eq. 4.21 could be applied to the incremental intraday prediction. It needs to re-consider three interpretations. They include that (i) $y(t)$ and $x(t)$ have a long-run equilibrium relationship; (ii) $y(t)$ and $x(t_i)$ have a unit root and a non-stationary model estimation problem can reduce to a stationary model; and (iii) $x(t_i)$ is known shortly in advance of $y(t)$. Both (i) and (iii) are the assumptions. Item (ii) is failed to be satisfied as $y(t)$ and $x(t_i)$ don't have a unit root. However, $y(t)$ and $x(t)$ are stationary. The difference of these series are stationary. Therefore, the forecast model is still a stationary model. A spurious regression doesn't exist in the forecast equation in Eq. 4.21. However, since the original series is stationary, these series instead of their difference should be used in the forecast equation directly. Further study should be conducted to derive a forecast function using the original series.

4.5.2 Empirical Results of Prediction

Similar to the prediction of daily high, a third-order autoregressive model was used to the linear forecast function. For the nonlinear forecast function, 3-layer FeedForward Neural Neworks [18] were used to the nonlinear forecast function. The number of neurons in each layer were (5, 3, 1) and the activation func-

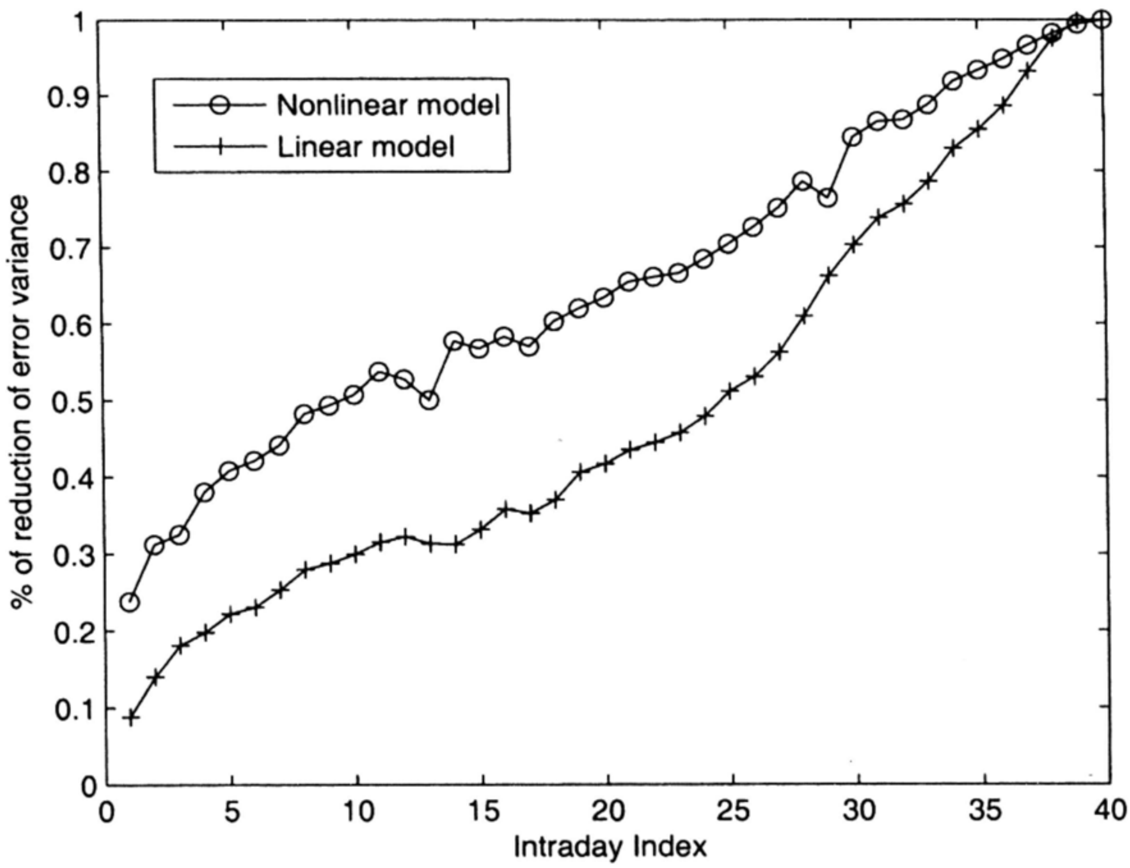


Figure 4.5: Predictability of Range-based Volatility using Linear and Nonlinear Models

tions of each layer were (tansig, tansig, linear). In Fig. 4.5, the predictability using linear and nonlinear forecast functions was plotted with intraday time. Similar to the linear model, the predictability using Neural Networks increased with intraday time. By comparing the relationship between the correlation and the predictability, it further discovered that the nonlinear model had a higher relationship than the linear model.

The predictability using Neural Networks forecast, as depicted in Fig. 4.5, was higher than that using linear model. The causal effect was represented by the reduction of error variance. Neural Networks forecast had a higher reduction of error variance. It thus implied that a stronger causal effect was captured in the neural networks forecast.

4.6 Chapter Summary

In summary, I derived the linear and nonlinear forecast functions using incremental intraday information. The incremental intraday information is useful to improve the prediction accuracy. To maximum the benefit of use of incremental intraday information, selection of a proper measure is crucial. Citing the prediction of daily high and GK range-based volatility as examples, their results supported that the prediction accuracy increased with intraday time when a proper measure was used. However, this was applicable not only to the daily high or GK range-based volatility prediction but also to the other incremental intraday predictions. Besides, a high linear relationship between the correlation and the predictability was found. It implied that correlation was a good indicator of predictability. Similar findings were observed in the nonlinear model. It was further found that Neural Networks forecast had a stronger causal effect on the predictand.

