APPLYING FUZZY LOGIC TO STOCK PRICE PREDICTION

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Abstract

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The major concern of this study is to develop a system that can predict future prices in the stock markets by taking samples of past prices.

Stock markets are complex. Their dramatic movements, and unexpected booms and crashes, dull all traditional tools

This study attempts to resolve such complexity using the subtractive clustering based fuzzy system identification method, the Sugeno type reasoning mechanism, and candlestick chart analysis. Candlestick chart analysis shows that if a certain pattern of prices occurs in the market, then the stock price will increase or decrease.

Inspired by the key information that candlestick analysis uses, this study assumes that everything impacting a market, from economic factors to politics, is distilled into market price.

The model presented in this study elicits, from historical data price, some of the rules which govern the market, and shows that rules which are drawn from a particular

stock are to some extent independent of that stock, and can be generalized and applied to other stocks regardless of specific time or industrial field. The experimental results of this study in the duration of 3 months reveals that the model can correctly predict the direction of the market with an average hit ratio of 87%. In addition to daily prediction, this model is also capable of predicting the open, high, low, and close prices of desired stock, weekly and monthly.

To my dearest Mahtab

Acknowledgments

I would like to thank my supervisors Dr. Peter Grogono, and Dr. Kudrat Demirli for their guidance, enthusiasm and encouragement. This thesis owes much to them; however, any mistakes are my own.

I am grateful to my wife Mahtab for her patience throughout this research.

Finally, I wish to thanks all my Professors for their support.

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Chapter 1

Introduction

1.1 Introduction

Stock markets are complex. Some researchers (Palmer *et al.*, 1994) are now suggesting that such complexity may be an intrinsic characteristic of such systems. The Santa Fe Artificial Stock Market, developed by Richard Palmer, Brian Arthur, and others (Palmer *et al.*,1998) indicates how simple factors in the stock market can cause very complex behavior.

Resolving such complexity has been a dream for traders. They have been in great need of powerful assistance in their financial decisions. Human capability in analyzing all the data has not been satisfactory, and traditional economic methods have not been promising. Stock markets' dramatic movements, unexpected booms and crashes, chaotic behavior and non-linearities, dull all traditional tools

Since the late 1980s, some researchers have proposed *Artificial Intelligence (AI)* techniques to predict and clarify stock market behavior. Various AI techniques have been utilized. Some models have adopted financial factors as inputs (Kim and Chum, 1998) while others have used indicators and historical market data (Asakwa, 1990 ; Kamijo, 1990 ; Yoda, 1994 ; Gencay, 1998 ; Ye and Gu, 1994 ; Benachenhou, 1994 ; Benckman, 1991). Rules which determine market behavior, have been elicited from raw data by AI methods in some research (Sikora and Shaw, 1994 ; Mahfod and Ganesh, 1995 ; Ye and Gu, 1994 ; Benchenhou, 1993), or through gathering expert opinions via interview in others (Man and Bolloju, 1995 ; Braun and Chandler, 1987). In a sense, AI based stock market behavior prediction models can be classified into four groups: models based on *neural networks, fuzzy logic, genetic algorithms* and *expert systems.*

In this thesis, we have used *objective fuzzy logic* as suggested by Takagi and Sugeno (Takagi and Sugeno, 1985) in order to predict short-term or long-term stock price movement. The following sections give a brief background of models employing various AI techniques in current literature.

1.2 Neural Networks

Neural networks, which are usually used for *pattern recognition* or *classification*, are a connected set of simple processing elements or nodes, where a weight is associated to each connection between nodes. Weights are initialized randomly at the beginning, and as the network begins to learn, the weights change.

Backpropagation training (Rumelhart *et al.*, 1986) is the most popular algorithm for optimizing these weights. Backpropagation repeatedly uses the difference between the network's current output, and the desired output to balance the weight of each connection, and in each iteration reduces the difference between the current output and the desired answer.

Several systems based on neural networks have produced promising results (Asakwa 1990, Kamijo and Tanigawa 1990). Most of them only use indicators and historical market data, such as *moving average*, or closing price.

