國立交通大學

資訊管理研究所

碩 士 論 文

基於籌碼面分析利用學習分類元系統於股票市場

Applying Learning Classifier System to Stock Market
Based on Institutional Analysis

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中 華 民 國 九 十 三 年 六 月

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摘要

人工智慧技術應用於股票市場已經是必然的趨勢，從許多的文獻以及實務上的應用可以發現傳統統計分析方法無法正確掌握到市場持續不斷變動的特性。本論文研究嘗試從籌碼面的角度切進，探討是否可由籌碼面因子來判斷未來股價之趨勢。

首先，本文採用相關分析(Correlation Analysis)方法，來探討選定之籌碼因素與未來股價的相關程度，實驗發現所選擇的因子雖然在實務界或是過去文獻常被利用來當作選股的先行指標，但大部分卻與未來股價趨勢有著很低的關聯性，甚或毫無相關。進而由這些因素來作股價之迴歸預測分析，根據簡單迴歸分析(Simple Regression Analysis)得到的結果，由這些因子過去的歷史資料並無法得到很好的預測價值。然而，這些因子確實有其價值所在，是否因為傳統統計方法無法瞭解整個環境的變動去作動態學習，導致其靜態地以線性方法作分析，而得到不佳的效果，則是以下的探討。

基本面或是技術面之股市分析已被廣泛地討論，相對地，籌碼面分析較少被研究，然而在台灣市場愈來愈開放、資金愈來愈充裕的情況下，法人對於台灣市場的影響力亦愈來愈重；再者，類神經網路(Neural Network)、模糊邏輯(Fuzzy Logic)、基因演算法(Genetic Algorithms)等人工智慧技術對於挖掘股票知識的研究已有相當充分的貢獻；而學習分類元系統(Learning Classifier System)擁有整合與外界的環境作互動以去學習和基因演算法的功能，為一個以規則為基準(Rule-Based)且在變動不確定的環境下運作良好的系統；因此，本文從學習分類元系統的角度切進，以更貼近人類生活的學習方式去瞭解股票市場脈動，進而計算所得的累積報酬，期望建構一個價值高、可以獲取高額利潤的市場機制。

本研究的目的在於利用學習分類元系統之適應動態環境學習的特性，將股票市場中之籌碼面資料予以模擬，由於統計分析有時無法解釋出影響環境的真正因素，而落入統計陷阱(Statistical Pitfalls)，造成預測結果的不準確性，大大影響了投資人的決策；而分類元系統可以將環境中複雜因素考量進去以利於學習之行為模式，此可作為提供決策者做正確抉擇的依據。

Applying Learning Classifier System to Stock Market
Based on Institutional Analysis

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ABSTRACT

Artificial intelligence technique in stock market fluctuation evaluation has been documented in other papers and applied in many application domains. Based on previous surveys, to accurately handle the uncertainties and variations of the environment is a significant task. The thesis tries to probe into the judgment of future price trend on the basis of the institutional factors.

Firstly, the traditional statistical tests are performed to discover whether there exists a relationship between the experimental indicators or not. The correlation analysis is performed on the five indicators as the condition part and future price trend. However, the experiment indicates low or non correlation between the stock price and the institutional factors. On the other hand, using institutional indicators as the simulated factors on the stock market has been proved to be quite persuasive in many documents. Thus, the simple regression analysis is used to perform for the prediction of the future price trend. However, according to the results, the future price trend cannot be accurately predicted based on the historical data. Though the consequences are unsatisfactory, the selected institutional indicators are certainly valuable for the dynamic stock market. The poor outcome has to be understood and discussed for discovering the statistical pitfalls.

Therefore, the thesis attempts to apply learning classifier system (LCS), which is intended as a rule-based framework that integrates the concept of genetic algorithms, to learn and interact with the stock market environment. There are a large number of elements affecting the stock environment, selecting the most significant ones is capable of making the best investment strategies and improving the system performance. As mentioned above, the thesis focuses on the institutional indicators for modeling the behaviors in such complex environment to help investors obtaining optimal and satisfactory profits. Surveys on the selected institutional indicators, such as buy/sell of qualified foreign institutional investors (QFII), buy/sell of securities investment trusts, balance of margin purchasing, balance of short

selling, and trading volume, show that market prices can be directly influenced by the above-mentioned indexes. The promising results demonstrate that, by implementing the LCS model, the rules that are discovered can be utilized to make investment strategies with progressive benefits. The statistical pitfalls might be occurred due to the incapability of understanding and modeling the uncertainties in such situation. However, the learning classifier system is capable of taking the complicated factors into account for discovering the unknown behaviors and learning the inward knowledge of the environment.

Table of Contents

List of Tables

List of Figures

Chapter 1 Introduction

1.1 Motivations

The motivation of this thesis is derived from the relationship among the investors, environment, and behaviors (See Figure 1). The behaviors of stock market are influenced by various factors. Based on this framework, environment-behavior or person-behavior are connected to meet the needs of a specific area from the past experiences and historical data. Investment is so significant that people in the society need to have the knowledge and participate in the game. Human economic decisions are very difficult to be understood and modeled because they are characterized by a large number of unknown and uncertain factors. There have been quite a few tools for solving the problems and optimizing the goal in stock environment, especially the traditional statistical approaches and modern artificial intelligence techniques. For example, regression analysis, time series analysis, neural network, expert system, genetic algorithms, case based reasoning, and so on. Most of the approaches should be analyzed logically for establishing a rational predictive architecture. The methods mentioned above are concerned with either human or environmental behaviors. The perceptual knowledge and subjective cognition are often mixed up with when making strategies. The mainly proposed learning classifier system (LCS) [1] in this thesis tries to learn the internal behaviors of the system and interact with the external environment. Darwin's evolutionary theory "survival of the fittest" is also implemented in the system.

On the other hand, as the economic market becomes more and more open, global, and liberalized, Taiwan government has also welcomed more foreign investors to be involved in Taiwan financial market. The policy is capable of stabilizing the uncertainties in the stock market. Accordingly, the thesis focuses on modeling the institutional factors in the stock environment.

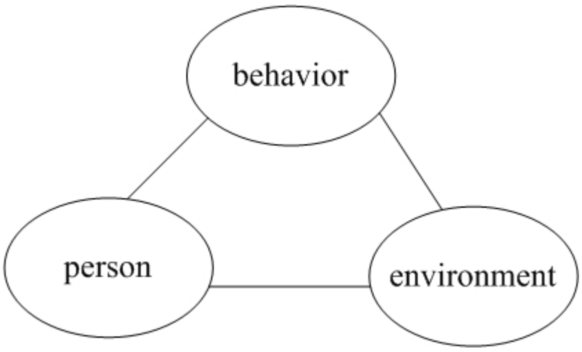

Figure 1 Relationships of person-environment-behavior

Moreover, from the literature reviews and the gathered news, institutional investors put into more money on value-weighted stocks. Therefore, as far as their importance and representatives in the market are concerned, nine value-weighted stocks are selected to be implemented in the experiment. Besides, we are in the time of knowledge explosion, continuing creating new knowledge and adapting to the environment enables us to catch up with the change of the age. Hence, based on the above-mentioned concepts, the thesis is eager to dig out the treasure for discovering new knowledge and achieving the expectation in the field of machine learning.

1.2 Research Scope

The thesis demonstrates an artificial intelligence technique to learn from the stock behavior. It is capable of using institutional indicators to analyze the stock price trend. Therefore, integrating the specifically-chosen indicators into such technique is regarded as the core of the thesis which will be stated in the following.

The behavior of stock market is influenced by many factors, including man-made and natural elements. Due to the open policy announced in recent years, the foreign investors have more and more impact on Taiwan stock market. Accordingly, the thesis focuses on using institutional indicators for discovering rules in the stock market.

Investment has been a necessity in daily life. How to correctly handle and observe the volatility in the stock market is an important task for investors. There are many causes influencing the stock market, such as politics, international statuses, economic variations, and news. For example, the presidential election will always greatly determine the stock trend before and after the announcement of the result. The petroleum crisis and terrorism attacks make people all over the world have such fears that they sell the stocks in large quantities in a short-term period. The variations in foreign currencies, such as the devaluation of U.S. dollars, or the revaluation of Euro, will also affect the global stock market promptly. The news is an immediate element in the stock market; for instance, the sudden release of SARS cases in Asia abruptly made Asian stock market go downward severely. Accordingly, news will shake or boost investors' confidence on the instant.

Learning classifier system (LCS), developed by John Holland in 1975 [1], is derived from the concepts of machine learning with the characteristics of genetic algorithms. Since then, many types of classifier systems have been generated, such as extended classifier system (XCS), zero-level classifier system (ZCS), anticipatory classifier system (ACS), and so on. Briefly, LCS is a parallel, message-passing, rule-based system that interacts with and learns from the environment. LCS embodies three basic mechanisms, including production system, credit apportionment system, and rule discovery system, which enable the model to learn and adapt to the constantly changing and complex environment. The system attempts to simulate the past behaviors and experiences to balance the corporation with competition for interacting with the environment. Furthermore, it can be applied to the real world cases for achieving the desired goal.

As a result, the concept of institutional analysis is implemented into the LCS model to help investors make investment strategies and discover valuable and profitable rules.

1.3 Contributions

As mentioned above, learning classifier system has the property of being adapted to the dynamic environment for reaching the desired goal. The institutional factors in the market change violently; thus, how to choose a suitable tool for discovering the inner knowledge and being a successful forecasting model is quite challenging. The thesis tries to make a start to find the statistical pitfalls. From the experiment, it shows that there exist some elements that the traditional statistical tools cannot interpret. However, LCS is capable of achieving the target through learning in the environment even filled with such unknown factors. Since the stock price is impacted by numerous uncertain and unpredictable causes, how to learn the behavior of the complex environment seems to be significant.

The proposed model has the ability to adjust itself to dynamically learn in the non-stationary environment, like stock market. The system contributes to the discovery of the rules that ought to be analyzed and discussed. Precisely, this effort proves that the LCS model performs better than the buy-and-hold method (B&H), and bucket brigade algorithm outperforms the Q-learning of the reinforcement learning part in the stock environment. In addition, LCS model can gain the knowledge of the rules, while the statistical methods cannot.

1.4 Thesis Organization

The thesis is organized into six chapters. First of all, the motivations, research scope, contributions, and organization of the thesis are described in Chapter 1. In Chapter 2, there will be some literature reviews which are related to the research, such as the institutional analysis, statistical analytical methods, learning classifier system, and reinforcement learning. The background over the thesis is based upon these proposed concepts. In Chapter 3, the system architecture will be detailed elaborated. The main three components will be stated respectively. Accordingly, the whole simulation procedures are provided in Chapter 4. The simulation results and the analysis of the outcome will be presented in Chapter 5. Finally, the conclusion and future works are proposed in Chapter 6. The workflow of this thesis is illustrated in Figure 2.

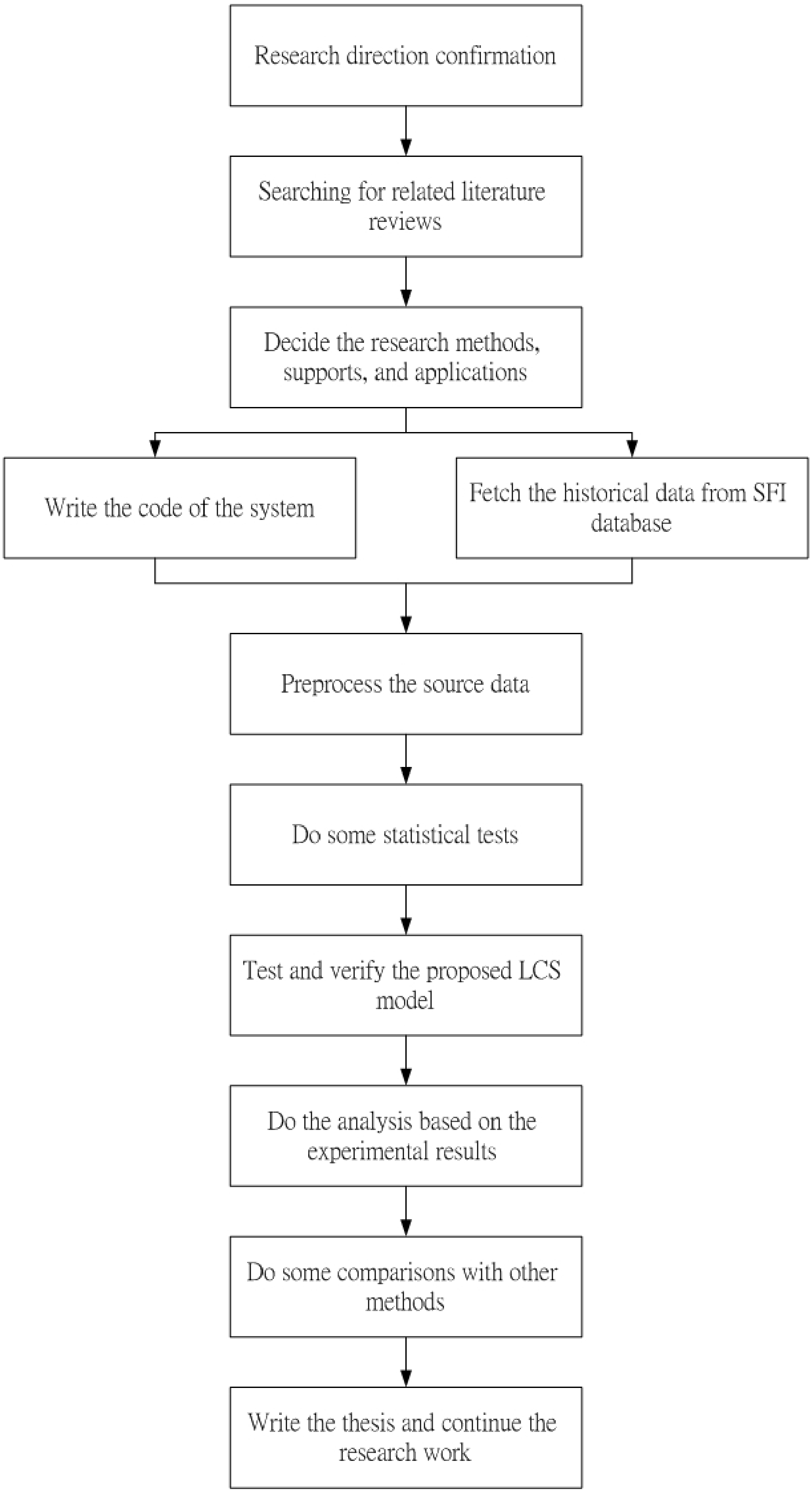

Figure 2 Workflow of the thesis

Chapter 2 Literature Review

The background of the proposed methods applied to the thesis will be discussed in this chapter. In section 2.1, the institutional analysis will be firstly introduced to have a basic description of the selected institutional indicators. In section 2.2, some limitations of simple regression model are indicated from the previous documents. In section 2.3, the overview of learning classifier system is elaborated to give an intuition of the underlying intelligent mechanism, including some important features, and the application domains. Different reinforcement learning methods applied in the credit apportionment system are respectively discussed in section 2.4.

2.1 Overview of Institutional Analysis

The thesis mainly focuses on the judgment of future price trend according to the institutional indicators. As a result, the selection of institutional indexes is one of the emphases of this thesis.

Institutional analysis is seldom discussed on stock market researches by using artificial intelligence techniques. Since Taiwan stock market has been in the era of institutional investors who are clearly the key participants with more and more impact in the stock market. They are often better informed of the sources, and thus they have better information advantages. The domestic and foreign juridical investors account for approximately 6 percent in 1994 to 23 percent in 2003 of the trading value on TSEC market. The stock price movements correspond to the activities of institutional investors closely. At present, the transactions are not only completed by calling for the operators, but also phone-based or internet-based stock trading. As a result, individual and institutional investors spread their investments more due to the convenience. The situation will exert a positive impact on stock price formation. Institutional investors represent the key drivers for the growth and stability of the stock market that enables the transactions to be more confidential, flexible, and efficient.