The existing linear forecast function is derived based on the non-stationary predictand and predictor. However, if the series are stationary, the difference of the series will not be necessary. A forecast function using original series for the incremental intraday prediction should be further explored.

□ **End of chapter.**

Chapter 5

Intra-daily Effect on Conditional Variance

Conventional GARCH and the more recent MEM-GARCH modeling is given in Section 5.1. Based on these modeling for return and absolute return for market data, the interpretation of GARCH volatilities is examined in Section 5.2. Section 5.3 gives some salient features for using MEM-GARCH in capturing intraday effects which are missing in conventional GARCH. Further study on a delayed control of intraday effects using exogenous input is given in Section 5.4. A summary is presented in Section 5.5.

5.1 GARCH(1,1) and MEM-GARCH modeling

GARCH(1,1) is probably the most widely used GARCH model in modeling conditional volatility $\sigma^2_{t|t-1}$ of the daily return r_t, based on the maximum-likelihood estimation of the parameter set $\theta = \mu, \omega, \alpha, \beta$ for the tightly coupled mean equation and variance equation:

$$r_t = \mu + \epsilon_t \tag{5.1}$$

$$\sigma^2_{t|t-1} = \omega + \alpha\epsilon^2 t - 1 + \beta\sigma^2_{t-1|t-2} \quad (5.2)$$

ϵ_t is a zero-mean additive error process for $r_t - \mu$ which measures the innovation between r_t and the estimated mean μ, and can be interpreted as $\sigma_{t|t-1} z_t$ where z_t is $i.i.d$ (identical independent distributed), $E(z_t) = 0$, and $Var(z_t) = 1$. $\omega > 0, \alpha > 0, \beta > 0$ are the required constraints in maximum likelihood estimation to ensure that $\sigma^2_{t|t-1}$ is positive in Eq. 5.2.

However, the conventional GARCH framework (e.g. GARCH(1,1) in Eqs 5.1 and 5.2) is not well suited for handling non-negative time series x_t where $x_t > 0$ for all t. Efficient estimation using maximum-likelihood is known to be difficult and requires very careful distribution specification for ϵ_t (see discussion in [20]). A more appropriate multiplicative-error model (MEM) has been recently proposed ([19], [20]); and three relevant cases for such non-negative x_t, including r_t^2, $\hat{\sigma}_4^2$ and $\hat{\sigma}_6^2$

$$\hat{\sigma}_4^2 = 0.511(u-d)^2 - 0.019[c(u+d) - 2ud] - 0.383c^2 \quad (5.3)$$
$$\hat{\sigma}_6^2 = a\frac{(O_t - C_{t-1})^2}{f} + (1-a)\frac{\hat{\sigma}_4^2}{1-f} \quad (5.4)$$

(i.e. Garman and Klass range-based volatilities) are considered using the following MEM-GARCH:

$$x_t = \sigma^2_{t|t-1}\epsilon_t \quad (5.5)$$
$$\sigma^2_{t|t-1} = \omega + \alpha x_{t-1} + \beta\sigma^2_{t-1|t-2} \quad (5.6)$$

Note that ϵ_t (in Eq. 5.5) is now a unit-mean $i.i.d$ process; and Eq. 5.5 thus specifies an MEM with "an error that is multiplied times the mean" [20]. Conventional GARCH software (using maximum-likelihood) can readily obtain the parameter set $\theta_m = \omega, \alpha, \beta$ simply by making the positive square root $\sqrt{x_t}$ (instead of r_t) the dependent variable in the mean equation (Eq. 5.1) with no mean.

5.2 GARCH volatilities for r_t and $|r_t|$

Two eight-year market data sets were evaluated in this section. The S&P 500 and NASDAQ composite index from January 2, 1998 to February 19, 2006, each with 2,045 days. The full data sets are used for both the GARCH(1,1) and MEM-GARCH estimation, and thus yield quite stable parameter sets for performance comparison. However, for simplicity and ease of graphical interpretation, only the last 245 days (with time index from 1800 to 2045) are focused on in our discussion. Unless stated otherwise, our observations and conclusions drawn should apply also to other time intervals as well.

Both the daily return r_t and absolute daily return $|r_t| = \sqrt{r_t^2}$ depend only on the close prices, and hence contain no other intraday information of price variation for the trading day. As r_t has a roughly zero mean, it is appropriate to use the conventional GARCH(1,1) (Eqs. 5.1 and 5.2) to estimate the conditional variance; whilst for $|r_t|$ the MEM-GARCH(1,1) (Eqs. 5.5 and 5.6) should be a better model developed specifically for non-negative time series.

Fig. 5.1 shows a graphical comparison that confirms our expectation for both the S&P 500 and NASDAQ data sets. Although different models are used for r_t and $|r_t|$, they give practically the same results for the estimated volatility $\hat{\sigma}^2_{t|t-1}$ (as shown in the significant overlap between the solid and dotted lines of the figure).