James Hall (Hall, 1994) built a stock selection system using neural networks. Unlike many stock selection methods, this system does not use expert rules. Instead, the system discovers some patterns in the market and selects attractive stocks based on them.

Yoda (Yoda, 1994) developed a neural network based model, which predicts the Tokyo stock market direction. The model takes four influential inputs as suggested by experts, and signals the timing to buy and sell. Four significant inputs in this model are as follows:

1. A *vector curve* consisting of *regression coefficients* over time of changes in the weekly Dow Jones index (DJI);

2. A moving average of the interest rate of the *long-term* Japanese Government *Bond* (JGB);

3. A vector curve for the JGB;

4. A technical indicator called the *IT* radar, developed by Nikko.

Gencay (Gencay, 1998) used a total of 90 years of daily Dow Jones Industrial Average Index from 1897 to 1988, to examine the predictability of the stock market. The market is modeled by single layer *feedforward networks*. The technical trading rules used in this study are very simple and popular, like the *moving average rule*. The simplest version of this rule suggests that traders sell, whenever the price climbs above its moving average, and buy when it drops below. The results report strong evidence of nonlinear predictability in the stock market returns by using the past buy and sell signals of the moving average rules. They also suggest that it is worth investigating more elaborate rules and the profitability of these rules after accounting for transaction costs.

Kim and Chum (Kim and Chum, 1998) presented a new architecture for graded forecasting using an *array probabilistic network (APN)*. The conventional architecture for a *probabilistic neural network* (PNN) yields only a bipolar output corresponding to '1' or '0'. They circumvented this limitation using a graded forecast of multiple discrete values. Also, evaluation of several backpropagation models against a *recurrent neural network (RNN)* as well as PNN, APN, and *case based reasoning* were explored. This array probabilistic network takes: stock price index, total return index, dividend yield, turnover by volume and earning ratio as inputs. The training data was daily observation of 10 years, and the model was tested during a period of 9 months. *Hit ratio (HD)*, or proportion of correct forecasts was measured as the metric of accuracy (hit ratio is defined in Section 5.2.3). The model shows a hit ratio about 75%.

1.3 Genetic Algorithm

The traditional genetic algorithm begins as a search technique for tackling complex problems. Through the process of *initialization, selection, crossover,* and *mutation*, genetic algorithms repeatedly modifying a population of artificial structures in order to chose an appropriate structure for a particular problem.

Some researchers have attempted to utilize genetic algorithms in the field of financial prediction. Packard (Packard,1990) used genetic algorithms in time-series prediction. Allen and Karjalainen (Karjalainen, 1993) used genetic programming to find trading rules for the S&P 500. Sikora and Shaw (Sikora and Shaw, 1994) applied genetic algorithms to forecast company bankruptcies. Richard Bauer (Bauer, 1994) in his book *Genetic algorithms and investment strategies*, suggested a stock selection method based on genetic algorithms, in which one or more variables are defined to determine an attractive stock, and a genetic algorithm finds thresholds for these variables, above or below which a stock is advised to be attractive.

Mahfoud and Mani (Mahfoud and Mani, 1995) applied genetic algorithms to predict the performance of individual stocks. A method was proposed by them to extend genetic algorithms from optimization problems to classification and prediction problems. The performance of a genetic algorithm system was compared to that of a neural network system. The results showed that genetic algorithms and neural networks are both promising methods due to their ability to learn nonlinear relationships among the input factors. However, in contrast to neural networks that are like black boxes, where the user can not comprehend the final rules that the model elicited, producing user-readable rules is one of the advantages that genetic algorithms offer. Both methods have a high degree of accuracy in forecasting the direction of the market. The authors suggested using a combined approach, since although both approaches produce similar results, it is possible that where one method fails, another might succeed. They (Mahfoud and Mani, 1996) showed the validity of their model using the results of over 1600 stocks, and examined the combined approach, which they had raised in their previous paper. They showed that the combined approach shows 21% improvement over the genetic algorithms alone, and a 50% improvement over the neural networks alone in a preliminary test.