In addition, margin purchasing and short selling are credit trading mechanisms which provide those who don't have sufficient money but would like to buy stocks, or who lack stocks but would like to short the stocks with buy/sell resources. According to the information about balance of margin purchasing or short selling, investors' points of view on the current stock market can be analyzed to become reference indexes about the quotations on the stock market.

Furthermore, the trading volume is an essential indicator in the stock market. The price-volume relationship has received increasing attention either from academic field and real world. Lee and Swaminathan (2000) [2] show that the past trading volume can predict the magnitude of the price momentum. In other words, trading volume can provide the important and valuable information about the security market. Therefore, it is a vital indicator to be considered in the thesis.

In the following sections, the institutional indicators will be detailed described to give an perception of the institutional analysis.

2.1.1 Selection of Institutional Indicators

Institutional indicators offer the most up-to-date measures on companies' performances. From the survey of some papers and the real market operation, the five indicators: foreign investors, securities investment trusts, margin purchasing, short selling, and trading volume, are the most influencing and well-known institutional factors that affect the future price trend. The five indexes can be the guides for making investment strategies due to the direct responses from the stock market volatility.

2.1.1.1 Institutional Investors

The institutional investors in Taiwan involve qualified foreign institutional investors (QFII), securities investment trusts, and dealers. The Taiwan Stock Exchange began operations in 1962 with foreign investors admitted in 1982. The trading patterns of QFII are mostly attentive at present time because the government has just scrapped a US$3 billion cap on a single QFII in the nation's stock market on October 2, 2003. The purpose for removing the restrictions is to speed up economic liberalization. In this way, Taiwan stock market can be more accessible to international investment, which is able to go forward at the same pace as the foreign counterparts. Moreover, foreign investors were the major supporters of Taiwan stock market when SARS scared the local investors into dumping shares earlier in 2003. This proves that foreign investors play a decisive role in Taiwan stock market.

Overseas institutional investors are capable of judging the stock trend more accurately because they involve more global information mechanisms. Under the advantages of finance and information capability, referencing the stocks that foreign investors focus is also a feasible way for stock trading. In recent years, the foreign investors invest more and more money; they have become the significant powers that affect the stock trend. For good to the retail investors, the operation of foreign investors is the most transparent. The securities stock exchange will make known to the public about the buy and sell of foreign investors. Thus, the super stocks in short-term can be found out as long as keeping a close watch on the exchange of stocks that the foreign investors buy and sell.

The securities investment trusts are capable of getting the information in advance, and they own abundant capital. However, they have the limitation of holding stocks whose goal is to beat the market. Hence, in the bear market, they will consider the stocks that are resistant to falling.

Vittas (1998) [3] concludes that the institutional investors can provide a strong stimulus to the development of stock market. They can act as countervailing forces to stimulate financial innovation, modernize capital market, and enhance the transparency and information disclosure.

Chiyachantana et al. (2003) [4] provide the information of understanding about institutional trading behavior. This paper demonstrates that institutional purchasing and selling are major determinants of the price impact.

Aras and Müslümov (2003) [5] prove that there is statistically significant positive relationship between the institutional investors and the stock market. Due to the causality relationship, the development of institutional investors should be promoted.

The institutional investors have great influences on the stock market because of the immense amount of investment money. However, when they sell overall stocks, there will be great impact on the confidence of retail investors. Therefore, it would be better to move in the same direction with the stock operation of institutional investors. The foreign investors and securities investment trusts are the selected indicators in the experiment due to their influences in the stock market as referenced above.

2.1.1.2 Margin Purchasing and Short Selling

Margin purchasing refers to borrowing money to leverage from the brokers. Short selling means the selling of stocks that the seller does not own, and he will be able to repurchase at a lower price. Margin purchasing and short selling are both so risky that investors should have plentiful experiences to afford the potential risks. The investor who would like to buy stocks on margin usually has the anticipation of the rising price but lack of money. Therefore, he will borrow money from the broker and use the money to purchase the stocks. Buying on margin can double the gains in a bull market; on the other hand, it can also double the losses in a bear market. Selling a stock that one does not own seems to be controversial. Even in the U.S., short selling has not been allowed for a long period of time because the opponents debated that this caused panic selling in the orderly market. However, there are still some advantages of short selling. For example, it is capable of making money in a stock with downward trend. The difference of the selling price and the lower buying price could be earned, which only a percentage of exposure is required.

Lin and Tong (1997) [6] apply vector error correction model (VECM) to analyze the relationship among weighted stock index, balance of margin purchasing, and balance of short selling in Taiwan stock market. The results reveal that there exists a positive relationship among the weighted stock index, balance of margin loan, and balance of short selling regardless of the stock trend.

Huang (1997) [7] uses time-frequency autoregressive and moving-average (TFARMA) model to discuss the impact of the change rate of balance of short selling and balance of margin purchasing on stock returns. The experimental results demonstrate that the two simulated indexes have either positive or negative impact on the simulated electronic stocks.

Henry and McKenzie (2003) [8] demonstrate that the market will display grater volatility following a period of short selling. It means that the short selling could be the direct indicator that influences the stock market. Short selling has many drawbacks but can produce high profits if the stock price declines. However, it is not recommended to engage in the short selling unless one has strong confidence about the future trend of the selected stocks because of high risks.

As the previous researches and real stock world have indicated, the balance of margin purchasing and the balance of short selling are the two important institutional indicators that should be taken into consideration while operating in the stock market.

2.1.1.3 Trading Volume

There have been quite a few investigations and discussions about the relationship between stock price and trading volume.

Gallant et al. (1992) [9] finds that there is a positive correlation between the volume and conditional volatility, and large price movements are followed by high volume. The daily trading volume is positively related to the daily price change.

Campbell et al. (1993) [10] use the first-order daily return autocorrelation to discover the relationship between the stock price decline and trading volume. This paper finds that a stock price decline on a high-volume day is more likely to be associated with an increase in the expected stock return than on a low-volume day.

Blume et al. (1994) [11] show that either in active or bad market, the stock price can be affected by the trading volume information. In their model, volume is capable of capturing the important messages contained in the quality of traders' signals and providing the information that is not impounded in the stock price. Hence, using the information conveyed by the trading volume can be quite useful for investors to operate in the stable or volatile market.

The trading volume is capable of providing the information about the price movement, which is quite significant as a benchmark of the stock trend. Since there is a close relationship between the trading volume and the stock price, volume is taken into account in the thesis as an experimental attribute.

2.2 Limitations of Simple Regression Model

From the surveys, simple regression model is usually applied to the prediction of stock price trend [12] [13]. However, there exist several constraints about the simple regression model, which are listed as follows. Firstly, a number of statistical assumptions should be met. The observations are independent from each other, which is referred as statistical independence. The observations are exactly or approximately normally distributed. Secondly, the non-linear relationship between the independent variables and the dependent component cannot be accurately and fairly expressed. Thirdly, the factors that are hard to quantify or inadequately measured will lead to under estimation of the regression coefficients while included in the model.

Since the stock environment is dynamic and complex, applying simple regression model to such situation is not proper due to the above-mentioned constraints. As a result, an adaptive model is presented to overcome the limitations, which is introduced in section 2.3.

2.3 Overview of LCS Model

Learning classifier system (LCS), a branch of artificial intelligence, is applied to the stock market in this thesis due to the innate characteristics though it is mostly applied to the engineering or medical fields. Based on the property of adaptively learning in the dynamic environment, the chosen institutional indicators will be simulated in the system for achieving the goal profit. In the following sections, the history, structures, features, and application domains of LCS will be described.

2.3.1 History

Learning classifier system was originally developed by John Holland in 1975. The first publishing of paper “Cognitive Systems Based on Adaptive Algorithms” was appeared in 1978 by Holland and Reitmann. Learning classifier system exploits reinforcement learning and evolutionary computation with condition-action rules which represent the target task that the system has learnt.

The evolution of learning classifier system is like a legend. There were considerable researches in the 1980s, but the field began to downgrade at the end of the decade. In the early 1990s, there were fewer reports about learning classifier system; in the mid 1990s, the field almost went to a dead end. However, during the last seven years, new models and applications were reproposed which led to a revival of this sphere.

In learning classifier system, an agent learns to perform a target task by interacting with the environment, using rewards and punishments to modify the rule-based model. The agent senses the information of the external environment via detectors on the basis of the past experiences and current sensations. It will then select an action that is sent to the effectors for performing a certain task in the environment. Depending on the effects of the action, the agent will get the payoff from the environment. The payoff may either be a reward or a punishment, according to how much the goal the agent has achieved. Holland brought into two ideas in his pioneer work, which innovated the history of machine learning. The first idea is Darwinian Evolution of the "survival of the fittest". The concept is used to trigger the rules with high strength for adapting to the unknown environment. The spirit of Darwinian principle is to imitate the evolution of living things in the environment naturally. Unlike the traditional approaches, genetic algorithms are not mathematical oriented. Genetic algorithms are regarded as mechanisms for optimization, rather than approximation. The idea has then been emerged as a powerful tool in many research domains, such as artificial life, adaptive behavior, and evolutionary computation. The second idea is that the agent attempts to learn a certain task by optimizing the payoff it receives from the external environment. The whole process of learning has been formulized in the area of reinforcement learning, which is now considered as a modern technique in machine learning. There are some primary structures that learning classifier system embodies, which are stated in the section 2.3.2.

2.3.2 Fundamental Structures

2.3.2.1 Environment Interaction

In the production component of learning classifier system, the interaction with the external environment is the main mechanism. The mechanism provides for the parallelism and coordination of a large number of rules that are active synchronously. As a great basketball player, Michael Jordon once said, “Talent wins games, but teamwork and intelligence win championships.” The rule-based system is similar as the saying which needs to deal with a wide range of circumstances. The combinative work for the system acts on a large quantity of rules; therefore, the development requires the coordination and cooperation to achieve the target task as playing a basketball or football game.

First of all, the detectors in the production system will encode the current state of the environment into messages. The effectors will translate the selected messages into actions on that environment. The messages in the message list will then be matched with those in the rule base, and more messages simply mean more active rules. The whole system can be viewed as a message processing system acting on the current list of messages.

2.3.2.2 Credit Apportionment

Thereafter, deciding which rules in the rule-based system are responsible for its success is an interesting but difficult problem. In learning classifier system, the rules are called classifiers. The work for credit apportionment system is to distribute the rewards that are received from the environment to the classifiers. A measure, called the strength, is associated with the credit assignment. The strength assesses the utility and adaptability of the classifier about the problem. Since the credit assignment is handled by the market mechanism, the overall process can be regarded as an auction situation that is set up for the bidders. At each discrete time step, rules in the message list with the satisfied condition bid for its right to become active. As an active rule, it then stands to profit from bids of subsequent bidders. Rules with the highest bid value at the time are capable of getting the payoff from the external environment. The system will evaluate the utility of the selected action, sending it to the environment to be performed. Depending on the current state and consequences, the system will receive a reward or punishment eventually.

The credit is accumulated by the classifier as the strength. In the thesis, bucket brigade algorithm is mainly implemented for assigning the credit in the system. Generally, stronger rules are more likely to win the bidding process. In other words, they are more probable to affect the system's behaviors.

2.3.2.3 Rule Discovery Mechanism

The rule discovery component exploits genetic algorithms, which is regarded as the most general and promising way for evolutionary computation in a target market. The genetic algorithms work on the sets of classifiers in the rule base. Basically, the discovery part randomly selects two classifiers in the rule base with probability proportional to their fitness values, which is called roulette wheel selection. Continuing on, it applies crossover operation on the selected two classifiers for generating an offspring. The concept follows the Darwinian theory of evolution for replacing worse rules with better ones into the population to keep the population size constant. Thereupon, the mutation is performed on each point of the offspring chromosome with low probability. In the thesis, the genetic algorithms will be evoked every 30 cycles for keeping the ecology of the system stable and continuing evolving.

2.3.3 Characteristics of Learning Classifier System

There are three advanced and important characteristics of learning classifier system that are stated in the following [14].

(1) Adaptivity: Learning classifier system has been regarded as an adaptive system which enables the classifiers to act on-line. Through learning, it is capable of changing its situation by receiving the information from the external environment. Furthermore, it also applies the concept of genetic algorithms to realize the goal of understanding, knowing, and adapting to the environment.

(2) Generalization: Generalization is a special feature in learning classifier system which

enables the system to represent a certain learning task in a compact form. In the thesis, generalization is a matter of classifier representation through the evolvement of general rules that match many environmental situations. The term, generalization, comes from the concept of default hierarchies [15]. Default Hierarchies refer to a multilevel structure whose top-level classifiers represent the general conception while the bottom-level ones express in a more specific way. Default hierarchies initially control the classifiers in the rule base. With the evolution of the system, more specific rules will replace the general ones because they are able to perform better. Default hierarchies are quite favorable to represent the knowledge in a rule-based system. For instance, Wilson (1998) [16] demonstrates the generalization capabilities of extended classifier system (XCS) which can evolve minimal sets of rules with maximal general classifiers. The result of the learning task can still be successfully and accurately performed.

(3) Scalability: The scalability refers to the rapidity of the learning time or how extensive the size of the system can grow as the problem complexity increases. So far, it is difficult to evaluate the computation complexity though scalability is an important requirement. Wilson has mentioned the complexity issue in his research application which shows that XCS's learning complexity on the multiplexer is polynomial in the input length, not in the learning space.

2.3.4 Areas of Learning Classifier System

The application domains that learning classifier system has been applied to are listed in the following.

(1) Autonomous Robotics:

Colombetti and Dorigo (1993) [17] develop a model about designing and building the learning autonomous robots. An autonomous robot is a remarkable device to perform a certain task through sensing, interacting, and responding in an unknown and complex environment. In artificial intelligence, robots have been regarded as the most useful devices which understand and analyze the behavior patterns through learning and training. By modeling the autonomous robots in learning classifier system, the behavior of animals and human beings can be more easily comprehensive. Even with limited amount of resources, the complex and unpredictable behavior patterns can be exploited by the learning classifier system in a natural way. Interestingly, autonomous robotics continues to be the most challenging study for learning classifier system.

Besides the simulation on robots, the behavior of mice is also modeled by the learning classifier system. Geyer-Schulz [18] simulates a mouse moving in a maze, which serves as a model of Markov processes. Compared to the previous versions of this kind of experiment, Geyer-Schulz adds the cover detector and cover effector operators. The Holland classifier system constitutes a fifteen percent performance increase. Therefore, it shows that the model is capable of adapting well to the environment with frequent and incomplete feedback.

(2) Knowledge Discovery:

A stimulus-response learning classifier system, EpiCS, is developed to address the needs of knowledge discovery in clinical database [19]. The accurate estimation of the disease risk and the ability to deal with the rare clinical outcomes are required to be dealt with. Compared with logistic regression analysis, EpiCS has shown to have the excellent classification accuracy and the capability of extracting different interesting medical knowledge.

Genetic based classifier system (GeB-CS) [20] is applied to solve the automatic diagnosis of mammary biopsy images problem. GeB-CS is used to convert each of the images into a set of describing features. Through the extracted features, the classifier system is able to answer whether the biopsy is cancerous or not. In this way, the classification accuracy is greatly improved, and the results can be the guide for human experts.

(3) Routing Problem:

Chen [21] improves the traditional limitation to establish a self-adaptive routing environment. The classifier system plays the role of traditional router and routing protocol. The system can prevent the noise from the real environment and make some simplification of the technical efforts. Using classifier system for solving the routing protocol problem enables the users to understand the meaning of each rule. Furthermore, the system will converge with good performance after hundreds of generations under different network and setting of parameters.