It is of much interest to study if there exists any relationship between intra-daily information and these GARCH volatilities, which are estimated from models without using much of such information except the daily close. In contrast, range-based volatility such as $\hat{\sigma}_4^2$ (Eq. 5.3) is a more useful intraday proxy that provides more information on price varation during the trading day; this proxy is reconstructed from an underlying dif-

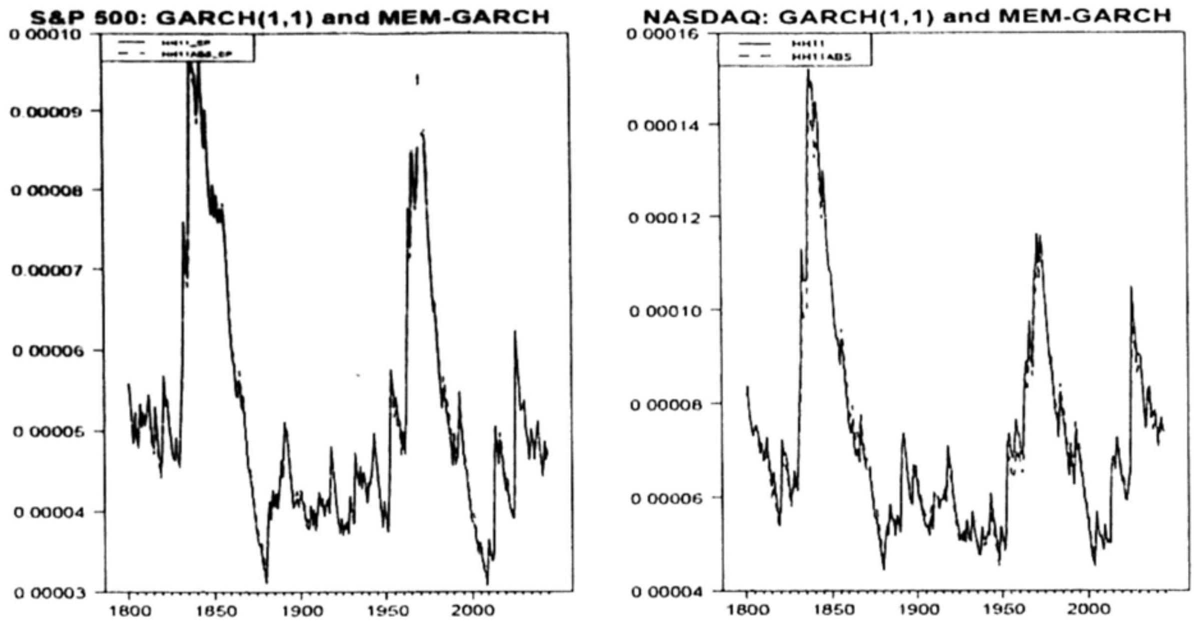


Figure 5.1: $\sigma^2_{t|t-1}$ using GARCH for r_t and MEM-GARCH for $|r_t|$ (Left: S & P 500 index; right: NASDAQ composite index)

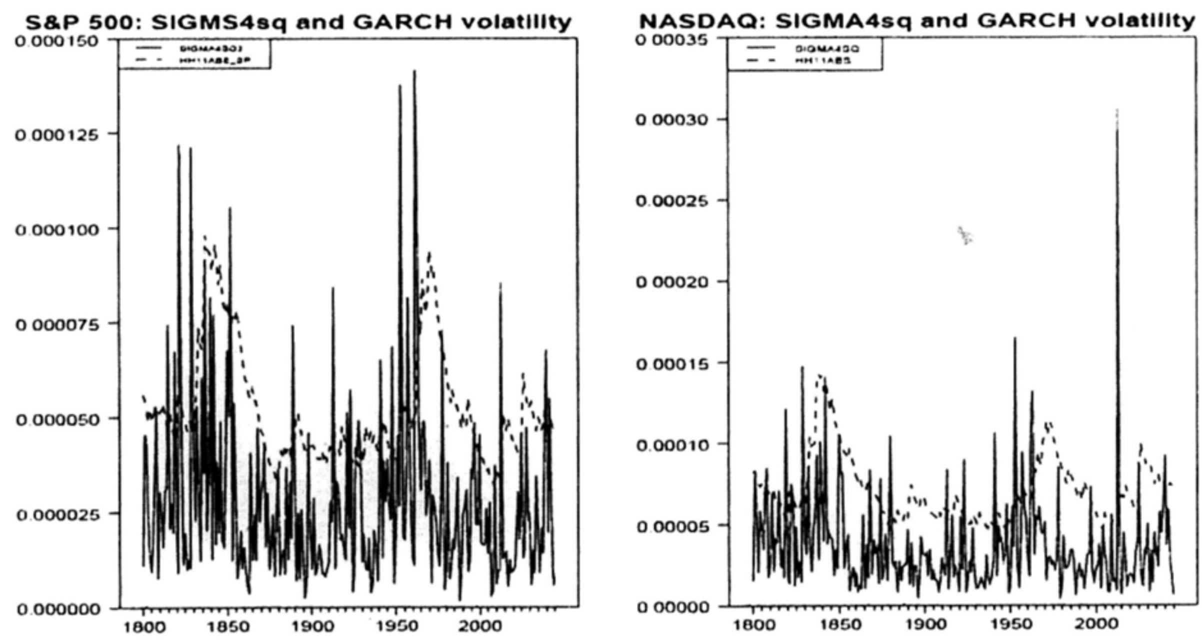


Figure 5.2: $\sigma^2_{t|t-1}$ using MEM-GARCH for $|r_t|$ (dotted line); range-based volatility $\hat{\sigma}^2_4$ (solid line)

fusion price model using the generating moments of u, d, c (the daily high, low, and close with reference to open). A graphical comparison between $\hat{\sigma}_4^2$ and $\sigma^2_{t|t-1}$ (using MEM-GARCH for $|r_t|$) is shown in Fig. 5.2. There appears to be mu h sharper fluctuations in range-based volatility, and the correlation between the two signals ($\hat{\sigma}_4^2$ and $\sigma^2_{t|t-1}$) is apparently weak.The intraday information as captured by $\hat{\sigma}_4^2$ is not well reflected within the GARCH volatilities of the daily return and the absolute daily return.