1.4 Fuzzy Logic

Trading models designed based on fuzzy logic, usually consist of a few fuzzy rules expressing the relationship between inputs and desired output of the market. In these models inputs are fuzzified, membership functions are created, association between inputs and outputs are defined in a fuzzy rule base, and fuzzy outputs are restated as crisp values. Fuzzy rules in such a model could be provided by traders (subjective fuzzy logic) or elicited from raw data (objective fuzzy logic). These concepts will be addressed in Chapter 2.

Wong and Wang (Wong and Wang,1991 and 1992) developed a *fuzzy-neural* systems for stock selection. Yuize et al. (Yuize et al., 1991) applied fuzzy logic approach to a decision support system for foreign exchange trading.

Ye and Gu (Ye and Gu, 1994) developed a hybrid *neuro-fuzzy* model in which fuzzy logic enhances a neural trading system. The model takes the closing price, and Shanghai Stock Indicator of individual stocks as inputs, and outputs three values indicating whether a trend is ascending, descending or stationary.

Fuzzy Associative Memories (FAM) a method proposed by Kosko (Kosko, 1992) is used to determine market rules. In Kosko's method, the weight vector of a network trained by input-output data is considered as the membership function of input-output space. The model is trained by daily data of six months, and the rate of correct prediction is found to be 74%. The duration in which this performance is achieved is not mentioned in the literature

Benachenhou, (Benachenhou,1994)developed a *fuzzy rule extraction tool (FRET)* that extracts fuzzy rules from input-output data by FAM method, and then uses them in a fuzzy decision support system. A fuzzy rule set derived from sample data is then used as a fuzzy expert system for trading. The model achieves the ratio of winning versus losing trades equal to 4.6.

Assisting the traders in arriving at purchase decisions, Man and Bolloju (Man and Bolloju, 1995) implemented a prototype of a fuzzy rule based decision support system. To extract and transfer dealers' expertise, they employed *unstructured interviews* with some experienced dealers. Fuzzy rules representing the dealers' decision making process are quite close to the terminology used by the dealers and the rules are easily interpretable by the dealers. Authors believe that use of fuzzy logic for knowledge representation has facilitated a high level of abstraction of the experts' knowledge. Moreover, the flexible relationship represented by membership functions and fuzzy rules, between the variables in the model have provided a robust model of the decision making process.

In research conducted by Braun and Chandler (Braun and Chandler, 1987), a single investment analyst was used as the expert for the study. To model the market *rule induction approach* a technique under the general topic of *learning-from-example (LFE)* was used. In this technique, the rule-induction system is presented with examples and attempts to induce a decision model. This is in contrast to *learning-by-being-told* methods, which try to extract the model from the experts using *extensive interviews*. In this study a commercial software system called *ACLS (Analog Concept Learning System)*, was used to analyze past examples and formulate rules. Predicting intermediate fluctuations in the movement of the market is selected as the decision to analyze.

1.5 Expert Systems

Expert systems use a *knowledge base* including a set of rules and an inference mechanism that provides computer reasoning through inductive, deductive, or hybrid inductive and deductive reasoning. Knowledge base rules usually are undertaken through interview with traders. Rules in such knowledge-based systems are represented in the form of computer readable sentences. Checking for consistency and validity of rules is essential for a knowledge-based system, which is complex and difficult in the financial field, even when it is a system with only a dozen rules.

In an attempt to forecast the direction of stock prices on the New York Stock Exchange (NYSE), Beckman, (Beckman, 1991) used internal stock market data, such as the number of issues traded daily in term of advancing, declining, and unchanged stocks, and utilizes a technical analysis method called *quants*. An author-constructed toolkit enables users to construct, modify, optimize, and evaluate indicators for conducting technical analysis using AI techniques.

Lee and Jo(Lee and Jo, 1999) developed an expert system based on candlestick analysis to determine the timing of when to buy or sell stocks. According to candlestick analysis there are several patterns in the stock price which can imply future stock price movements. Various such patterns were used to construct the knowledge base. Several aspects, such as recognition of patterns, formulization of pattern definition, rule generation based on the patterns, performance evaluation of the rules, should be considered, which requires much effort. The performance of the system was examined through experiments using real stock data gathered over five and half years and an average hit ratio of 72% was observed.