There are still other applications by utilizing learning classifier system to achieve their goal. Liao and Chen exploit a dynamic trading strategy learning model (DTSLM) [22] to simulate on the security market. The experiment results show that the average profits are better than the traditional buy-and-hold trading strategy by using technical indicators. Richards and Sheppard (1996) [23] apply LCS to 3-D shape optimization; Smith et al. (2000) [24] use genetic based learning system to simulate on novel fighter combat maneuvers; Frey and Slate (1991) [25] utilize Holland-style adaptive classifiers to letter recognition. Since the learning classifier system has been applied to a wide range of domains, there must be more new knowledge for being discovered.

2.4 Reinforcement Learning

The credit assignment component of LCS is one kind of reinforcement learning (RL) [26] [27], which is closely related to the whole system. In the thesis, bucket brigade algorithm is the main focus of the reinforcement learning, where Q-learning is the later-proposed approach for comparison about apportioning the credit to the classifiers.

2.4.1 Introduction

Reinforcement learning literally means learning to map the state to the action for achieving the target task. In reinforcement learning, target solution is not provided; rather, the system senses the information, takes the action, receives the feedback, and adjusts its situation for higher rewards. This kind of machine intelligence will learn to optimize the goal by trial-and-error interactions with the dynamic environment. In the thesis, RL is applied in the credit apportionment system which enables the reward to be distributed to the active and significant classifiers. The bucket brigade algorithm and Q-learning are the two primary forms of model-free reinforcement learning. As a result, both mechanisms will be applied to the stock data for comparing the results of the simulation goal.

2.4.2 Bucket Brigade Algorithm

Bucket brigade algorithm [28] is one of reinforcement learning developed by John Holland. As mentioned above, it is designed to solve the credit apportionment problem. In each time step, a strength value is apportioned to each classifier. The strength represents the correctness and significance of a classifier. Stronger rules with higher strength are more likely to win the bidding process to post its messages on the message list and place the action on the output list. In bucket brigade algorithm, the classifiers are similar to those who join in the auction market where each of them has the opportunity for bidding, and only the winner can post its action according to the strength. At each time step t, the bidding value $B_{t,i}$ of classifier X_i is defined as equation (1).

$$B_{t,i} = \gamma \cdot S_{t,i} \cdot u_i \qquad (1)$$

In equation (1), $\gamma \in [0,1]$ is a learning rate, $S_{t,i}$ is the strength of classifier X_i at time t, and u_i is the specificity. The specificity refers to the number of non-wildcard symbols in the condition part of classifiers. If the learning rate is set small, the system will adapt slowly (and vice versa). Therefore, choosing a suitable learning rate depends on the environment and the processing tasks.

After calculating the bidding value of classifiers, the rules need to compete for their right to post their actions on the message list. For each classifier, the probability for winning at the time is proportional to its bid value as shown in equation (2):

$$P(X_i wins) = \frac{\mathrm{B}_{\mathrm{t,i}}}{\sum_{\mathrm{j \in Sat_t}} \mathrm{B}_{\mathrm{t,j}}} \qquad (2)$$

In equation (2), Sat_t represents the rules with satisfied condition at time t. Classifiers which get the highest bid value are able to have the authority to post their actions, and they are called winning classifiers. More than one winning classifier is allowed. If only one classifier has the highest bid value, it is obviously that the rule can directly post its output message. However, if more than one winning classifier, there will be competition of getting the payoff from the environment. After obtaining the payoff from the environment, the conflicting classifiers with the same bid value will determine the final winner. For this purpose, the strength for a new classifier is shown as equation (3).

$$S_{t+1,i} = S_{t,i} + \frac{P_t}{w_t} - B_{t,i} \qquad (3)$$

In equation (3), the strength for a classifier at time $t+1$ is increased by the payoff P_t received from the environment, and reduced by its bid value at time t; w_t represents the number of winning classifiers in the same time step.

Furthermore, the strengths of other classifiers will be reduced by a predetermined factor, called tax. The tax mechanism is used to punish the classifiers which have no contributions to the system. With the perception, redundant classifiers will be weeded out if they have never been active. The process of paying the tax is as shown in equation (4), where T is a small number from 0 to 1.

$$S_{t+1,i} = S_{t,i}(1-T) \qquad (4)$$

2.4.3 Q-learning

Q-learning is also a kind of reinforcement learning which can work in the unknown environment. Q-learning was firstly proposed by Watkins (1992) [29], which can be regarded as an extension of traditional dynamic programming. It is capable of being used online, and a model is not required. At each instant, the agent senses the current state x from the external environment and chooses an action a of the state x accordingly. By interacting with the environment, the immediate payoff r for the state-action pair will be obtained. $Q(x,a)$ represents the value of action a in state x. Then, the agent will observe the subsequent state x' from the external environment, and choose an action a'. The Q-function will be optimized during the learning process, which is shown in equation (5), where α is a learning rate and γ is a discounted factor. The update of Q algorithm is used to optimize the policy, as the algorithm shown in Figure 3.

$$Q_{t+1}(x,a) = Q_t(x,a) + \alpha[r_{t+1} + \gamma \max Q(x',a') - Q_t(x,a)] \quad (5)$$

Initialization

Set Q_0 arbitrarily $\forall(x,a)$

Repeat

Perceive x

Repeat

Choose an action a from x

Take the action a, receive an immediate reward r, and observe the next state x'

$Q_{t+1}(x,a) = Q_t(x,a) + \alpha[r_{t+1} + \gamma \max Q(x',a') - Q_t(x,a)]$

$x \leftarrow x'$

Until x is terminated

Figure 3 The algorithm of Q-learning

Chapter 3 System Architecture

3.1 The Architecture of LCS Model

Learning classifier system, proposed by John Holland in 1975, incorporates the ideas from artificial intelligence, machine learning, evolution, and computer design into a framework. Four structural parts are contained in the system to deal with the interaction of the internal system and external environment, which are listed in the following.

- Input interface: It consists of detectors for encoding the incoming information from the environment into messages.
- Output interface: It contains effectors for enabling the system to interact with the external environment.
- A rule base: It comprises several rules, called classifiers. Each classifier X_i is in the form of $Cond_{i1}, \ldots, Cond_{in}/Act_i$, where $Cond_{ij}$ and Act_i are in bit strings with fixed length L over {0, 1, #}. A value, called strength, is associated with each classifier.
- A message list: It involves the messages that are binary strings with fixed length L over {0, 1} to be sent by the effectors.

The architecture of LCS embodies three basic parts: production system, apportionment of credit system, and rule discovery system (See Figure 4).

- A production system contains a rule base that processes the incoming messages from the external environment through an input interface. The messages will then be translated into actions by the effectors for interacting with the environment through an output interface.
- In apportionment of credit system, bucket brigade algorithm is used to decide which rules are responsible for its success through receiving the payoffs from the external

environment. The component assigns the strength to the rules in the rule base for representing the usefulness and importance of the classifiers.

- In rule discovery mechanism, genetic algorithms are applied to discover better rules and replace the worse ones.

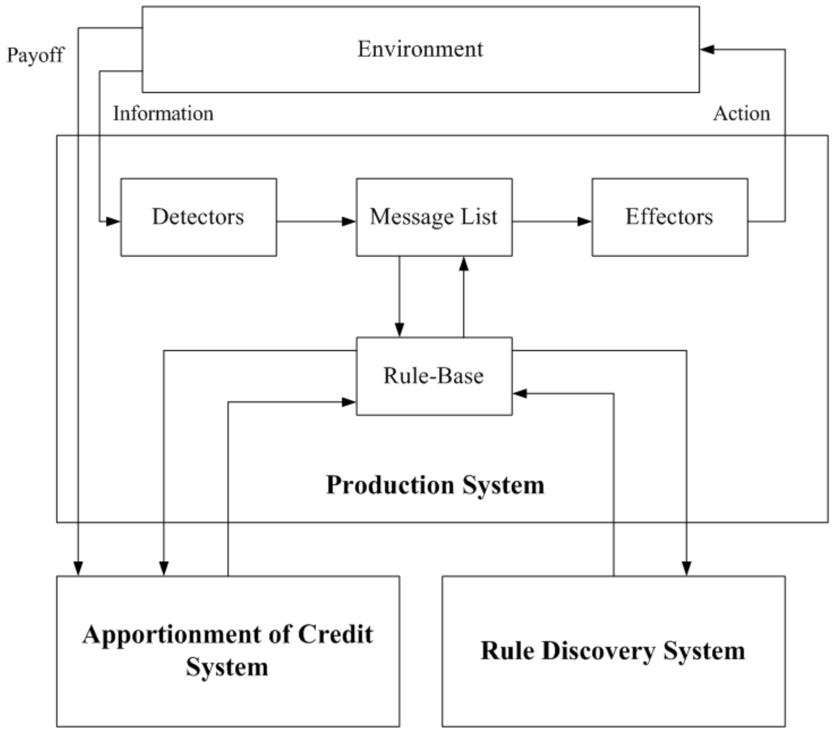

Figure 4 System Architecture of the experiment

The system process follows the algorithms of LCS, which is listed in Table 1.

Originally, the system randomly initializes some trading classifiers in the rule base. Each classifier is in the form of condition/action, which represents the implicit knowledge and patterns of the environment. In other words, one receives some states of the environment, and it will go into action for its trading strategy.

Secondly, the system begins to fetch the real-time information of the environment constantly. Then, the detector encodes the information into messages of binary format by the proposed data mining method. The classifiers in the rule base will then be matched with the incoming message in the message list. The matching classifiers will be fired to have the chance of bidding. The winner, which has the highest bid value, is capable of getting the payoff from the environment. The feedback may be either rewards or punishments according to the accuracy of the action.

Overall, the system instantly triggers the algorithms of LCS to learn trading rules based on the environmental states. Genetic algorithms (GA) are also implemented in the evolutionary computation. The purpose of GA is to generate good offspring, and eliminate the low-fitted classifiers. Thus, the operators, including selection, crossover, and mutation, are applied to the system for trading cycles. The final results will be stored in the rule base to be the indications for traders.

Table 1 Learning Classifier System Algorithm

```
t:=0;
initMessageList M(t);
initClassifierPop P(t);
while not terminate do (time, fitness,...)
        t:=t+1;
        M:=dectectInfo(t);
        MA:=MatchClassifier(M, P(t));
        MA:=WinClassifier(MA, P(t));
        MA:=TaxPosting(MA,P(t));
        M:=Effector(MA(t));
        PA:=ReceivePayoff(t);
        C:=AssignCredit(PA, P(t));
        if mod(t, k) =0 then
                P:=GenerateNewRules P'(t);
        else
                P:=P'
end loop
```

However, the work of applying the stock market data to the learning classifier system still needs a lot of efforts and considerations for obtaining the goal. For example:

(1) How to encode the input information from the external environment?

(2) What is the threshold of choosing the action for a certain state?

(3) What parameters should be set for achieving the optimal goal?

(4) How to interpret the circumstances of the system?

The first problem belongs to the phase at the beginning of the production system. The format of the input information depends on the application domain. The thesis uses the concept of data discretization to assign the input data to an appropriate cluster. As a result, the encoding method is tough and significant that will influence the follow-up work. The second problem also belongs to the phase in the production system, which is so significant that will influence both internal and external environments. The third problem involves the parameters used in the credit apportionment system and rule discovery mechanism. The parameters should be adjusted through trial and error for gaining the best benefit, and they will be introduced in section 3.2. The fourth problem refers to the interpretation for the results of the final existing rules. By examining the outcome, the rules corresponding to certain situations should be evaluated and explained in a proper way.

3.2 LCS Parameters

LCS is parameterized as shown in Table 2. Initial population size is the number of classifiers in the rule base which are generated randomly at the beginning. The population size is the number of classifiers which hold in a steady state in the system's rule base. The initial strength of all classifiers is set 100. If the actions of the classifiers comply with the correct sets, the strengths will be multiplied by the reward ratio. However, those whose actions fall into the wrong sets are multiplied by different penalty coefficients accordingly, based on the prediction of the trend direction. The remaining parameters will be later discussed in Chapter 4.

Table 2 Parameters applied to LCS

Parameter	Value
Initial population size	15
Population Size	30
Initial strength	100
Reward Ratio	1.7
Penalty Coefficient	0.9, 0.8, 0.6
Bidding rate	0.01
Life Tax Rate	0.01
Bid Tax Rate	0.005
Genetic algorithm iteration	30
Crossover Rate	0.7
Mutation Rate	0.01

3.3 The Classifier Syntax

In most classifier systems, the detectors and effectors are represented by bit strings with fixed length. Generally, the classifier conditions are strings with ternary alphabets {0, 1, #}, while the actions are encoded as strings with binary alphabets {0, 1}. The regulation of a classifier in this experiment is defined as the following IF-THEN rule.

IF <condition1> & <condition2> & <condition3> & <condition4> & <condition5>

THEN <action>

Before implementing the system, the preprocessing work of the selected indicators has to be done. Data discretization technique [30], viewed as the preceding process of the simulation, is used to cluster the input information. The follow-up experiment is unable to be implemented without suitable clustering techniques.

Data discretization technique is used to reduce the number of values for a given continuous attribute, by dividing the range of the attribute into intervals. Interval labels will then be used to replace the actual data values. The statistical measures “mean” and “standard deviation” are required in this data mining method. The input information will be encoded into bit strings that the system is able to understand and interpret. That is the reason why the preprocessing work has to be performed in advance. In the thesis, the input information will be distributed to a cluster that the assignment work has been predefined. As a result, data discretization is used as a clustering technique for preprocessing the attributes of the model. As far as the actual operation procedure about the data discretization is concerned, it will be introduced in the following.

The regulation of encoding the input has to be predefined and expressible. The proper syntax for classifiers depends on the application, which will influence the ongoing system performance. Hence, bit strings, real numbers, intervals, or fuzzy representations are the forms that express the system’s behavior in different ways. The preprocessing work of this simulation is to encode each incoming message into 2-bit string with fixed length. The encoding method is presented in the following, and the detailed steps will be stated in chapter 4.

In Figure 5, assume the 15 days data is the condition part; the steps for clustering the condition part is stated as follows. The condition part is set 15 days from January 15 to February 4. The previous 40-day data is used to discretize the condition part, assigning it to a cluster.

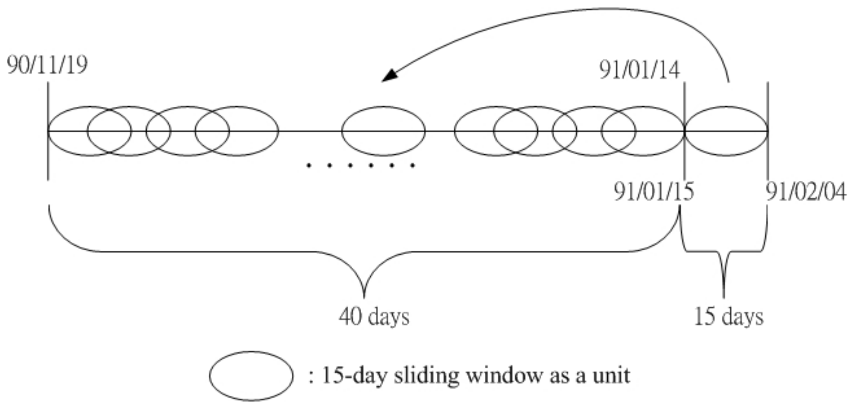

Figure 5 Data Discretization Sample

(1) The 15-day data is regarded as a unit.

(2) By moving a one-day sliding window of the preceding 40-day data, there will be 26 units.

(3) Then, the mean and standard deviation of the 26 units will be calculated.

After the computation of step (3), four blocks, [00, 01, 10, 11], are formed as shown in Figure 6. Therefore, the above-mentioned condition part will be distributed to one of them.