5.3 Intraday Effects of MEM-GARCH

The use of two range-based volatilities, $\hat{\sigma}_4^2$ and $\hat{\sigma}_6^2$, are proposed to have a better capture of intraday information for MEM-GARCH models. Their respective MEM specifications are readily obtained from Eq. 5.5 by defining x_t appropriately:

$$\hat{\sigma}_4^2 = \sigma^2_{t|t-1}\epsilon_t \tag{5.7}$$

$$\hat{\sigma}_6^2 = \sigma^2_{t|t-1}\epsilon_t \tag{5.8}$$

Notice that Eqs 5.7 and 5.8 are the no-mean (or mean) equations of MEM-GARCH for $\hat{\sigma}_4^2$ and $\hat{\sigma}_6^2$, respectively, which are to be used with the variance equation (Eq. 5.6) for the estimation of the conditional variance $\sigma^2_{t|t-1}$. Such type of specifications follow that of Engle & Gallo [19] for their MEM-GARCH formulation of high-low spread and realized volatility. Here our focus is on using range-based volatility in MEM-GARCH directly; and the relevance with previous work lies in several aspects: (i) $\hat{\sigma}_4^2$ and $\hat{\sigma}_6^2$ include information on the high- low spread, (ii) the 8-year S&P 500 and NASDAQ data sets currently do not have a complete record of high-freqency data for calculating realized volatility over the entire time period, and (iii) range-based volatilites are reasonable intraday proxies that demonstrate quite similar be-

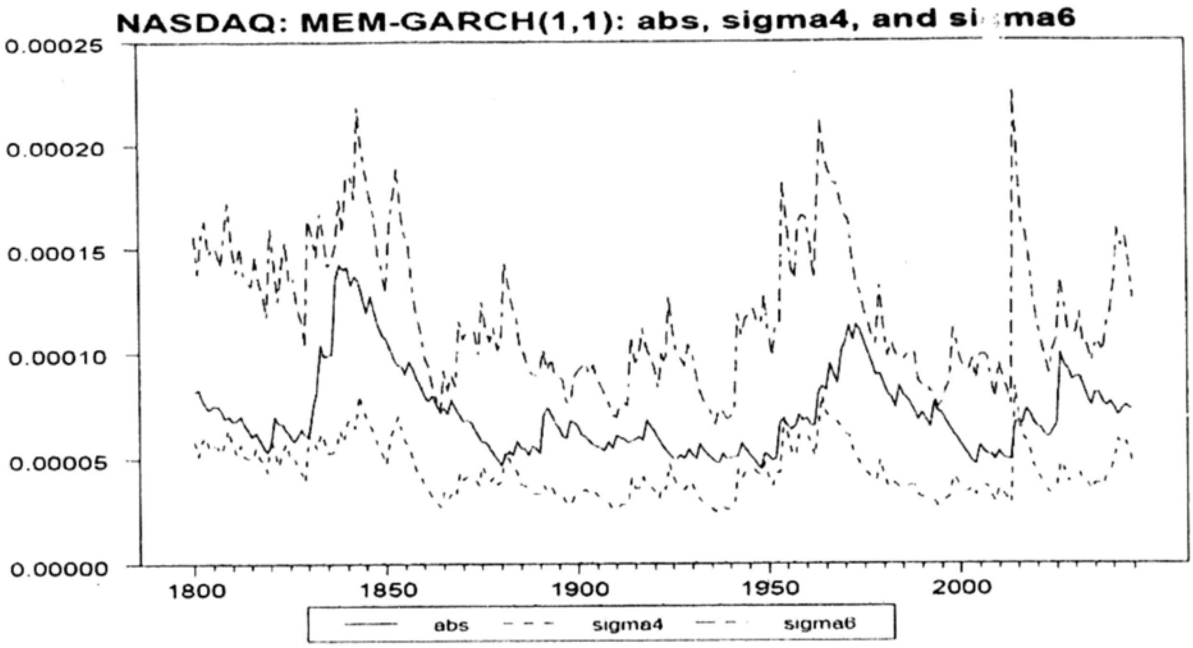


Figure 5.3: NASDAQ: $\sigma^2_{t|t-1}$ using MEM-GARCH for (i) $|r_t|$ (middle curve) (ii) $\hat{\sigma}_4$ (lower curve) (iii) $\hat{\sigma}_6$ (upper curve)

havior and characteristics when compared with realized volatility

Fig. 5.3 compares the three MEM-GARCH volatilities for $|r_t|$, $\hat{\sigma}_4$, and $\hat{\sigma}_6$ using the NASDAQ data set. There are some observations which readily lead us to answer questions on the intraday effects on MEM-GARCH. Firstly, the curves for $\hat{\sigma}_4$, and $\hat{\sigma}_6$ both show sharp changes (say, at day indices around 1845, 1955, 2015) that are absent in the curve for $|r_t|$. As range-based volatilites contain more intra-daily information than that from the daily return or absolute daily return $|r_t|$ (driven by close prices only), it should not be surprising for reasonably large changes in intraday information to give a significant impact on the corresponding MEM-GARCH volatilities. Secondly, we demonstrate their close relationship using Fig. 5.4 which clearly shows that sharp changes in the estimated volatilities correspond to large variation in intraday information (as captured by the dotted line for $\hat{\sigma}_4^2$). Third, by measuring the cross correlation