1.6 Strengths and Weaknesses of AI Techniques

As far as the learning capacity of various AI techniques is concerned, expert systems, fuzzy logic, neural networks, and genetic algorithms can be ordered from low to high. Expert systems and fuzzy logic, as suggested by Zadeh (who first proposed subjective fuzzy logic), are not capable of learning anything. Neural networks and genetic algorithms have learning capability, although on average, pure genetic algorithms usually need a longer learning time (Russo, 1998). But, on the other hand, when *a priori* knowledge is concerned, the order is inverted. Genetic algorithms need no a prior knowledge; neural networks need very little; and fuzzy logic and expert systems need quite detailed knowledge of the problem to be solved. Advantages and disadvantages of each of these four areas of AI can be summarized as follows (+ indicates an advantage and - indicates a disadvantage):

1.6.1 Neural Networks

+ They are capable of learning and can therefore be used when all that is available are some significant examples of the problem to be solved, rather than a solution algorithm.

— They are capable of learning from examples, but what is learned is not easy for humans to understand. Complexity and interactions between the hidden nodes of a neural network make it unattainable to understand how a decision is made. The outputs have to be trusted blindly, and this is what does not endear the neural network to traders and investors.

— There are difficulties in incorporating any *a priori* knowledge about financial markets.

1.6.2 Genetic Algorithms

+ They are affected much less than neural networks by the problem of local optima; that is, a genetic algorithm has far less likelihood than a neural network of finding a local optimum rather than a global one; this is likely to correspond to a less significant learning error.

– Their learning speed is generally slower. They are computationally intensive, and require much processing power.

1.6.3 Expert Systems

+ Rules can be adjusted over time, and when the system doesn't perform properly. In other words, expert systems are more flexible to modification than neural or genetic based systems.

– It is impossible to build in the absence of experts and *a priori* knowledge

– In comparison with a fuzzy system, more rules are needed in expert systems to cover possible outcomes.

1.6.4 Subjective Fuzzy Logic

+ Its linguistic representation is very close to human reasoning.

+ It is much less complex in terms of computational effort.

+ Unlike in expert systems, overlap or ambiguity between rules can be managed in fuzzy logic.

− It is not capable of learning.

− It is impossible to use when experts are not available.

1.6.5 Objective Fuzzy Logic

The employed approach in this study, i.e., objective fuzzy logic as suggested by Takagi and Sugeno (Takagi and Sugeno, 1985), inherits all the advantages of subjective fuzzy logic, but not the less desirable features.

+ It possesses good learning capacity and can therefore be used when all that is available are some significant examples of the problem to be solved, rather than a solution algorithm.

+ The system generates a fuzzy knowledge base, which has a comprehensible representation. Therefore, one can easily understand how a decision is made.

+ It is independent of experts.

+ It has a low degree of computational complexity.

− The optimization of a fuzzy model requires firm effort in order to arrive at the optimal combination of membership functions, and number of fuzzy rules. Lack of available tools that optimize these functions is the main bottleneck.

Based on these capabilities we have used objective fuzzy system modeling in this study in order to predict short-term or long-term stock price movement.

Chapter 2 of this thesis explains how stock prices are affected by many complex factors arising from economic or political domains, and suggests the stock price itself as the distillation of all these factors.The candlestick charts, an old but still popular method to visualize stock price, is also addressed in Chapter 2. In order to derive dominant rules in stock markets, one of the most applicable *fuzzy clustering* algorithms, i.e., *subtractive clustering*, is considered in our approach; this algorithm is explained in Chapter 3. Chapter 4 introduces major techniques to identify influential and significant inputs that affect the desired output, and employs these techniques in order to select the most dominant inputs of the model. Experimental results of the stock market model and its performance are depicted in detail in Chapter 5.