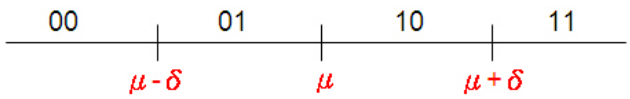

Figure 6 Classifiers bits

In the thesis, there are five attributes of the condition part, and one of the action part. Two bits, which represent part of the input information at the time, will be assigned to each of the attribute synchronously. Hence, there are ten bits for the condition part and two for the action part to form a classifier rule (See Figure 7). The detailed procedures of discretizing the selected institutional attributes will be elaborated in section 4.4. The attribute will be dynamically assigned to one of the four possibilities according to the sliding window mechanism. The approach is quite objective and efficient.

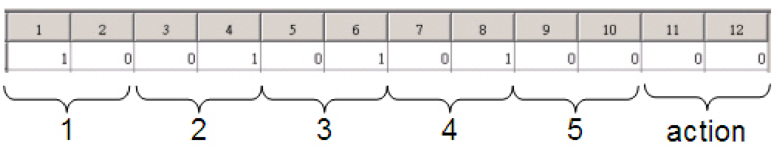

Figure 7 An example of a classifier rule

3.4 The Credit Assignment

The second component of LCS model is the credit apportionment system which enables the satisfied classifiers in the rule base to be performed for the bidding process. However, only the rules with the highest bid value can post itself to the message list. The effectors will then translate the message into action for getting the payoff from the external environment. If the action coordinates with the environment, the rule will obtain a reward; otherwise, it will get a punishment. The credit assignment procedures involve two requisite taxes, life tax and bid tax.

3.4.1 Life Tax

The life tax is an important mechanism in the learning process. Each classifier in the rule base will be taxed during the life cycle. As long as the rule exists in the rule base, it has to fulfill its obligation. The mechanism can keep the system alive and prevent the rules from making no contributions to the system. As a result, at each instant, classifiers in the rule base have to be levied on one percent of the strength.

3.4.2 Bid Tax

Once the classifier is fired, it will be levied by the bid tax. In real world, everyone has the duty to be levied for the national expenses. Likewise, the rules are in a competition world; thus, each of them should contribute to a portion of its strength for keeping the society alive. In addition, the winning agent who posts the useless message will be taxed more for penalizing the unsuccessful classifiers. In general, whatever the apportionment scheme is, the purpose of the bidding process is to give the auctioneer an idea of bidders' valuation during the auction.

3.5 The Discovery Components

The rules that receive little credit should be replaced and eliminated through competition. For instance, if a person who does not work hard for the company, he will soon be knocked out from the team because of low contribution toward the enterprise. In the thesis, genetic algorithms are exploited to discover the rules with more influences in the environment. The stochastic, parallel search algorithms are based on the mechanics of natural selection and the evolution process. They are designed to search in large and non-linear space efficiently. According to the "survival of the fittest" guideline, crossover and mutation are performed in the rule discovery component. The basic operators for genetic algorithms involve selection, crossover, and mutation, and the workflow is shown in Figure 8.

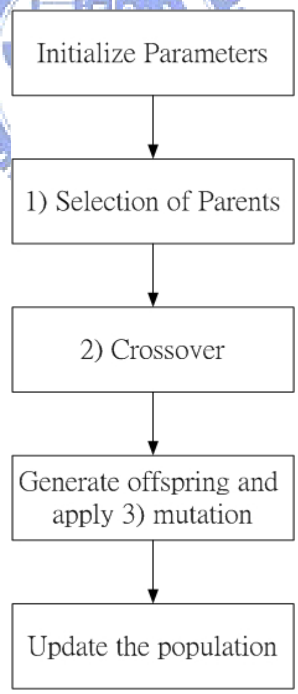

Figure 8 Rule Discovery Workflow

Chapter 4 Experiment

4.1 Simulation Architecture

In this chapter, the experimental work of the thesis will be detailed described. The simulation architecture is illustrated in Figure 9.

(1) The source data, including daily buy/sell of qualified foreign investors, buy/sell of securities investment trusts, balance of margin purchasing, balance of short selling, trading volume, and stock price, is fetched from the database of Securities and Futures Institute (SFI).

(2) The source data will then be adjusted to the form on the demand. For example, the data of the buy/sell of foreign investors for every 15 days will be summed up as a unit; the change of balance of margin purchasing from the 1^{st} day to the 15^{th} day, regarded as a unit, will be calculated. Likewise, data of other indicators will be computed based on the application requirements. Thus, the source data is adjusted.

(3) The next step is to do the correlation test between each attribute of the condition part and the price trend. The purpose of this test is to verify whether there exists a significant relationship between any one of the states and the later-formed action.

(4) Thereupon, the regression analysis will be modeled for obtaining the information about the price prediction. From the regression function, how much the future price trend will be responded on the basis of the selected indicators will be shown.

(5) The main simulation of this thesis is performed from this step. Firstly, the data preprocessing work is done through data discretization technique. The detectors encode the input information from the external environment into bit strings, enabling the system to realize the translated messages. Then, the matching procedure will be implemented.

The rules with satisfied condition are capable of being fired at that time.

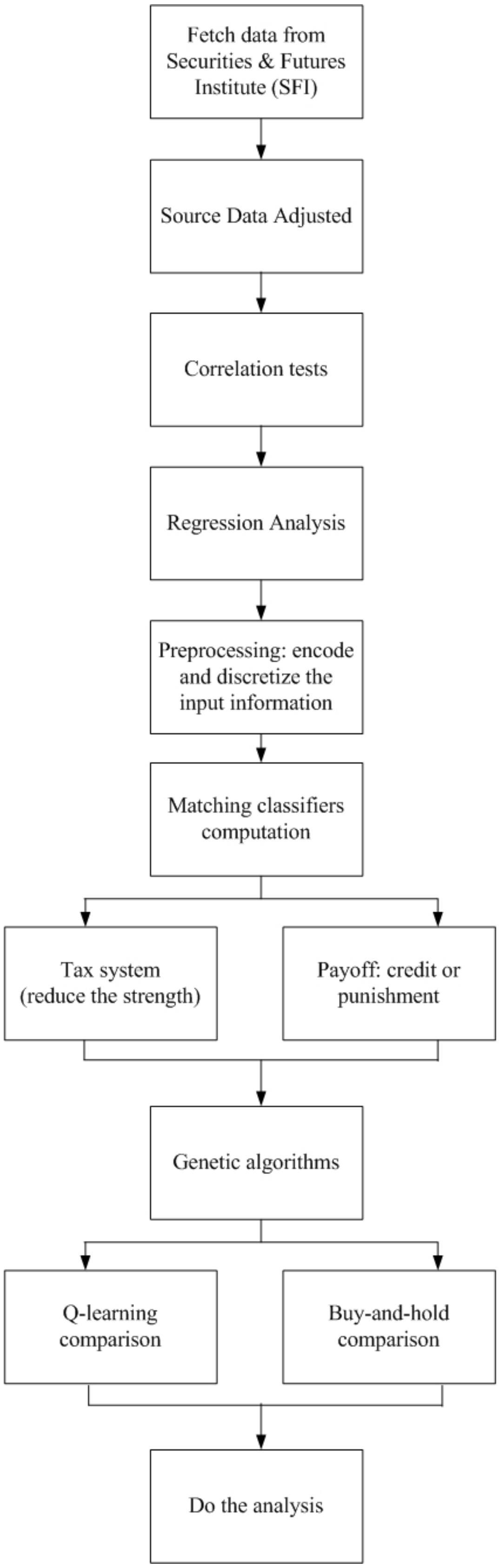

Figure 9 Simulation procedures

(6) The classifiers with matching condition will then be processed in the credit apportionment system. In credit assignment, the whole process is like an auction mechanism. The rules will compete and pay the required taxes. The rule with the highest strength is capable of getting the feedback from the external environment.

(7) Besides, the genetic algorithms will be evoked every n cycles in the rule discovery component, where n is predefined.

(8) After simulating the main processes of learning classifier system, some comparisons will be performed on the accumulated profit. Q-learning in the credit assignment system and buy-and-hold strategy are included.

(9) The last step is to do the analysis and discussion from the experimental outcomes.

4.2 Simulated Data

The experiment is performed on Taiwan stock data, which is derived from Securities & Futures Institute (SFI). The trading period of the experiment is from February 2, 1999 to February 27, 2004 (5 years). Since the simulation corresponds to the institutional investment, the value-weighted stocks are considered in the experiment. That is because the upward or downward trends are dominated more by the value-weighted stocks that can be easily controlled by the institutional investors. As a result, the simulated data focuses on the value-weighted stocks.

The condition part of the classifiers is within 15 days, while the action part is the trend of the next 5 days. The work is to apply the stock data to LCS model for finding the profitable rules, offering the investors to make strategies. From modeling the system's behaviors, the future price trend can be forecasted. The source data of the experiment is listed as follows.

(1) Sum of volume shares of buy/sell from qualified foreign institutional investors within fifteen days (thousand shares).

(2) Sum of volume shares of buy/sell from securities investment trusts within fifteen days (thousand shares).

(3) Change of balance of margin purchasing (thousand shares) during fifteen days.

(4) Change of balance of short selling (thousand shares) during fifteen days.

(5) Sum of trading volume (thousand shares) during fifteen days.

(6) Followed by the previous fifteen days, the change rate of the closing price for the subsequent five days.

There are 1,292 records for each of the simulated indicators. Take the stock “TSMC” for example; the original source data and the adjusted data for simulation are listed in Table 3 and Table 4 respectively. The meaning of the attributes of Table 3 and 4 is explained as follows. QFII: Sum of buy/sell of foreign investors. TRUST: Sum of buy/sell of securities investment trusts. MARGIN: Change of balance of margin loan. SELLING: Change of balance of short selling. VOLUME: Sum of trading volume. PRICE: Change rate of closing price for the subsequent five days.

Table 3 Original source data (TSMC)

Date	QFII	TRUST	MARGIN	SELLING	VOLUME	PRICE
880201	0	0	187,615	16,856	21,367	81
880202	0	0	183,770	14,762	21,157	79.5
…	…	…	…	…	…	…
890801	1,613	0	146,090	2,870	16,025	126
890802	1,353	0	145,381	2,927	11,475	125
…	…	…	…	…	…	…
891212	19,028	1,189	98,301	6,002	41,186	92.5
891213	2,961	-171	97,561	5,482	11,195	92
…	…	…	…	…	…	…
900626	-302	-1,550	38,963	17,678	54,003	61
900627	-11,843	1,270	42,068	17,383	32,408	63.5
…	…	…	…	…	…	…
930225	-13,160	159	106,441	1,761	40,881	61.5

930226	6,009	-572	107,359	2,150	43,636	63.5
930227	10,626	469	103,648	1,975	36,863	63.5

Table 4 Adjusted data (TSMC)

Date	QFII	TRUST	MARGIN	SELLING	VOLUME	PRICE
880226	0	0	-18,364	-3,087	194,684	-0.02286
880301	0	0	-11,038	-1,778	190,812	0.017647
…	…	…	…	…	…	…
890818	49,005	0	-9,026	2,188	67,196	0.01444
890819	51,926	0	-9,369	1,631	68,884	0
…	…	…	…	…	…	…
891230	59,415	-3,227	-7,906	4,139	80,823	0.071856
900102	42,672	-4,165	-5,214	6,219	86,522	0.15528
…	…	…	…	…	…	…
900716	4,060	4,748	-525	4,798	258,392	-0.072
900717	2,689	6,942	-3,374	3,894	261,991	-0.07258
…	…	…	…	…	…	…
930218	-159,526	-15,219	25,049	-2,139	46,925	-0.0315
930219	-145,820	-15,962	23,862	-1,772	44,668	0
930220	-139,408	-15,446	26,677	-1,729	42,580	0.016

4.3 Correlation Test and Regression Prediction

The correlation test among the experimental variables of “TSMC” is listed in Table 5. The variables QFII, TRUST, MARGIN, SELLING, and VOLUME are the information calculated from the previous 15 days, while the PRICE is the price trend of the succeeding 5 days. It is shown that the future price trend (PRICE) is low correlated with the buy/sell of foreign investors (QFII), buy/sell of securities investment trusts (TRUST), balance of short selling (SELLING), and trading volume (VOLUME) at the 0.01 level. However, there is no significant correlation between the price trend and balance of margin purchasing (MARGIN), as shown in Table 5. The correlation tests on other stocks are appendixed to this thesis (Table

11-18).

Table 5 Correlation Test of TSMC

Correlations

		QFII	TRUST	MARGIN	SELLING	VOLUME	PRICE
QFII	Pearson Correlation	1.000	.293*	-.694*	.191*	.051	.145*
	Sig. (2-tailed)	.	.000	.000	.000	.152	.000
	N	790	790	790	790	790	790
TRUST	Pearson Correlation	.293*	1.000	-.352*	.457*	.167*	-.138*
	Sig. (2-tailed)	.000	.	.000	.000	.000	.000
	N	790	790	790	790	790	790
MARGIN	Pearson Correlation	-.694*	-.352*	1.000	-.334*	.026	-.041
	Sig. (2-tailed)	.000	.000	.	.000	.473	.244
	N	790	790	790	790	790	790
SELLING	Pearson Correlation	.191*	.457*	-.334*	1.000	.078*	-.103*
	Sig. (2-tailed)	.000	.000	.000	.	.029	.004
	N	790	790	790	790	790	790
VOLUME	Pearson Correlation	.051	.167*	.026	.078*	1.000	-.442*
	Sig. (2-tailed)	.152	.000	.473	.029	.	.000
	N	790	790	790	790	790	790
PRICE	Pearson Correlation	.145**	-.138**	-.041	-.103**	-.442**	1.000
	Sig. (2-tailed)	.000	.000	.244	.004	.000	.
	N	790	790	790	790	790	790

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

In the regression test, the price is the dependent variable, and the other five indicators are the explanatory variables. In the multivariate case, the equation is capable of being constructed of many the variables. By using the simple multiple regression model, as shown in equation (7), the estimates of the parameters are listed in Table 6.

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i}, i = 1,2,\ldots,790 \qquad (7)$$

Table 6 Estimates of parameters (TSMC)

Variables	Estimates of Parameters
Constant (β_0)	89.693
QFII (X_1)	3.528E-05 (β_1)
TRUST (X_2)	-1.37E-04 (β_2)
MARGIN (X_3)	1.160E-04 (β_3)
SELLING (X_4)	-8.88E-05 (β_4)
VOLUME (X_5)	-3.62E-05 (β_5)

4.4 Preprocessing and Encoding of the Data

The preprocessing work, data discretization, is done before implementing the stock data into the model.

(1) The five indicators, buy/sell of qualified foreign institutional investors (QFII), buy/sell of securities investment trusts, balance of margin purchasing, balance of short selling, and trading volume are chosen as the condition part of classifiers. Each condition is distributed to one of the four clusters on the basis of the discretization technique.

(2) The action part is discretized into one of the four clusters corresponding to the level of the upward or downward trend for the subsequent trading days. The format of classifiers is shown in Table 7.

The model is implemented by the rules analogous to:

IF (CONDITION) THEN (ACTION)

Table 7 Format of classifiers

Condition (15 days)	Action (5 days)
Sum of Buy/sell of QFII	Change Rate of closing price
Sum of Buy/sell of Securities Investment Trust	
Change of balance of margin purchasing	
Change of balance of short selling	
Sum of Trading Volume	

The rule implements a mapping from the input information of the stock data to the price trend. The input information is assigned dynamically due to the changing environment. The condition parts are bit strings with fixed length 10 over {0, 1, #}, where '#' is a don't care symbol which matches either 0 or 1. The action part is bit strings with length 2 over {0, 1}.

The first step of the modeling is to discretize the attributes, which has been described in section 2.4, and the detailed procedures are illustrated as follows. In Figure 10, the approach is applied to the stock "TSMC", where the condition part is from January 15, 2002 to

February 4, 2002. The data of the preceding 40 days [90/11/19, 91/01/14] is used to cluster the condition part. The mean and standard deviation of the five indicators are calculated respectively as listed in Table 8.