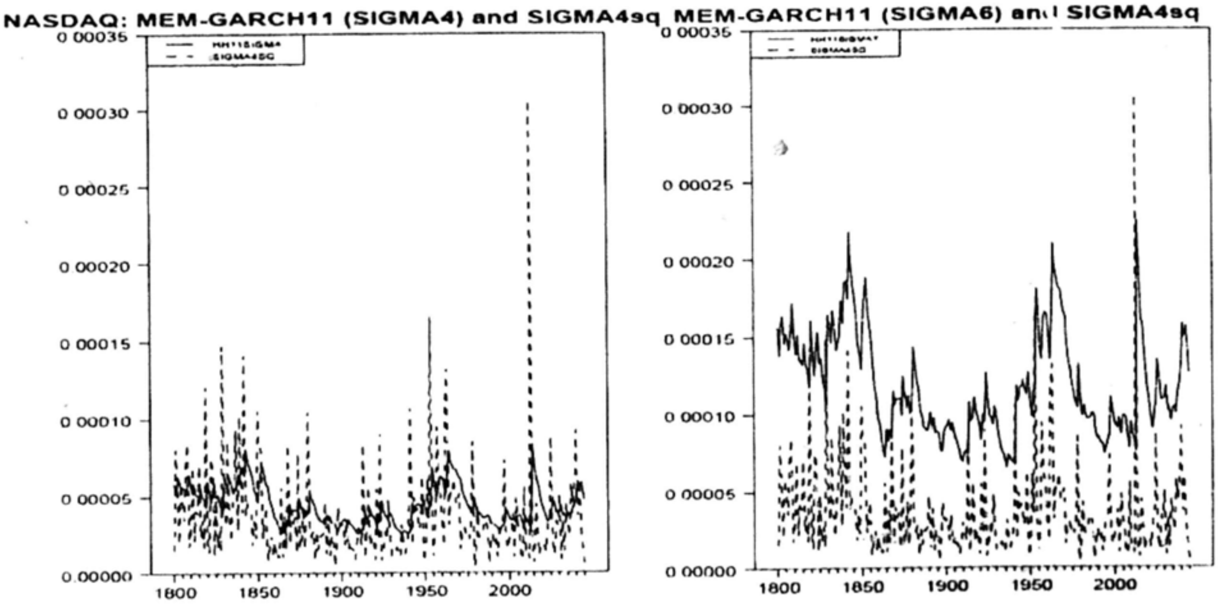


Figure 5.4: NASDAQ: $\sigma^2_{t|t-1}$ using MEM-GARCH for (a) (left) $\hat{\sigma}_4$ (solid line) and (b) (right) $\hat{\sigma}_6$ (solid line) against range-based volatility $\hat{\sigma}_4^2$ ([illegible]ted line)

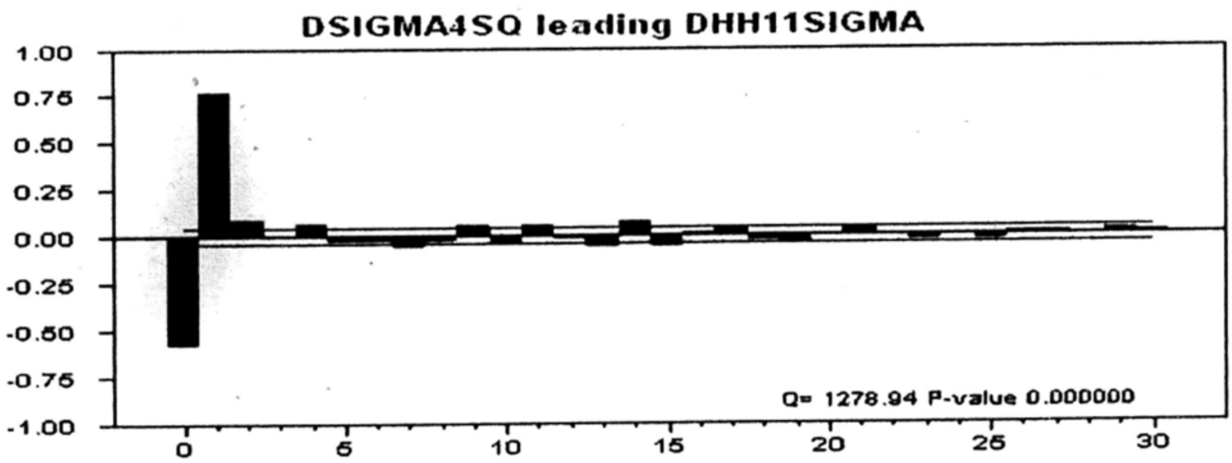


Figure 5.5: Cross Correlation between $\Delta\sigma^2_{t|t-1}$ using MEM-GARCH for $\hat{\sigma}_4$ and $\Delta\hat{\sigma}_4^2$ for NASDAQ and S&P 500 data sets

(Fig. 5.5 between the difference signals $\Delta\sigma^2_{t|t-1}$ (using MEM-GARCH for $\hat{\sigma}_4$) and intraday information (as captured by $\Delta\hat{\sigma}^2_4$), a significant correlation of 0.75 occurs when the former signal leads the latter by one V thus further confirming the intraday effects on MEM-GARCH modeling.