Chapter 2

Candlestick Chart

2.1 Introduction

Assume you want to trade in the copper market. To be a successful trader you have to know many things about copper. The supply of copper probably is the most essential factor. But this can be subject to many different variables. The United States, Chile, Canada, Russia, Zaire, Zambia and Peru are major producers of copper. Political and economical conditions have changed dramatically in Russia in the last few years. Chile's economy has been improved. In Africa news reports suggest that AIDS diminish the labor force for mine excavation. In Zaire a mine copper is shutting down because of a labor strike. How would any of these events affect the market?

Now turn to the other side of the equation, the demand side. How much copper consumption is there in the world? Historical data of consumption indicates what past consumption has been, but what about future? What would happen to demand if the Canada Mint decides to stop making copper pennies? How would demand change if a new use were found for copper?

In addition to copper supply and demand, there are numerous economic reports and aspects which have to be taken into consideration, inflation rate, interest rate, capacity utilization and many other economic factors. Now you have to become an economic expert to put all of these factors together and draw a realistic perspective of the market.

As an outsider, you may find it almost impossible to figure out accurate information about all influential factors. Even if you were an insider and you had perfect and accurate information about all supply, demand and economic factors, a lot of traders who participate in the market do not have such information. They buy and sell stocks of copper industries, and affect the stock price. What they do affect the market and what the market does affect all traders, including you.

In other words, although all economic factors must be considered to have an authentic perspective of the market, it must also be taken into account that traders, firms, individuals, etc. may not deduce their behavior by logical processes of the market circumstances, or they may not have complete information. They may not be perfectly rational, or they may not have common expectations; nevertheless, they participate in the market and affect it. One of the consequences of not considering these assumptions is that the traders dream up how the future of market should be, and then the market just plays itself out, and there are no dynamics.

Research conducted by Palmer, and Brian Arthur (Palmer and Arthur, 1998) shows that what really happens in the market, is that the expert, and non-expert traders assert whatever they see, become aware of patterns and rules, generalize patterns and rules, and form models, and act based on those models. They learn from the market and evaluate their models after seeing how well they work; however, their models and rules could be irrational and built on unreliable beliefs. But, even traders who trade based on irrational models and rules greatly influence the market.

Obviously it is impossible to take all economic factors and all rational and irrational models and rules into consideration and builds a model based on them in order to predict the behavior of the market in the future.

The problem of predicting the market future movement can be observed from another point of view and tackled with different approach. Everything that impacts a market from economic factors to politics and even trader's models and beliefs is distilled down into one thing, the price. All market participants interact with each other, drive the market, and determine the price. Instead of trying to estimate supply and demand and all other factors that run a market, the action of prices on the market can be studied. We can look at price and what it has done in the past, and suppose that *under similar circumstances*, it will perform in the same way in the future.

Several ways have been developed to look at price and its effect on the market. Most of them have been founded on the base of experience. Some of them have been around for decades; among them the candlestick chart has had increasing popularity. Lee and Jo (Lee and Jo, 1999) developed an expert system based on candlestick analysis in 1999. Their study with stock price data during a period of five and half years from January 1992 to June 1997 shows the usefulness of candlestick analysis. Also, their research has proven that candlesticks are time-independent and field-independent, which means that they can be applied and used regardless of particular time and industrial fields.

2.2 Candelestick Chart

The candlestick chart, a useful tool to visualize the stock price, became popular in the western world in the late 1980s, even though it has been around for hundreds of years. The Japanese were the first to use technical analysis to trade one of the first futures markets in the world . They started trading in this market in the 1600s. In the book, *The Fountain of Gold*, purportedly written by Homma in 1755, the author states: 'After 60 years of working day and night I have gradually acquired a deep understanding of the movements of the rice market. When all are bearish, there is cause for prices to rise. When everyone is bullish there is cause for the price to fall.'

(Nison, 1994)

This was the base of candlestick chart analysis; however, candlestick chart analysis has passed through several stages to reach the current form:

- Stopping charts, the earliest type of chart, drawn by joining only closing prices.

  See Figure 1.

- Pole chart, which just added the extra information imparted by showing the range between the high and the low of the session.

  See Figure 2.

- Bar chart, a combination of the stopping and pole charts.

  See Figure 2.