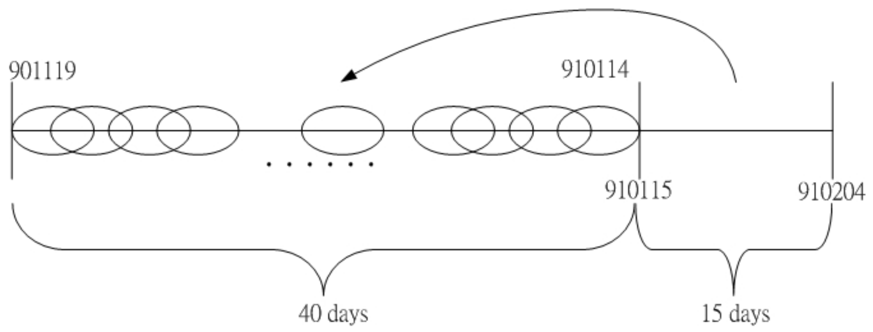

Figure 10 Data discretization for the condition part

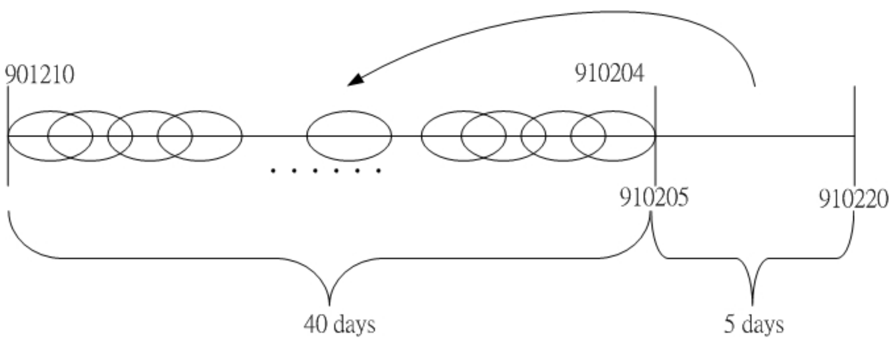

Figure 11 Data discretization for the action part

From the computation shown in Figure 12 and Table 8, it is clear that the condition part between [91/01/15, 91/02/04] will be ‘0000111000’ by calculating the information from the data of the previous 40 days.

Followed by the simulated time period of condition part, the price change rate from 91/02/05 to 91/02/20 (Figure 11) is -0.04094, which implies that the action part is ‘01’ as shown in Figure 13.

Table 8 Data information calculated for discretization

Date	QFII	TRUST	MARGIN	SELLING	VOLUME
901119~901207	100,179	2,164	30,379	-10,088	989,303
901120~901210	62,489	155	38,029	-8,975	994,177
901121~901211	56,183	-241	29,830	-5,938	987,109
901122~901212	77,306	1,572	35,546	-3578	989838
901123~901213	66,970	2,231	29,581	-5,018	1,004,740
901126~901214	55,206	1,197	29,337	-5,383	1,007,889
901127~901217	49,529	-1,989	32,890	-7,273	983,458
901128~901218	12,382	-3,391	26,033	-6,073	917,158
901129~901219	27,151	-2,561	16,334	-1,805	924,661
901130~901220	45,138	-2,337	22,119	-6,188	926,991
901203~901221	-36,052	-4,761	32,097	-9,233	962,537
901204~901224	-26,581	-6,581	26,709	-8,081	948,046
901205~901225	-26,711	-5,297	31,549	-9,754	930,291
901206~901226	-83,378	-6,480	23,602	-9,101	843,310
901207~901227	-101,615	-7,873	21,368	-4,779	776,291
901210~901228	-82,053	-5,533	14,541	-2,082	761,122
901211~901231	-37,838	724	9,179	-1,168	780,463
901212~910102	-39,639	7,215	1,782	-2,273	762,456
901213~910103	-33,141	9,663	-4,123	-436	737,126
901214~910104	18,137	14,444	-13,020	1,282	768,938
901217~910107	75,684	18,161	-18,737	2,844	808,224
901218~910108	82,802	22,417	-17,934	-493	810,077
901219~910109	77,983	21,967	-19,974	-2,473	799,774
901220~910110	63,230	18,456	-24,976	-1,725	775,004
901221~910111	68,353	15,481	-41,363	78	767,749
901224~910114	139,355	16,919	-41,875	-1,143	690,872
(Mean, StDev.)	(23,502.65, 63,100.31)	(4,069.115, 9,745.889)	(10,342.42, 2,4811.6)	(-4,186.77, 3,703.525)	(871,061.69, 103,381.67)
910115~910204	-158,761 (00)	-11,810 (00)	50,247 (11)	-3,647 (10)	733,313 (00)

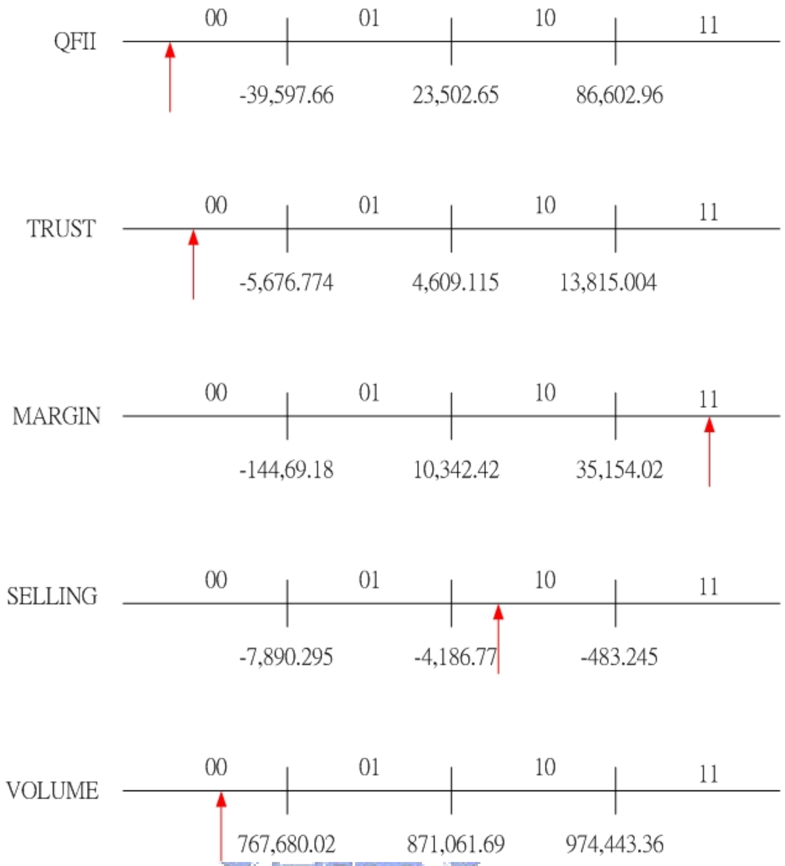

Figure 12 Bit assignment between [91/01/15, 91/02/04] of the five indicators for the condition part

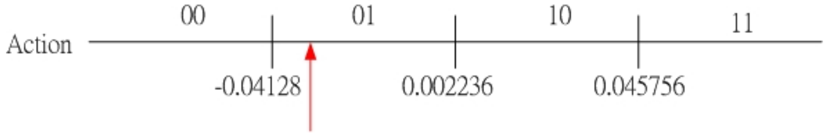

Figure 13 Bit assignment between [91/02/05, 91/02/20] of the price trend for the action part

4.5 Phases of Training

Initially, 15 classifiers are randomly generated in the rule base. The condition part of the incoming data will be matched with those in the rule base. Once the condition part of the classifiers in the rule base is satisfied, they have the chance to go into the subsequent bidding process. For example, in Figure 14, if the incoming message is ‘0100000100’ that matches the rule 12 and 18, the two rules will be activated for the succeeding bidding process. On the contrary, if the incoming message is ‘1100011001’ that matches no rules in the rule base, a new classifier with such condition will be generated and inserted into the rule base. The maximum number of rules in the rule base is set 30 in this simulation. If there are more than 30 rules in the rule base, the one with the minimum strength will be replaced and eliminated. The whole bidding process is handled in the credit apportionment system that only the rules with satisfied condition have the chance to bid.

	1	2	3	4	5	6	7	8	9	10
1	0	0	1	1	1	1	1	0	0	1
2	1	1	1	1	1	1	1	0	1	1
3	0	0	1	0	1	1	0	1	1	1
4	0	1	0	0	0	1	0	1	1	1
5	1	1	0	1	0	0	1	1	0	1
6	1	1	1	0	0	1	0	1	1	1
7	0	1	0	0	1	0	0	1	1	0
8	0	1	0	0	1	1	0	1	0	1
9	1	1	0	0	0	0	0	1	1	0
10	1	0	1	0	0	0	1	1	0	1
11	0	0	0	0	1	1	0	1	1	0
12	0	1	0	0	0	0	0	1	0	0
13	1	0	0	0	1	0	0	1	1	0
14	1	0	0	1	1	0	0	0	1	0
15	0	1	1	1	0	1	1	0	0	0
16	0	1	0	0	1	1	0	1	1	0
17	0	0	1	0	1	1	1	0	1	1
18	0	1	0	0	0	0	0	1	0	0
19	0	1	0	0	1	1	0	0	1	0
20	0	1	1	1	1	0	1	0	0	0
21	0	1	1	0	0	0	1	1	0	1
22	1	1	1	1	0	0	1	0	0	1
23	1	1	1	0	0	0	0	1	1	0
24	1	0	1	0	1	0	0	0	1	0
25	1	1	1	1	0	1	0	1	1	0
26	1	1	0	1	0	0	1	0	0	0
27	1	1	1	1	0	0	1	0	1	0
28	0	0	1	1	1	1	1	0	1	0
29	0	1	0	0	1	0	0	1	0	1
30	1	1	1	1	0	0	1	0	0	0

Figure 14 An example of classifiers in the rule base (condition part)

Reinforcement refers to the awarded classifiers that satisfy specific market mechanism. The assignment of reinforcement is based on certain algorithms. The algorithm applied in the thesis is bucket brigade algorithm, which is used for learning the system's behavior. Different reinforcement learning methods will result in different outcomes which will be discussed in Chapter 5.

Taxation is an important and practical mechanism applied in the system. The life tax is levied to all classifiers with a fixed rate at each cycle. In the thesis, the life tax rate is set 0.01, which enables the strength of the low-firing classifiers to be slowly removed. Besides, each candidate will be forfeited 0.5 percent of the bid tax rate. And 1 percent of the bidding tax is granted for penalizing the active classifiers which post useless message.

4.6 Rule Discovery

In the experiment, the genetic algorithms are invoked every 30 iterations. The crossover point is randomly selected. In crossover process, two chromosomes are randomly selected from the rule base. The selection for mating is proportional to their fitness, which is known as roulette wheel selection. The individuals with higher fitness values have more chance to be selected. In the thesis, the crossover rate is set 0.7 so that the parents can occasionally survive into next generation without being altered. After generating the offspring, the child and the parent with the higher fitness will be kept. The fitness of the offspring is the mean value of the parents'. For example, in Figure 15, the crossover point is selected on position 5. As a result, binary string from the beginning of Parent 1 to the crossover point is copied, and the rest is copied from Parent 2. The fitness value of the offspring, 83, is the mean value of 90 and 76.

	1	2	3	4	5	6	7	8	9	10	11	12	fitness
Parent 1	0	0	0	1	1	1	1	0	0	1	0	1	90
Parent 2	1	1	1	1	0	1	1	0	1	1	1	0	76

	1	2	3	4	5	6	7	8	9	10	11	12	fitness
offspring	0	0	0	1	1	1	1	0	1	1	1	0	83

Figure 15 Crossover

Child 1	1	2	3	4	5	6	7	8	9	10	11	12
Before Mutation	0	0	0	1	1	1	1	0	1	1	1	0

	1	2	3	4	5	6	7	8	9	10	11	12
After Mutation	0	0	0	1	1	1	0	0	1	1	1	1

Figure 16 Mutation

After dealing with the crossover mechanism, the mutation is applied to each position of the classifier for making the rule more adapted to the noisy environment. In the thesis, the mutation rate of each bit is set 0.01 with low probability. For instance, in Figure 16, the mutation mechanism is performed on position 7 and 12. The bit of the two positions will be converted from 1 to 0 and 0 to 1 respectively. The evolution can promote the exploration of the search space, bring out better classifiers, and discard the low-fitness rules that are not suitable for the environment. Therefore, rule discovery can improve the performance of the system. Most learning situations for animals and human beings have the characteristics to evolve into better states.

Chapter 5 Simulation Results and Discussion

5.1 Correlation and Regression Analysis

From Table 5, it is shown that the attribute "PRICE" is low-correlated with "QFII", "TRUST", and "SELLING" of the correlation coefficient 0.145, -0.138, and -0.103 respectively. "PRICE" is medium-correlated with "VOLUME" and non-correlated with "MARGIN" of the correlation coefficient -0.442 and -0.041 separately. In other words, by using the correlation test, the price trend of the subsequent 5 days is not closely related to the other selected indicators of the previous 15 days. The simulation results on other stocks have similar interpretation of the relationship among the variables (See Appendix). Besides the correlation test, the regression prediction of the price trend is based on the equation (7), as shown in Figure 17.

$$Y = 89.693 + 3.528E-05X_1 - 1.37E-04X_2 + 1.160E-04X_3 - 8.88E-05X_4 - 3.62E-05X_5 \quad (7)$$

In Figure 17, the simulation time period is between 89/12/12 and 93/02/26 for 790 days. The data with missing values will not be taken into account in the regression model. The computation of the indicators of the preceding 15 days will be calculated as the independent variables. It is clear that the regression prediction by using the computed regression equation cannot be correctly estimated. That is because the dynamic situation is unable to be interpreted and learned by the simple regression model. The non-linear relationship between the independent variables X_i and dependent variable Y cannot be expressed through the traditional linear regression model. Therefore, the artificial intelligence techniques are applied more to such cases, which are sensitive to the complex and noisy circumstances. They can solve the problems that are unable to be explained by the traditional statistical approaches. The simulation on learning classifier system, which is the leading role of the thesis, will be described in the next section.

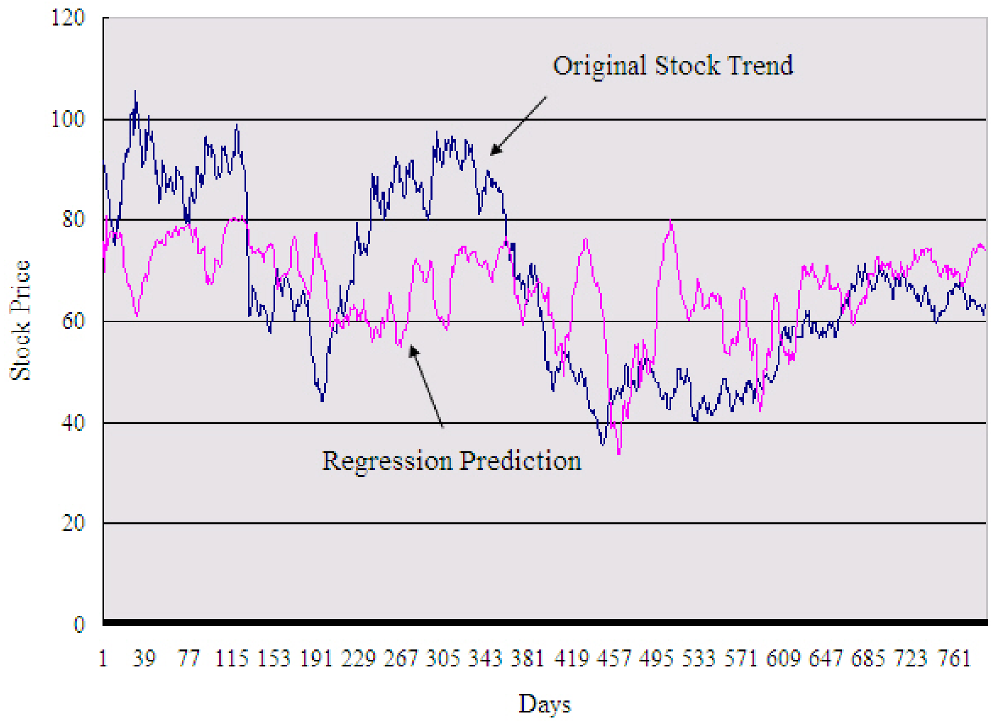

Figure 17 Regression Prediction vs. Original Stock Trend of Stock Price (TSMC)

5.2 Simulation on Learning Classifier System

The main simulation in the thesis is to apply learning classifier system to the stock data. Nine value-weighted stocks are selected for being implemented into the experiment because the data source focuses on institutional investment. The experiment of the thesis is performed on nine different companies, containing three different industries. The corporations, Taiwan Semiconductor Manufacturing Company (TSMC), United Microelectronics Corporation (UMC), and Hon Hi Precision Industry Corporation (Foxconn), are the representatives of the electronics industry. Cathay Pacific Holdings (Cathay), Fubon Financial Holding Company (Fubon), and Mega Financial Holding Company (Mega) belong to the financial industry.