5.4 Delayed Control of Intraday Effects using Exogenous Input

An alternative way for incorporating intraday information in GARCH modeling is to use exogenous input $\hat{\sigma}^2_4$ in the variance equation. Consider the modification of Eqs. 5.2 and 5.6 with a general k-step ($k > 0$) delayed $[\hat{\sigma}^2_4]_{t-k}$.

$$\sigma^2_{t|t-1} = \omega + \alpha\epsilon^2_{t-1} + \beta\sigma^2_{t-1|t-2} + \gamma[\hat{\sigma}^2_4]_{t-k} \quad (5.9)$$

$$\sigma^2_{t|t-1} = \omega + \alpha x_{t-1} + \beta\sigma^2_{t-1|t-2} + \gamma[\hat{\sigma}^2_4]_{t-k} \quad (5.10)$$

Simulation tests on two categories of GARCH models with and without the prior embedding of intra-daily information were performed. For the first category, it includes MEM-GARCH models using range-based volatilities $\hat{\sigma}_4$, and $\hat{\sigma}_6$. The second category includes GARCH(1,1) using the daily return r_t and MEM-GARCH using the absolute return $|r_t|$. Preliminary results indicated that, for the first category, the inclusion of exogenous input in the variance equation (Eq. (14)) and for $k > 1$ would not give much changes to the estimated variance $\sigma^2_{t|t-1}$. One noticeable exception is that for k = 0 (and hence intraday information for day t is also included), the estimated variance changes to resemble closely the exogenous input $\hat{\sigma}^2_4$. As for the tests on the second category, we observed that exogenous input can be effectively used for delayed control of intraday effects by varying k (and $k > 0$). When k is large, the estimated variance is identical with that as if there is no exogenous input. Fig.

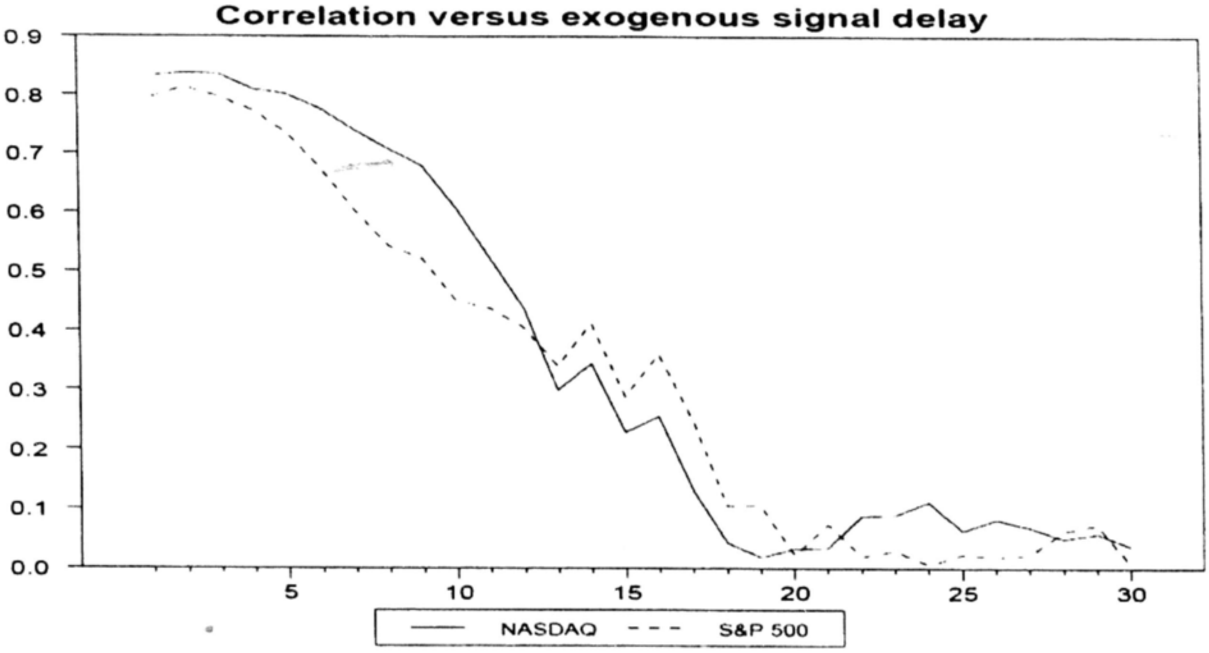


Figure 5.6: S&P 500 and NASDAQ: Correlation between the conditional variance $\sigma^2_{t|t-1}$ using MEM-GARCH for $|r_t|$ (or using GARCH(1,1) for r_t) and the k-step delayed $[\hat{\sigma}_4^2]_{t-k}$

7 shows the correlation between $\sigma^2_{t|t-1}$ and $\hat{\sigma}_4^2$, depicting that intraday effects diminish with increase in k.

5.5 Summary

Using Engles multiplicative-error models (MEM), we have formulated successful MEM-GARCH modeling procedures for the embedding of intra-daily information using range-based volatilities. Verification tests on two reasonably extensive (8 years) and well-known market data sets, the S&P 500 index and the NASDAQ composite index, were performed and demonstrated similar results. Future research in using realized volatility and multipower variation will be of much interest, pending the availability of high-frequency data over a long time period.

□ **End of chapter.**

Chapter 6

Conclusion and Future Work

In conclusion, the genetic fuzzy trading model aggregates the output signal of trading rules to suggest the coming action. It eliminates the discontinuities of jumps due to the Boolean operations. It further incorporates the vague trading rules under the ill-defined stock market in the trading model. It can identify the optimal trading rules to tackle with different market situations. Under the dynamic stock market, both incremental and dynamic training approaches are very useful to tackle with the market change. By comparing the trading systems formed by genetic algorithm and genetic programming, the genetic fuzzy trading model gives the simple structure and can identify the most profitable and moderate risk trading strategy. The incremental intraday information is useful for the forecast. A proper selection of incremental intraday measure can increase the forecast accuracy with intraday time. This forecast accuracy can further be estimated by the correlation between predictand and the predictor using incremental intraday information. A MEM-GARCH modeling procedure was formulated for the embedding of intra-daily information. Verification test on 8-year S&P 500 index and NASDAQ composite index were performed and demonstrate the similar result.