- Anchor chart, in which, the opening price information was added to create a chart with an open, high, low and close.

  See Figure 3.

- Candlestick chart, which focuses on the open, close, high and low price of a time period, when the time period can be a day, a week, a month or any other possible period.

  See Figure 3 and Figure 4.

Each candlestick consists of a rectangle and two shadow lines. The difference between the open and close makes the rectangle, which is called the *real body*. At

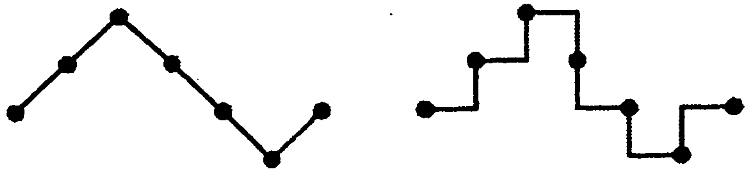

Figure 1: Stopping chart (close)

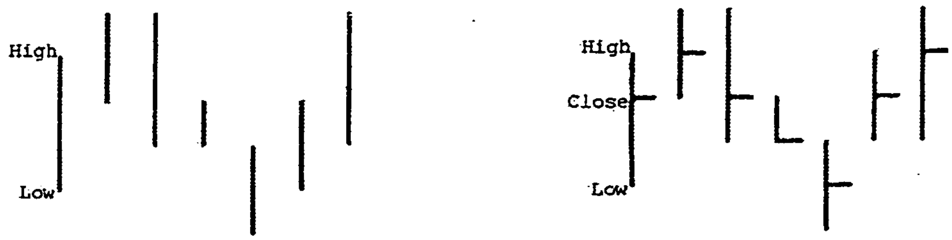

Figure 2: Pole chart (High-Low) and bar chart (High-Low-Close)

either end there is a line, which looks like a wick, or a tail, known as the *shadow.* If the closing price is higher than the opening price, the real body is white and candlestick is called a *clear* or *white candlestick.* On the contrary, if the closing price is lower than the opening price, the candlestick is called a *black* or *solid candlestick.* The white candlestick indicates a raising signal and implies an upturned or bullish market and the black candlestick indicates a falling signal and implies a downtrend or bearish market.

Interpretations that can be given by individual candles, however, are not enough to predict future stock price movements. A sequence of individual candlesticks represents a certain pattern, and these patterns also give important clues to predict future stock prices: when a certain pattern occurs, then the stock price will increase or decrease. The following sections describe some of the major candlestick patterns and what they

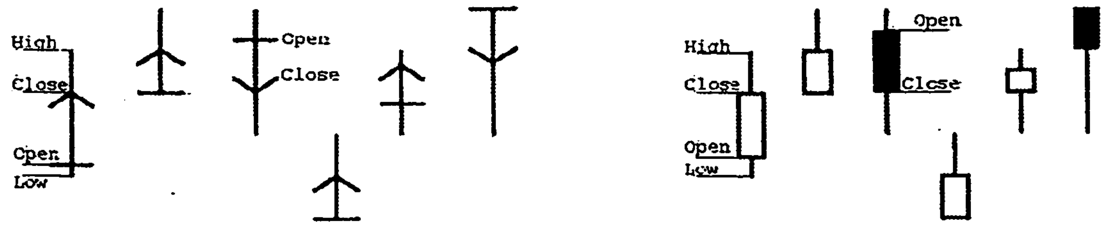

Figure 3: Anchor chart (High-Low-Close-Open) and candle chart (High-Low-Close-Open)

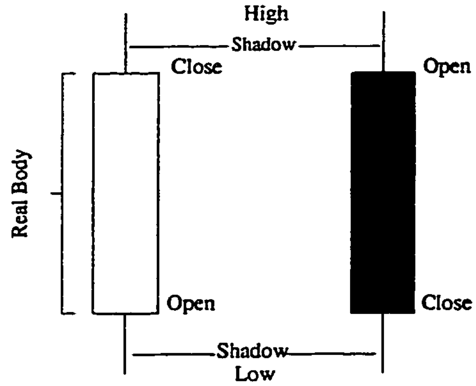

Figure 4: Candlestick

suggest.