China Steel Corporation (CSC), Nan Ya Plastics Corporation (NPC), and Formosa Plastics Corporation (FPC) are part of the traditional manufacturing industry. The detailed procedures have been stated in Chapter 4, and the results of the experiment are shown from Figure 18 to Figure 26 on the nine corporations. The accumulated profit will be presented as the desired outcome. From the displayed figures (Figure 18 to 26), it is obvious that the accumulated profit will be converged to a satisfactory maximum. In the beginning, the loss may be occurred. However, since the learning classifier system has the ability to learn and adapt itself to the environment, the accumulated profit will continue soaring as time goes on.

In addition, the profit of the experiment is to be proved positively increasing. By using the basic form of simple regression equation $Y = a + bX$, the parameters a and b will be estimated. The experiment is to calculate the trend of the profit on each company; the parameters a and b are the mean value computed for 30 times. The results, displayed in Table 9, evidently show that the slope 'b' of every simple regression equation is confidently positive, which can prove that the profit is certainly rising as time goes by. In other words, by simulating LCS on stock market data based on the selected institutional indicators, the profit is constantly climbing. In the next sections, some comparisons with the LCS model will be discussed, including the alteration of the credit apportionment system and the B&H strategy.

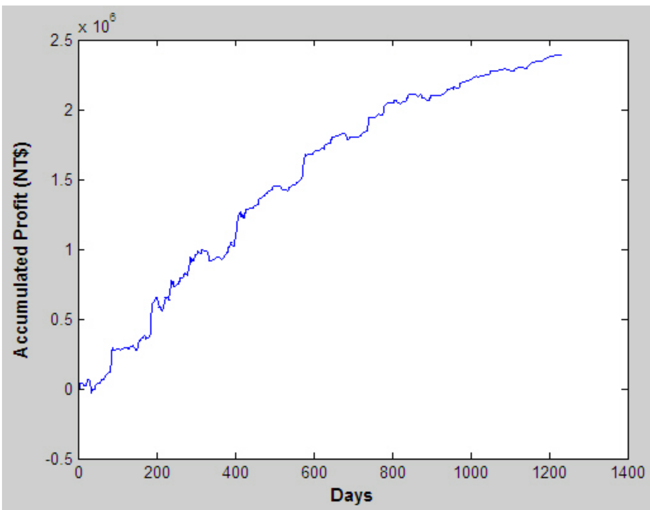

Figure 18 The accumulated profit of TSMC on LCS model

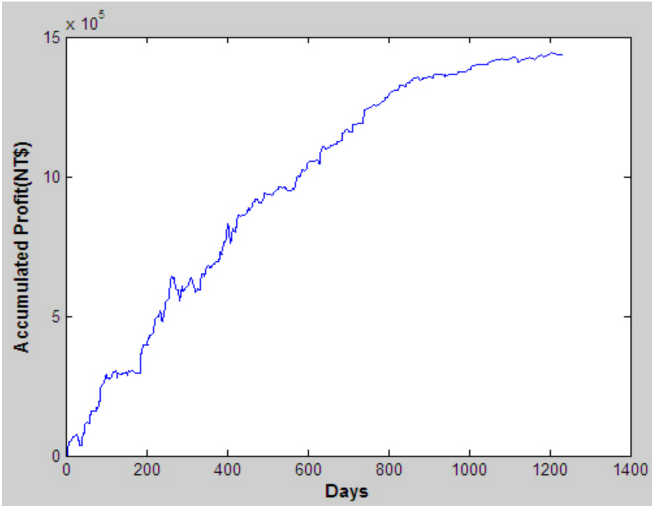

Figure 19 The accumulated profit of UMC on LCS model

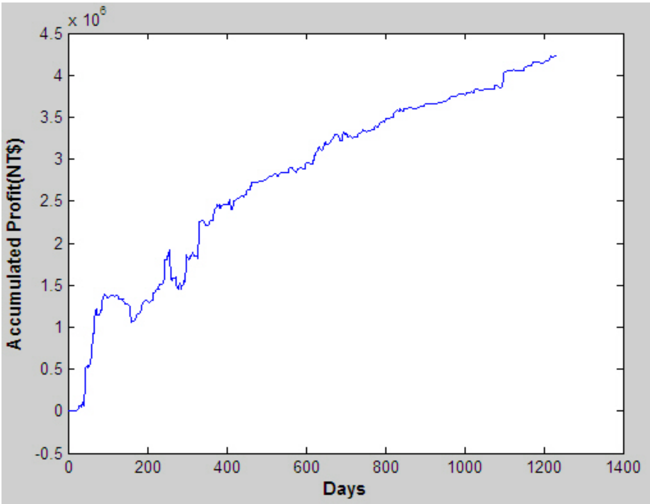

Figure 20 The accumulated profit of Foxconn on LCS model

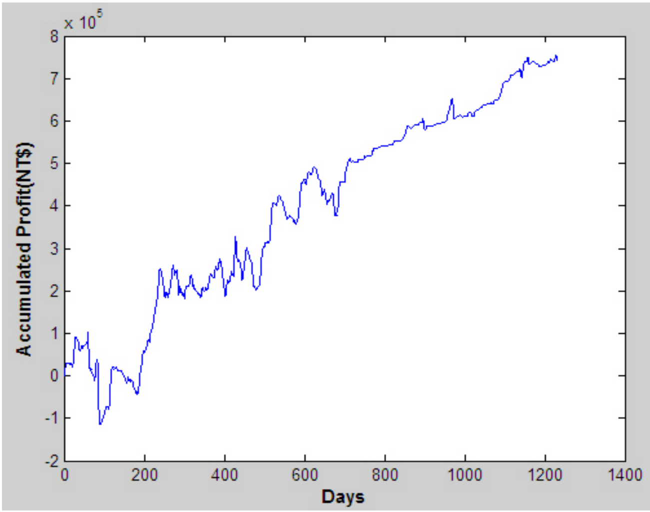

Figure 21 The accumulated profit of Cathay on LCS model

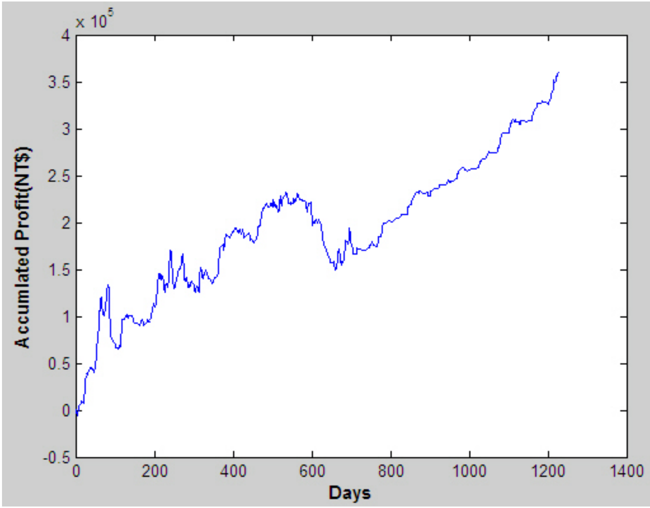

Figure 22 The accumulated profit of Fubon on LCS model

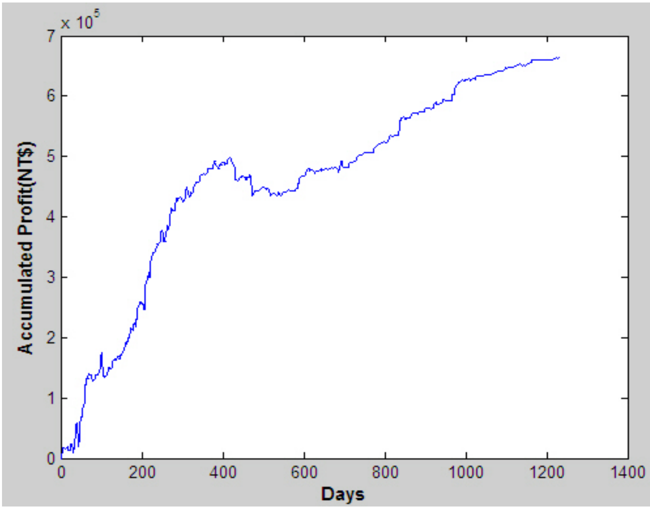

Figure 23 The accumulated profit of Mega on LCS model

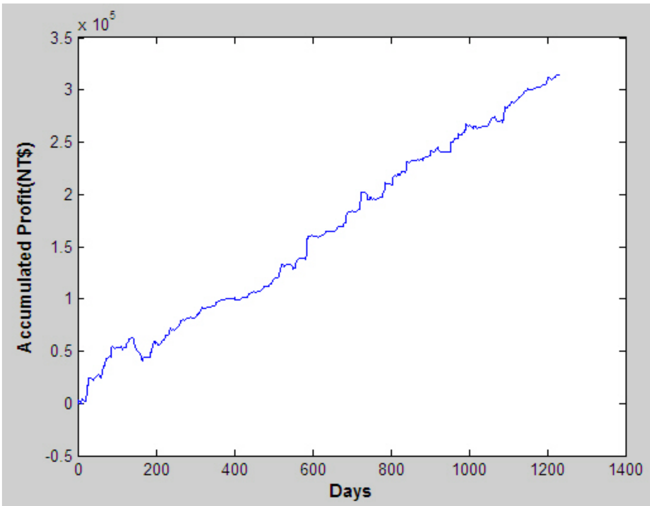

Figure 24 The accumulated profit of CSC on LCS model

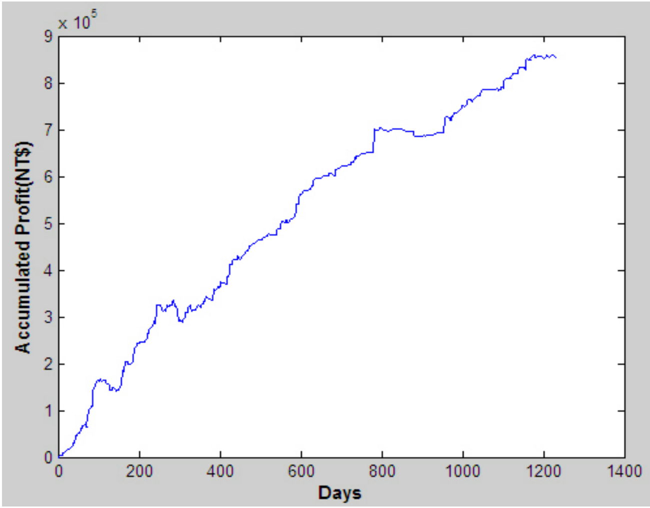

Figure 25 The accumulated profit of NPC on LCS model

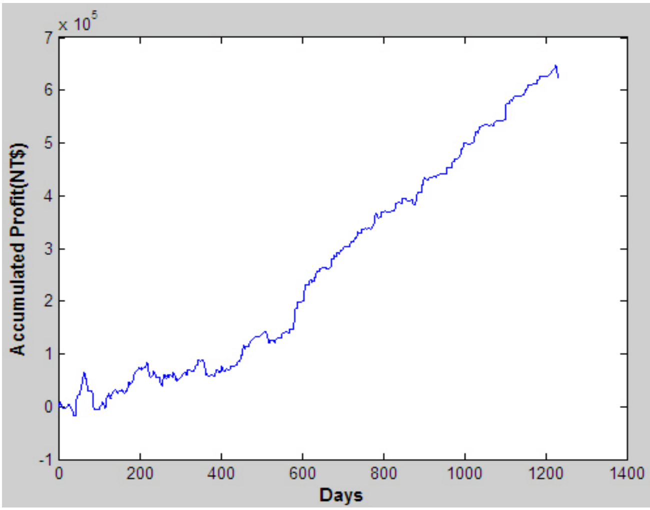

Figure 26 The accumulated profit of FPC on LCS model

Company	Regression Equation
UMC	$Y = 1262.06 + 0.4996X$
TSMC	$Y = 2059.59 + 0.5335X$
Foxcann	$Y = 3250.40 + 0.5915X$
Cathay	$Y = 225.505 + 0.8151X$
Fubon	$Y = 51.9373 + 0.7801X$
Mega	$Y = 386.545 + 0.5513X$
CSC	$Y = 273.806 + 0.4610X$
NPC	$Y = 529.261 + 0.4593X$
FPC	$Y = 772.306 + 0.4420X$

Table 9 Regression estimation of profit

5.3 Simulation on Buy-and-Hold Strategy

Buy-and-hold (B&H) [31], as implied by its name, is an investment strategy that stocks are bought and held for a long period of time, regardless of the volatility in the stock market. The profit calculated by other methods is usually compared with the B&H strategy, based on the assumption that stock prices will go up in the long term. However, investors would not know the future trend of the stock price because there are lots of uncertain and unknown elements existing in the environment. The logic behind the idea of B&H strategy is that the economy will keep growing in the capitalist society, so the stock price and profits will also increase.

In the thesis, the buy-and-hold strategy is used as a comparison approach with learning classifier system about the accumulated profit. The B&H method in the experiment is a random walk model. As the action for the LCS model is set 5 days, the time period for holding the stock by using B&H strategy is as the same as the LCS. The point is that every 5 day, the quantity for buying or selling stocks will be randomly generated. In other words, as the action is set 5 days, the stocks will not be traded until the fifth day. There are four possibilities for each stock trading. In Figure 27, the 1^{st} day is randomly assigned to buy two units of the stock, and they will be sold out at the 5^{th} day. Likewise, one unit of the stock is sold at the 6^{th} day and bought up at the 10^{th} day; two units of the stock are sold at the 11^{th} day and bought up at the 15^{th} day; one unit of the stock is bought at the 16^{th} day and sold out at the 20^{th} day. The procedures will keep continuing based on the B&H strategy; the accumulated profit is thus calculated as shown from Figure 28 to Figure 36. The computation of the profit is based on the criteria of Taiwan Stock Exchange (TAIEX), which means the commission and securities transaction tax need to be counted in. The tax rate levied from the seller is 0.3% of the value traded, and the commission is subject to 0.1425% of the traded value.

The B&H strategy is unable to learn or adapt to the behavior of environment. Therefore, the variation of the accumulated profit is so great and unpredictable that it may gain or lose a lot. The results of B&H strategy are illustrated from Figure 28 to Figure 36. It is clear that the variation of gain/loss is quite violent that is unlike the convergence situation of LCS model. For example, the left diagram of Figure 28, the accumulated profit may rise to about two million dollars, but it may also fall to lose two million dollars. Similarly, the right diagram of Figure 34, though the accumulated profit is positive, the vibration is quite uncertain.