Regarding the future work, it can extend the existing study on the application of reinforcement learning to the mapping of market state to action. In [12], Dempster used the reinforcement learning to learn the optimal policies for the mapping of the market state to the action. Based on the Q-values of each mapping, the optimal policy was found. In reality, a market state in out-of-sample data may not exist in in-sample data. This brings to an undetermined action. It is also a disadvantage if many market states in out-of-sample data do not exist in in-sample data. On the other hand, RL problems have a simple goal in form of single state. By comparing the processing time with evolutionary algorithms, it is much faster to find the optimal policy. If the online trading is the ultimate goal for developing a trading system, this learning algorithm is most suitable for online training in addition to online trading. The extension may consider using the interval of aggregate signal as the input state. As the aggregate signals are distributed within (-1,1), it is easy to identify all input state in in-sample training. Thus the missing state in out-of-sample data will not be existed.

Regarding the future work of the incremental intraday prediction, the forecast function is modeled by the linear model and feedforward neural networks. Also, it can be modeled by the support vector machines. The comparison among these models is interesting. The existing prediction is limited in the in-sample data. The effect on the out-of-sample should be tested.

Regarding the future work of the intra-daily effect on MEM-GARCH, Study of intra-daily effect using realized volatility and multi-power variation will be the future work.

□ **End of chapter.**

Appendix A

Technical Indicators

A.1 Simple Moving Average

Simple Moving Average (SMA) is an arithmetic average of the last k days. Formally, k-day simple moving average at day t $(0 \leq t, k \leq t\ )$ is defined by

$$sma(k,t) = \frac{1}{k}\sum_{j=0}^{k-1} p(t-j) \tag{A.1}$$

5-day SMA and 20-day SMA are used in the experiment. When the closing price or the short moving average crosses above the long moving average, it initiates a buy signal. On the other hand, when the closing price/short moving average crosses below the long moving average, it initiates a sell signal.

A.2 Exponential Moving Average

Exponential Moving Average (EMA) at time periods $t \geq 2$ is defined by

$$ema(i,t) = \alpha p(t) + (1-\alpha) ema(i,t-1) \tag{A.2}$$

4-day EMA and 19-day EMA are used in this study. The trading rules are defined similar to those of SMA.

A.3 Weighted Moving Average

Weighted Moving Average (WMA) at time periods $t \geq 2$ is defined by

$$wma(i,t) = \frac{1}{k}\sum_{j=0}^{k-1} j * p(t-j) \qquad (A.3)$$

Similar to SMA, 5-day EMA and 20-day EMA are used in the experiment. Similar trading rules like those of SMA are defined.

A.4 Relative Strength Index (RSI)

Relative Strength Index (RSI) is developed by J. Welles Wilder [66]. It is an oscillator capturing price strength by comparing upward and downward movements. rsi is formulated to fluctuate between 0 and 100 and enables a fixed overbought and oversold levels. It is defined by

$$rsi(i,t) = \frac{100 * AU(t,i)}{AU(t,i) + AD(t,i)} \qquad (A.4)$$

where AU is exponential moving average of upward movement, and
AD is exponential moving average of downward movement.

5-day RSI and14-day RSI are used in the experiment. Normally, a buy signal is triggered when rsi is smaller than the oversold level. A sell signal is triggered when RSI is larger than the overbought level.

A.5 Simple Moving Average of Relative Strength Index

Simple Moving Average of Relative Strength Index (MA-RSI) consists of a rsi indicator and moving average of rsi. It is defined as follows:

$$marsi(i, j, t) = sma(rsi(i, t), j) \tag{A.5}$$

In this study, i and j are 5. Normally, the trading rule is set up by comparing MA-RSI with RSI. If RSI crosses above MA-RSI, it triggers a buy signal. If RSI crosses below MA-RSI, it triggers a sell signal. This usage of this indicator is close to SMA.

A.6 Moving Average Convergence-Divergence

Moving Average Convergence-Divergence (MACD) is created by Gerald Appel [4]. The MACD can signal overbought and oversold trends. The market is oversold when both lines are below zero and is overbought when two lines are above the zero line. It is defined by

$$macd.osc(i, j, t) = ema(i, t) - ema(j, t) \tag{A.6}$$

$$macd(i, j, k, t) = ema(macd.osc(i, j, t), k) \tag{A.7}$$

where k is smoothing period. In this experimental, i, j and k are 39, 9 and 2. The general practice for a buy or sell signal is followed in the experiment.

A.7 Momentum

Momentum (MOM) is the difference between today's closing price and the closing price i days ago. Momentum refers to continous prices trend. Normally, when it crosses below zero, a buy signal is initiated. When it crosses above zero, a sell signal is triggered.

$$mom(i, t) = p(t) - p(t - i) \tag{A.8}$$

$i = 5$ is used for the testing. In the experiment, the trading rules are set up based on its nature.

A.8 Rate of Change

Rate of Change (RoC) is close to MOM but scales by the i-day closing price.

$$roc(i,t) = \frac{p(t) - p(t-i)}{p(t-i)} \tag{A.9}$$

In this study, i is equal to 5. As it is close to MOM, the buy and sell trading rules are set up similar to those of MOM.