2.3 Single Candle Lines

2.3.1 Hammer

Figure 5 shows the *hammer*; it features a small real body where the lower shadow is at least twice the height of the real body and the close is near or at the high. The hammer is understood to be a bullish signal and reversal indicator. It appears after a significant downturn and shows the lower level of the market, and also indicates that the market was unable to sustain a downturn move and closes near or at the high. The hammer reverses a downturn move to an upturn one.

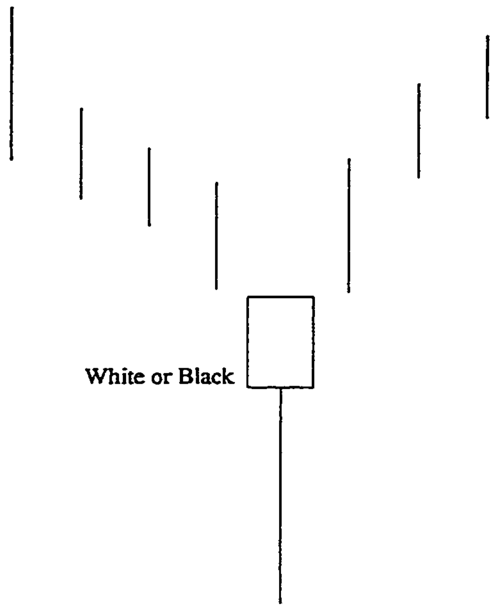

Figure 5: Hammer

2.3.2 Hanging Man

As shown in Figure 6 the *hanging man* looks like a hammer and, similar to the hammer, is a reversal indicator, except that it occurs at the top of an uptrend market and suggests that price will decrease. This means that the same shape line can be bullish or bearish, depending on where it occurs.

There are several single candle lines; among them, *shooting star*, and *Doji*, deserve mention.

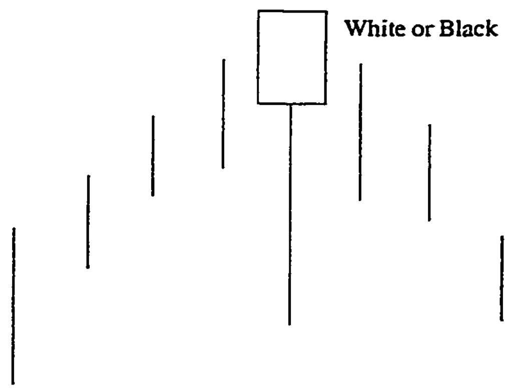

Figure 6: Hanging man

2.4 Dual Candle Line

2.4.1 Dark Cloud Cover

A *dark cloud cover*, as shown in Figure 7 occurs when a wide-range white candle is followed by a higher wide range black candle and bottom of the black candle falls below the center of the first candle. This pattern reflects a poor chance of the market rising, or in other words, a slowing of the upturn.

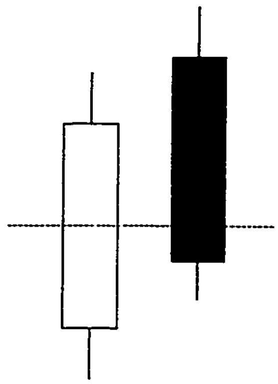

Figure 7: Dark cloud

2.4.2 Engulfing Patterns

A pattern is called an *engulfing pattern* when the second real body engulfs a real body with the opposite color. Depending on the order of the real body's color, there are two types of engulfing pattern: bearish and bullish. A bearish engulfing pattern shown in Figure 8 appears during an upturned market. It is composed of a large black candle that engulfs the previous white candle. In other words, the market opens higher than the previous day's close, and closes lower than the previous day's open. In contrast, a bullish engulfing pattern (shown in Figure 9) which occurs during a downtrend, consists of a large white candle that engulfs the previous black candle, indicating a market that opens lower than the previous day's close, and closes higher than the previous day's open. The engulfing pattern indicates the last gasp of extending a move before a reversal occurs.