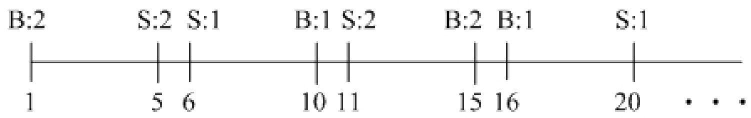

Figure 27 B&H procedure for the simulation

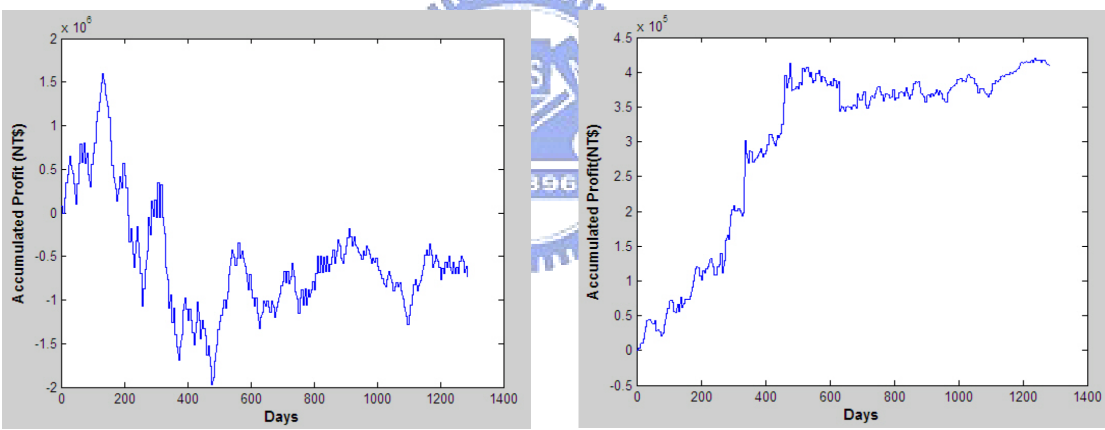

Figure 28 The accumulated profit of TSMC on B&H strategy

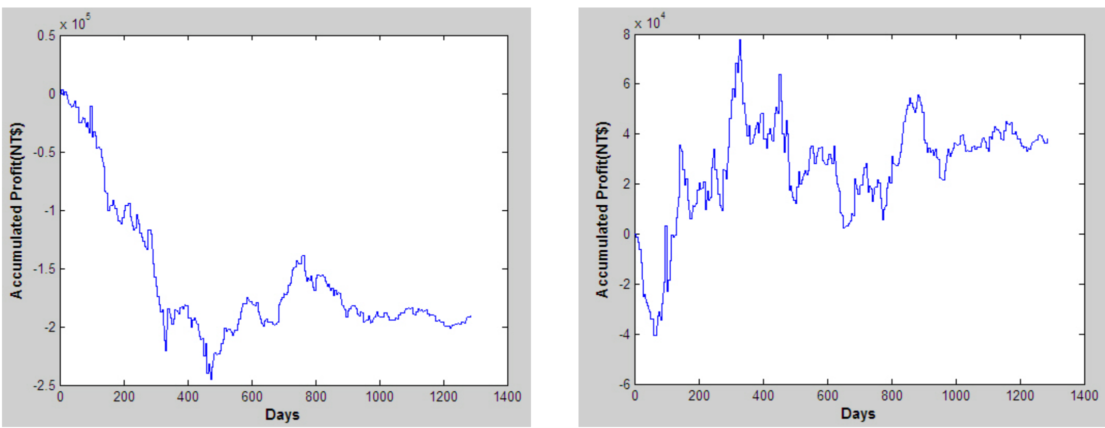

Figure 29 The accumulated profit of UMC on B&H strategy

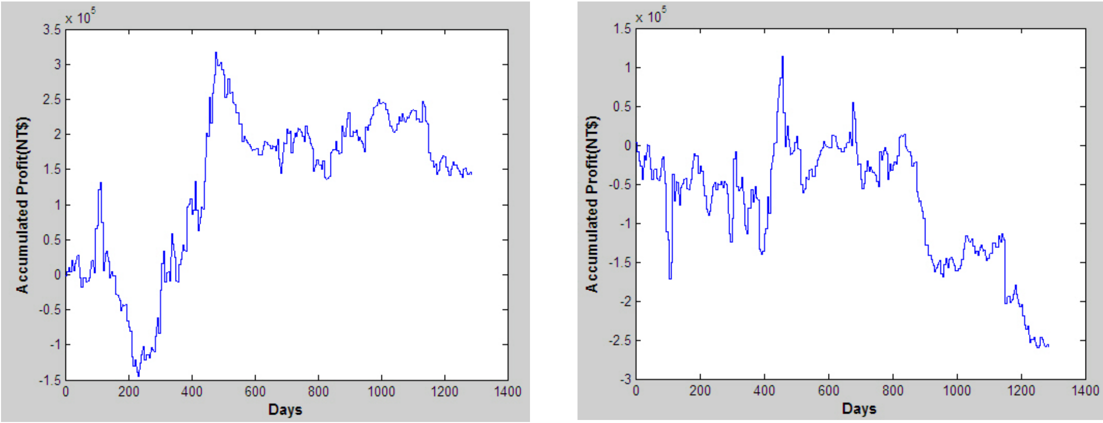

Figure 30 The accumulated profit of Foxcann on B&H strategy

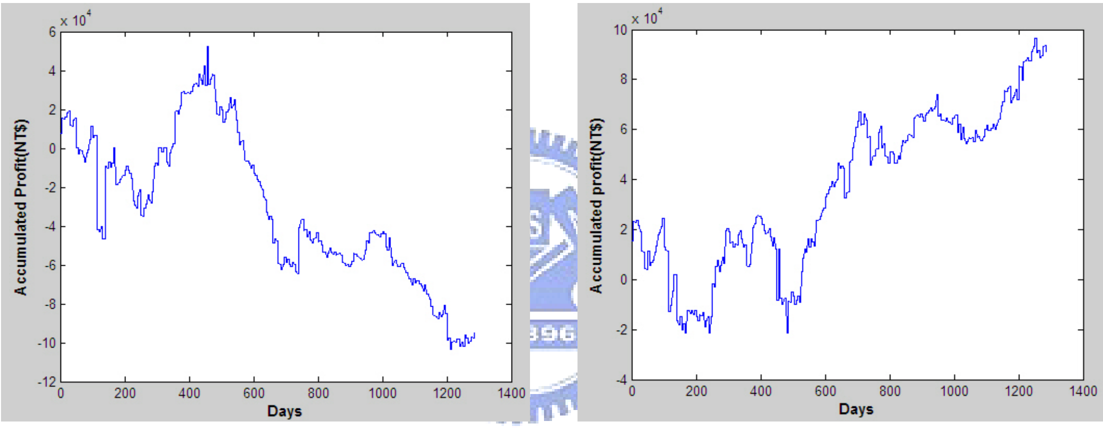

Figure 31 The accumulated profit of Cathay on B&H strategy

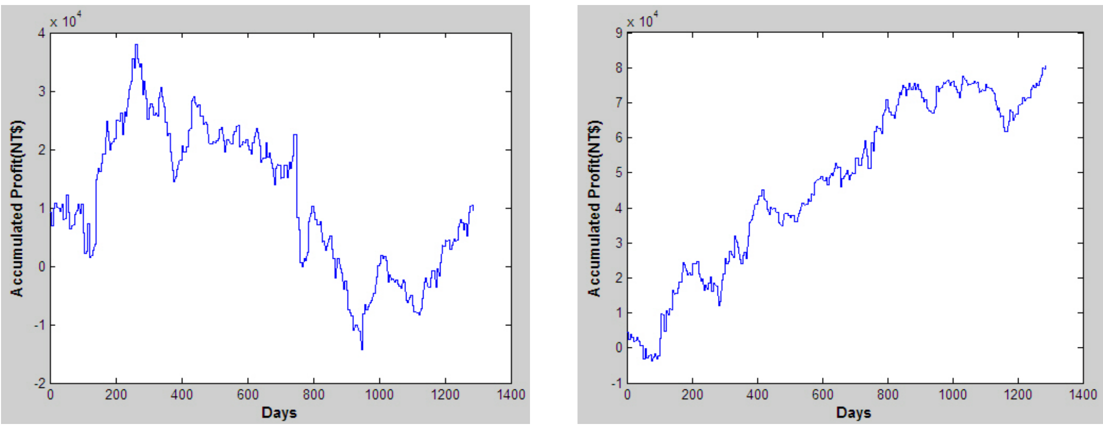

Figure 32 The accumulated profit of Fubon on B&H strategy

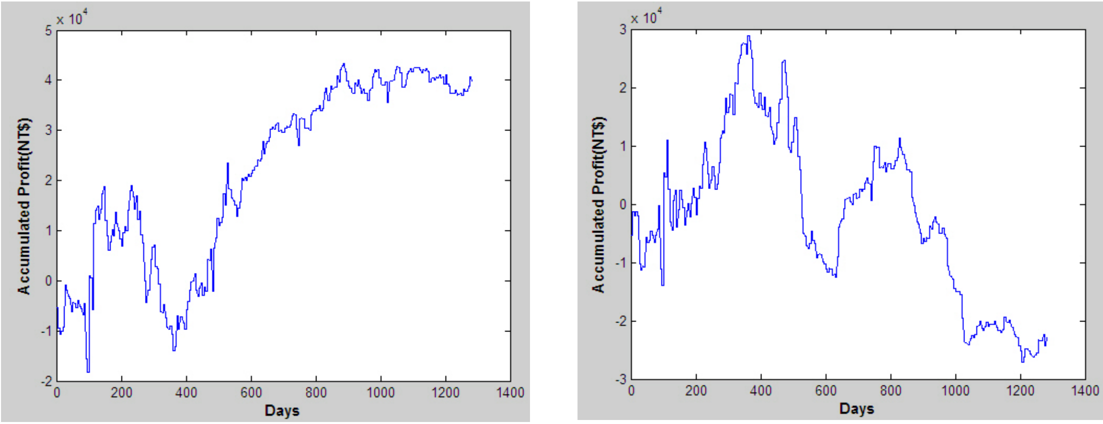

Figure 33 The accumulated profit of Mega on B&H strategy

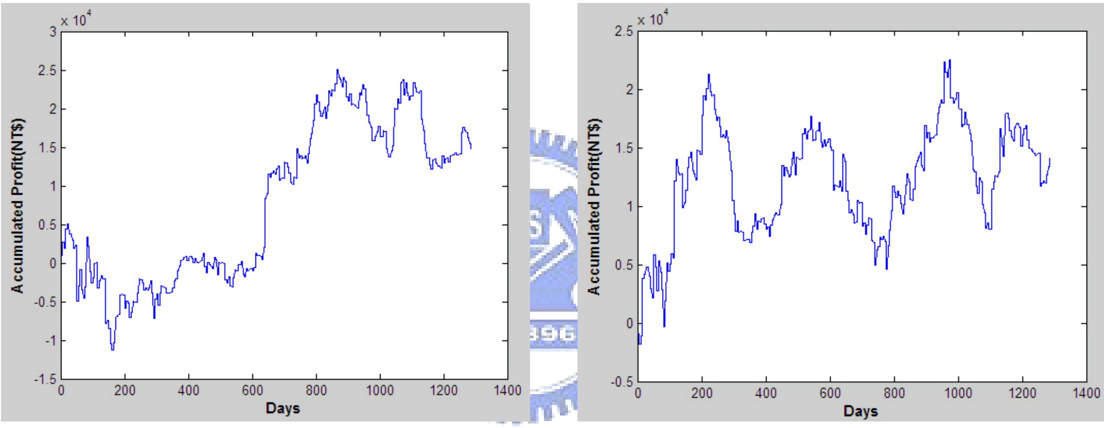

Figure 34 The accumulated profit of CSC on B&H strategy

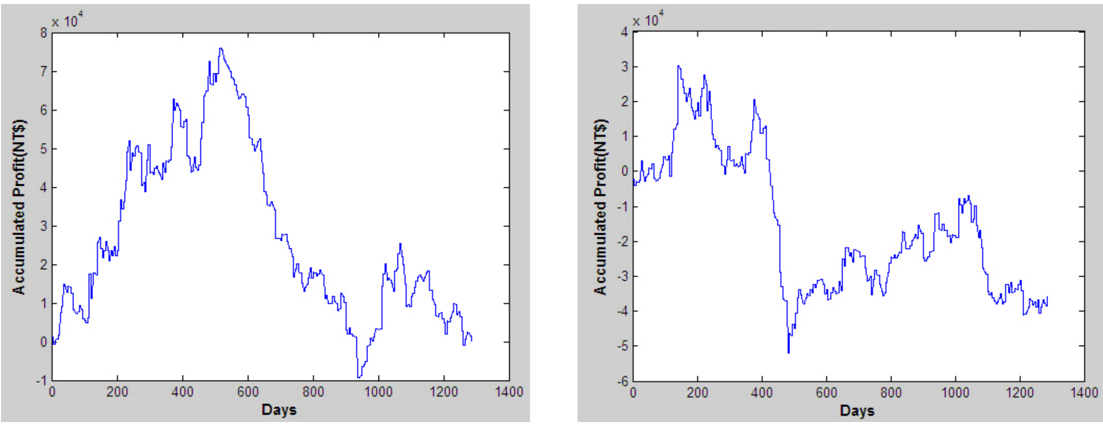

Figure 35 The accumulated profit of NPC on B&H strategy

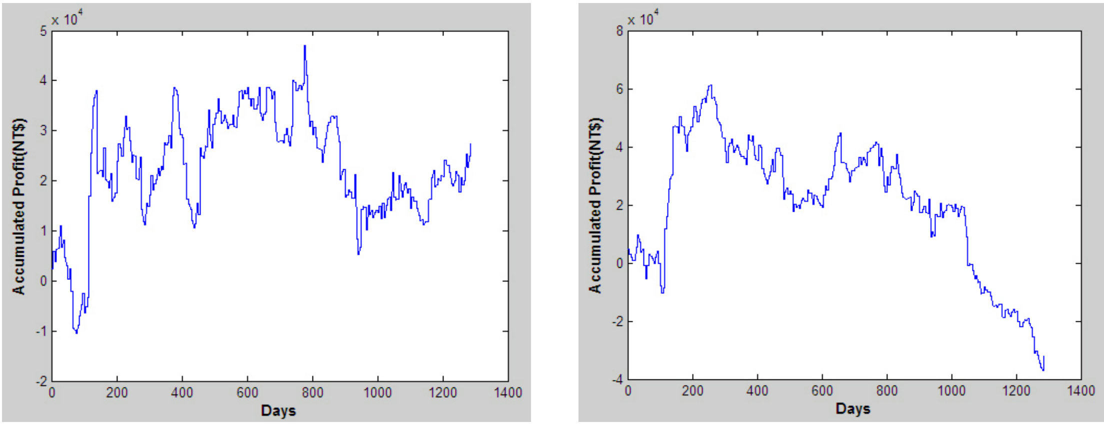

Figure 36 The accumulated profit of FPC on B&H strategy

5.4 Reinforcement Learning Comparison – Q-Learning

Q-learning and bucket brigade algorithm are the two most popular methods of reinforcement learning [32]. In this thesis, Q-learning replaces the bucket brigade algorithm in the credit apportionment system in order to compare the final results of these two methods.