A.9 William percent-R

Larry William developed a trading formula called William percent-R (%R). The system attempts to measure overbought and oversold market conditions. The %R always falls between a value of 100 and 0. The formula is given by

$$\%R(i,t) = \frac{h(t,t-i) - p(t)}{h(t,t-i) - l(t,t-i)} \tag{A.10}$$

where $h(t,t-i)$ is the highest price during the period of (t-i,t), and

$l(t,t-i)$ is the lowest price during the period of (t-i,t).

In this study, i is equal to 4. If %R is higher than a overbought level, a sell signal is initiated. If %R is smaller than a oversold level, a buy signal is initiated.

A.10 Stochastic Oscillator

The Stochastic Oscillator is introduced by George Lane in 1960. It is a momentum indicator that shows the location of the current close relative to the high/low range over a set number of periods. If the closing price is near the top/bottom of the range, it will imply buying or selling pressure. If the value is below

20 or above 80, it will consider oversold or overbought respectively. Two stochastic oscillators, fast stochastic %K and slow stochastic %S, are always used to evaluate the future variations in prices. They are calculated by

$$\%K(i,t) = \frac{100(p(t) - l(t,t-i))}{h(t,t-i) - l(t,t-i)} \quad (A.11)$$

$$\%D(j,t) = \frac{100h(t,t-j)}{l(t,t-j)} \quad (A.12)$$

In this study, i and j are equal to 5. kd line is the difference between %K line and %D line.

A.11 Volatility Indicator

Volatility Indicator is defined based on Average True Range (ATR). ATR is introduced by Welles Wilder [66]. It is a measure of volatility. The True Range (TR) indicator and the ATR are defined in Eq. A.13 and Eq. A.14 respectively. If a stock experiences a higher level of volatility, the ATR will be higher. A low volatility results in a lower ATR.

$$tr(t) = max[h(t) - l(t), |h(t) - p(t-1)|, |l(t) - p(t-1)|] \quad (A.13)$$

$$atr(i,t) = ema(i,t,tr) \quad (A.14)$$

In this study, $i = 4$ is used. A volatility indicator (vi) is further defined by

vi(t-1)	$p(t) > sar(t-1)$	vi(t)	sar(t)
1	True	1	p(t) - atr(t)
1	False	-1	p(t) + atr(t)
-1	True	1	p(t) - atr(t)
-1	False	-1	p(t) + atr(t)

A.12 Directional Movement Index

Directional Movement Index is also developed by Welles Wilder.

$$
\begin{aligned}
pdm(t) &= h(t) - h(t-1) \\
ndm(t) &= l(t) - l(t-1) \\
pdi(i,t) &= \frac{sma(i,t,pdm)}{sma(i,t,tr(t))} \quad (A.15) \\
ndi(i,t) &= \frac{sma(i,t,ndm)}{sma(i,t,tr(t))} \quad (A.16)
\end{aligned}
$$

$i = 5$ is used for the testing. Normally, if pdi crosses below ndi, a sell signal is initiated. If pdi crosses above ndi, a buy signal is initiated.

□ **End of chapter.**

Appendix B

36 Fuzzy Trading Rules

1. If (the closing price crosses above 5-day moving average), (a buy signal is initiated).
2. If (the closing price crosses below 5-day moving average), (a sell signal is initiated).
3. If (5-days moving average crosses above 20-day moving average), (a buy signal is initiated).
4. If (5-days moving average crosses below the 20-days moving average), (a sell signal is initiated).
5. If (the closing price crosses above 5-day weight moving average), (a buy signal is initiated).
6. If (the closing price crosses below 5-day weight moving average), (a sell signal is initiated).
7. If (5-days weight moving average crosses above 20-day weight moving average), (a buy signal is initiated).
8. If (5-days weight moving average crosses below the 20-days weight moving average), (a sell signal is initiated).
9. If (the closing price crosses above 5-day exponential moving average),(a buy signal is initiated).

10. If (the closing price crosses below 5-day exponential moving average), (a sell signal is initiated).

11. If (5-days exponential moving average crosses above 20-day exponential moving average), (a buy signal is initiated).

12. If (5-days exponential moving average crosses below the 20-days exponential moving average), (a sell signal is initiated).

13. If (5-day rsi is small), (a buy signal is initiated).

14. If (5-day rsi is moderate), (a hold signal is initiated).

15. If (5-day rsi is large), (a sell signal is initiated).

16. If (14-day rsi is fewer than 35 and 5-day rsi is greater than 5-day moving average of 5-day rsi), (a buy signal is initiated).

17. If (14-day rsi is larger than 65 and 5-day rsi is smaller than 5-day moving average of 5-day rsi), (a sell signal is initiated).

18. If (MACD is negative), (a sell signal is initiated).

19. If (MACD equals 0), (a hold signal is initiated).

20. If (MACD is positive), (a buy signal is initiated).

21. If (k-line is small and d-line is small), (a buy signal is initiated).

22. If (k-line is large and d-line is large), (a sell signal is initiated).

23. If (kd-line is negative), (a sell signal is initiated).

24. If (kd-line is positive), (a buy signal is initiated).

25. If (oscillator is negative), (a buy signal is initiated).

26. If (oscillator is positive), (a sell signal is initiated).
27. If (rate of change is high), (a sell signal is initiated).
28. If (rate of change is low), (a buy signal is initiated).
29. If (momentum is declining), (a buy signal is initiated).
30. If (momentum is inceasing), (a sell signal is initiated).
31. If (%R is low), (a sell signal is initiated).
32. If (%R is high), (a buy signal is initiated).
33. If (pdi crosses below ndi), (a sell signal is initiated).
34. If (pdi crosses above ndi), (a buy signal is initiated).
35. If (vi is long), (a buy signal is initiated).
36. If (vi is short), (a sell signal is initiated).

□ **End of chapter.**

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