In Q-learning approach, Q-value is regarded as the strength of each classifier for optimizing the target goal. As mentioned in section 2.5.3, Q-function will be updated and optimized during the learning process. Likewise, the input information will be inserted into the production system for the matching process at each time step. Firstly, the classifiers in the rule base with the satisfied condition have the opportunity for further steps. Secondly, each classifier has a corresponding value, called Q-value. In reinforcement learning, the classifier with the maximal Q-value at that time will be chosen for taking an action a according to the current state x of the external environment. Through interacting with the environment, the classifier will receive an immediate payoff r and observe the next state x' accordingly. Hence, the Q-value will be updated as listed as the equation (5). In this simulation, the learning rate α and discounted factor γ are both set 0.6. The purpose of the discounted factor is to determine how much of the possible future states should be taken into consideration at current time. By trial and error, the values for the two parameters are selected, which should be within the range [0, 1].

The genetic algorithms will be evoked every 30 iterations as well. The only difference of the whole process is the reinforcement learning component. The accumulated profit will be computed at each time step.

The average accumulated profits for 30 times of the simulation on the three models are calculated and displayed in Table 10. The experimental results significantly find that applying bucket brigade algorithm is more profitable than Q-learning in the stock market data. Besides, Q-learning outperforms buy-and-hold strategy. It is obvious that the artificial intelligence techniques outperform the random walk model. As a result, finding out the most profitable and suitable model for certain tasks is the work that should be done continually.

	Bucket brigade	Q-learning	Buy-and-hold
UMC	1,626,432	1,499,446	-18,074
TSMC	2,303,351	2,114,002	-16,730
Foxcann	4,888,222	4,778,892	51,700
Cathay	816,842	547,951	1,605
Fubon	333,917	221,547	9,036
Mega	735,229	727,235	-1,024
CSC	312,746	311,265	-2,240
NPC	807,925	760,481	6,016
FPC	706,309	642,667	-18,801

Table 10 The average accumulated profit (NT dollars) for 30 trials

Chapter 6 Conclusions

6.1 Conclusion

The learning classifier system is not so popular as neural network, fuzzy logic, or genetic algorithms in the finance domain. However, this thesis shows that the LCS model is quite favorable for finding the in-depth knowledge in such field. The LCS model has the capability of continually learning and adapting itself to the dynamic environment. The simulation results demonstrate that the accumulated profit is rather promising based on the significant selected institutional indicators. From this consequence, the rule-based system enables the factors to be beneficial and valuable though they are proved to be low-or-non-correlated with the subsequent price trend and have inability to predict the future price by the statistical tests. Sometimes, lots of important information, realities, and highly complicated trading messages are hidden behind the statistics. That is the reason why the statistical pitfalls should be investigated and studied for some cases.

In the credit apportionment system, Q-learning attempts to substitute for the work of bucket brigade algorithm. Nevertheless, Q-learning seems to be less confidential than bucket brigade algorithm. That is because every tool has its characteristics to suit the measure to certain situations. Bucket brigade algorithm is better handling in the stock market than Q-learning. Compared with the buy-and-hold strategy, the trading rules within the LCS model lead to more positive returns that are statistically significant. In conclusion, the LCS model is such a practical and credible system that operates well in the stock market, which enables to profit stably for the long-term.

6.2 Future Works

There is still some work needs to be improved for discovering the knowledge based on the institutional analysis, which is stated in the following.

(1) The institutional indicators are not the only determinants in the stock market, where fundamental and technical indexes should be taken into account as well. Since the influencing factors of the stock trend will change dynamically, deciding the most important and representative indexes at the time seems to be quite contributive. The significance level of each element will change as time goes by; therefore, the weight of every influencing factor should be adjusted.

(2) Extended classifier system (XCS) can be applied to simulate on the institutional stock data for being compared with the accumulated profit of LCS. That is because LCS model is strength-based system, while XCS is accuracy-based [33]. Through the experiment, some interesting rules may be discovered and a new classifier system that suits such domain may also be newly developed.

(3) In credit apportionment, other reinforcement learning approaches can be implemented into the system, such as recurrent reinforcement learning and direct learning. The above-mentioned two reinforcement learning methods are proved to be quite fit in with the dynamic optimization in the finance domain.

(4) The meaning of the final existing rules in the rule base should be particularly analyzed and discussed. If so, the subsequent price trend can be almost accurately predicted under certain discovered situations.

(5) The statistical pitfalls should be discussed for interpreting some patterns or situations that cannot be discovered or implemented through statistical tools.

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Appendix

Table 11 Correlation Test of UMC

Correlations

		QFII	TRUST	MARGIN	SELLING	VOLUME	PRICE
QFII	Pearson Correlation	1.000	.528**	-.457**	.218**	.364**	.021
	Sig. (2-tailed)	.	.000	.000	.000	.000	.452
	N	1273	1273	1273	1273	1273	1273
TRUST	Pearson Correlation	.528**	1.000	-.372**	.354**	.303**	-.005
	Sig. (2-tailed)	.000	.	.000	.000	.000	.854
	N	1273	1273	1273	1273	1273	1273
MARGIN	Pearson Correlation	-.457**	-.372**	1.000	-.195**	.157**	-.022
	Sig. (2-tailed)	.000	.000	.	.000	.000	.438
	N	1273	1273	1273	1273	1273	1273
SELLING	Pearson Correlation	.218**	.354**	-.195**	1.000	.094**	.002
	Sig. (2-tailed)	.000	.000	.000	.	.001	.942
	N	1273	1273	1273	1273	1273	1273
VOLUME	Pearson Correlation	.364**	.303**	.157**	.094**	1.000	.054
	Sig. (2-tailed)	.000	.000	.000	.001	.	.055
	N	1273	1273	1273	1273	1273	1273
PRICE	Pearson Correlation	.021	-.005	-.022	.002	.054	1.000
	Sig. (2-tailed)	.452	.854	.438	.942	.055	.
	N	1273	1273	1273	1273	1273	1273

**. Correlation is significant at the 0.01 level (2-tailed).

Table 12 Correlation Test of Foxconn

Correlations

		QFII	TRUST	MARGIN	SELLING	VOLUME	PRICE
QFII	Pearson Correlation	1.000	.145**	-.416**	.249**	.155**	.035
	Sig. (2-tailed)	.	.000	.000	.000	.000	.208
	N	1273	1273	1273	1273	1273	1273
TRUST	Pearson Correlation	.145**	1.000	-.222**	.310**	.100**	-.003
	Sig. (2-tailed)	.000	.	.000	.000	.000	.929
	N	1273	1273	1273	1273	1273	1273
MARGIN	Pearson Correlation	-.416**	-.222**	1.000	-.414**	.182**	-.055*
	Sig. (2-tailed)	.000	.000	.	.000	.000	.048
	N	1273	1273	1273	1273	1273	1273
SELLING	Pearson Correlation	.249**	.310**	-.414**	1.000	.095**	.078*
	Sig. (2-tailed)	.000	.000	.000	.	.001	.005
	N	1273	1273	1273	1273	1273	1273
VOLUME	Pearson Correlation	.155**	.100**	.182**	.095**	1.000	.019
	Sig. (2-tailed)	.000	.000	.000	.001	.	.504
	N	1273	1273	1273	1273	1273	1273
PRICE	Pearson Correlation	.035	-.003	-.055*	.078**	.019	1.000
	Sig. (2-tailed)	.208	.929	.048	.005	.504	.
	N	1273	1273	1273	1273	1273	1273

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 13 Correlation Test of Cathay

Correlations

		QFII	TRUST	MARGIN	SELLING	VOLUME	PRICE
QFII	Pearson Correlation	1.000	.439**	.022	.393**	.437**	.060*
	Sig. (2-tailed)	.	.000	.428	.000	.000	.033
	N	1273	1273	1273	1273	1273	1273
TRUST	Pearson Correlation	.439**	1.000	.227**	.319**	.331**	.011
	Sig. (2-tailed)	.000	.	.000	.000	.000	.694
	N	1273	1273	1273	1273	1273	1273
MARGIN	Pearson Correlation	.022	.227**	1.000	.096**	.467**	-.019
	Sig. (2-tailed)	.428	.000	.	.001	.000	.497
	N	1273	1273	1273	1273	1273	1273
SELLING	Pearson Correlation	.393**	.319**	.096**	1.000	.067*	.013
	Sig. (2-tailed)	.000	.000	.001	.	.017	.650
	N	1273	1273	1273	1273	1273	1273
VOLUME	Pearson Correlation	.437**	.331**	.467**	.067*	1.000	.023
	Sig. (2-tailed)	.000	.000	.000	.017	.	.410
	N	1273	1273	1273	1273	1273	1273
PRICE	Pearson Correlation	.060*	.011	-.019	.013	.023	1.000
	Sig. (2-tailed)	.033	.694	.497	.650	.410	.
	N	1273	1273	1273	1273	1273	1273

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 14 Correlation Test of Fubon

Correlations

		QFII	TRUST	MARGIN	SELLING	VOLUME	PRICE
QFII	Pearson Correlation	1.000	-.026	-.323**	.016	.263**	.030
	Sig. (2-tailed)	.	.358	.000	.561	.000	.277
	N	1273	1273	1273	1273	1273	1273
TRUST	Pearson Correlation	-.026	1.000	.350**	.000	.228**	-.006
	Sig. (2-tailed)	.358	.	.000	.998	.000	.836
	N	1273	1273	1273	1273	1273	1273
MARGIN	Pearson Correlation	-.323**	.350**	1.000	-.326**	.308**	-.019
	Sig. (2-tailed)	.000	.000	.	.000	.000	.499
	N	1273	1273	1273	1273	1273	1273
SELLING	Pearson Correlation	.016	.000	-.326**	1.000	-.113**	-.020
	Sig. (2-tailed)	.561	.998	.000	.	.000	.473
	N	1273	1273	1273	1273	1273	1273
VOLUME	Pearson Correlation	.263**	.228**	.308**	-.113**	1.000	-.060*
	Sig. (2-tailed)	.000	.000	.000	.000	.	.032
	N	1273	1273	1273	1273	1273	1273
PRICE	Pearson Correlation	.030	-.006	-.019	-.020	-.060*	1.000
	Sig. (2-tailed)	.277	.836	.499	.473	.032	.
	N	1273	1273	1273	1273	1273	1273

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 15 Correlation Test of Mega

Correlations

		QFII	TRUST	MARGIN	SELLING	VOLUME	PRICE
QFII	Pearson Correlation	1.000	.299**	-.067*	.094**	.527**	-.044
	Sig. (2-tailed)	.	.000	.017	.001	.000	.116
	N	1273	1273	1273	1273	1273	1273
TRUST	Pearson Correlation	.299**	1.000	.269**	-.145**	.302**	.030
	Sig. (2-tailed)	.000	.	.000	.000	.000	.283
	N	1273	1273	1273	1273	1273	1273
MARGIN	Pearson Correlation	-.067*	.269**	1.000	-.067*	.270**	-.007
	Sig. (2-tailed)	.017	.000	.	.017	.000	.804
	N	1273	1273	1273	1273	1273	1273
SELLING	Pearson Correlation	.094**	-.145**	-.067*	1.000	-.106**	-.019
	Sig. (2-tailed)	.001	.000	.017	.	.000	.509
	N	1273	1273	1273	1273	1273	1273
VOLUME	Pearson Correlation	.527**	.302**	.270**	-.106**	1.000	-.009
	Sig. (2-tailed)	.000	.000	.000	.000	.	.755
	N	1273	1273	1273	1273	1273	1273
PRICE	Pearson Correlation	-.044	.030	-.007	-.019	-.009	1.000
	Sig. (2-tailed)	.116	.283	.804	.509	.755	.
	N	1273	1273	1273	1273	1273	1273

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 16 Correlation Test of CSC

Correlations

		QFII	TRUST	MARGIN	SELLING	VOLUME	PRICE
QFII	Pearson Correlation	1.000	-.257**	-.405**	-.167**	-.173**	-.019
	Sig. (2-tailed)	.	.000	.000	.000	.000	.500
	N	1273	1273	1273	1273	1273	1273
TRUST	Pearson Correlation	-.257**	1.000	.296**	.148**	.370**	.044
	Sig. (2-tailed)	.000	.	.000	.000	.000	.115
	N	1273	1273	1273	1273	1273	1273
MARGIN	Pearson Correlation	-.405**	.296**	1.000	.280**	.343**	.030
	Sig. (2-tailed)	.000	.000	.	.000	.000	.283
	N	1273	1273	1273	1273	1273	1273
SELLING	Pearson Correlation	-.167**	.148**	.280**	1.000	-.021	.050
	Sig. (2-tailed)	.000	.000	.000	.	.453	.076
	N	1273	1273	1273	1273	1273	1273
VOLUME	Pearson Correlation	-.173**	.370**	.343**	-.021	1.000	.020
	Sig. (2-tailed)	.000	.000	.000	.453	.	.475
	N	1273	1273	1273	1273	1273	1273
PRICE	Pearson Correlation	-.019	.044	.030	.050	.020	1.000
	Sig. (2-tailed)	.500	.115	.283	.076	.475	.
	N	1273	1273	1273	1273	1273	1273

**. Correlation is significant at the 0.01 level (2-tailed).

Table 17 Correlation Test of NPC

Correlations

		QFII	TRUST	MARGIN	SELLING	VOLUME	PRICE
QFII	Pearson Correlation	1.000	.058*	-.128**	.022	.045	-.031
	Sig. (2-tailed)	.	.038	.000	.433	.111	.277
	N	1273	1273	1273	1273	1273	1273
TRUST	Pearson Correlation	.058*	1.000	.377**	.036	.422**	-.005
	Sig. (2-tailed)	.038	.	.000	.194	.000	.861
	N	1273	1273	1273	1273	1273	1273
MARGIN	Pearson Correlation	-.128**	.377**	1.000	-.118**	.402**	.023
	Sig. (2-tailed)	.000	.000	.	.000	.000	.414
	N	1273	1273	1273	1273	1273	1273
SELLING	Pearson Correlation	.022	.036	-.118**	1.000	-.102**	.023
	Sig. (2-tailed)	.433	.194	.000	.	.000	.422
	N	1273	1273	1273	1273	1273	1273
VOLUME	Pearson Correlation	.045	.422**	.402**	-.102**	1.000	.015
	Sig. (2-tailed)	.111	.000	.000	.000	.	.602
	N	1273	1273	1273	1273	1273	1273
PRICE	Pearson Correlation	-.031	-.005	.023	.023	.015	1.000
	Sig. (2-tailed)	.277	.861	.414	.422	.602	.
	N	1273	1273	1273	1273	1273	1273

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 18 Correlation Test of FPC

Correlations

		QFII	TRUST	MARGIN	SELLING	VOLUME	PRICE
QFII	Pearson Correlation	1.000	.014	-.132**	.073**	.131**	-.022
	Sig. (2-tailed)	.	.607	.000	.009	.000	.426
	N	1273	1273	1273	1273	1273	1273
TRUST	Pearson Correlation	.014	1.000	-.016	.041	.137**	.018
	Sig. (2-tailed)	.607	.	.563	.144	.000	.524
	N	1273	1273	1273	1273	1273	1273
MARGIN	Pearson Correlation	-.132**	-.016	1.000	-.009	.367**	-.014
	Sig. (2-tailed)	.000	.563	.	.742	.000	.620
	N	1273	1273	1273	1273	1273	1273
SELLING	Pearson Correlation	.073**	.041	-.009	1.000	-.117**	-.043
	Sig. (2-tailed)	.009	.144	.742	.	.000	.130
	N	1273	1273	1273	1273	1273	1273
VOLUME	Pearson Correlation	.131**	.137**	.367**	-.117**	1.000	-.030
	Sig. (2-tailed)	.000	.000	.000	.000	.	.282
	N	1273	1273	1273	1273	1273	1273
PRICE	Pearson Correlation	-.022	.018	-.014	-.043	-.030	1.000
	Sig. (2-tailed)	.426	.524	.620	.130	.282	.
	N	1273	1273	1273	1273	1273	1273

**. Correlation is significant at the 0.01 level (2-tailed).