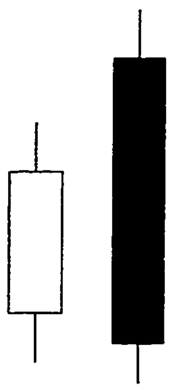

Figure 8: Bearish engulfing

Last engulfing patterns, the *piercing pattern*, and the *harami* could be mentioned as important dual candle lines.

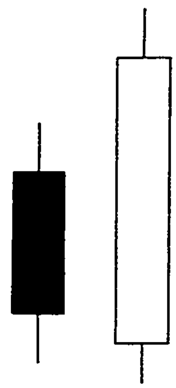

Figure 9: Bullish engulfing

2.5 Three or More Candle Lines

2.5.1 The Evening Star

The *evening star* features a small body candle in between a large white candle and a large black one. The small real body of the second candle may be black or with and should not touch the real body of the first and third candles. Evening star confirms a top to the market, and promises a bearish behavior.

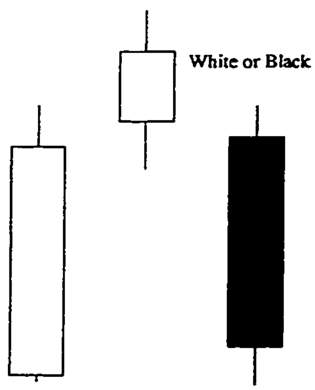

Figure 10: Evening star

The *morning star* is another well known three candle lines.

The key information that the candlestick analysis uses can be employed in order to construct a stock price predictor. The next chapter introduces one of the most applicable tools that provides such a possibility: objective fuzzy system modeling.

Chapter 3

Fuzzy Modeling

3.1 Introduction

Fuzzy modeling can be categorized into two categories: *subjective modeling*, and *objective modeling*. In the subjective modeling approach, which has been examined by many researchers (Tong, 1979 ; Sugeno and Yasukawa, 1993), it is assumed that *a priori* knowledge about the system is available and that this knowledge can be directly solicited from experts. By contrast, in the objective modeling, it is assumed that either there is no *a priori* knowledge about the system, or the expert's knowledge is not trustworthy enough. Therefore, instead of any*a priori* interpretation of the system, raw input and output data is used to augment human knowledge or even generate new knowledge about the system. This approach was initially proposed by Takagi-Sugeno-Kang (Takagi and Sugeno, 1985) and called *TSK fuzzy modeling.* Inspired by the classic system theory, TSK modeling is also referred to as *system identification* (Sugeno and Yasukawa, 1993).

The subjective approach is a qualitative expression of the system using natural language. Fuzzy quantities are associated with linguistic labels, and both antecedent and consequent parts of IF-THEN rules are embodied as fuzzy predicates. Therefore, the output of the model is a fuzzy set, and an appropriate *defuzzification* method is needed to translate the model's output to a crisp value. This is an example of subjective rules:

IF $Market$ is High THEN Sell

IF $Market$ is Lull THEN No Action

IF $Market$ is Low THEN Buy

Objective (TSK) models, with a combination of fuzzy and nonfuzzy predicates, have effective potential to be a quantitative expressing of the system. The antecedent part of IF-THEN rules consists of vague predicates, while the consequent part is expressed as a linear or quadratic combination of antecedent variables. Therefore there is no need to defuzzify the output, since the consequent parts of rules are crisp values rather than vague and fuzzy ones. This is an example:

IF $Open(t)$ is 20.3 AND $High(t)$ is 23.2 THEN Open(t+1) = 0.5 Open(t) + 0.4 High(t) where 20.3 and 23.2 represents two fuzzy sets such that in the first one 20.3 and in the second on 23.2 have membership equal to one.

In this study we are concerned only with the second approach, which in the technical literature referred to as objective modeling, TSK modeling or fuzzy system identification.

3.2 Fuzzy System Identification (TSK)

The problem of fuzzy system identification is the problem of eliciting IF_THEN rules from raw input and output data. This proceeds through two steps:

1) Clustering

2) Specification of input-output relations (IF_THEN rules)

3.2.1 Clustering

Clustering is a process in which numerical data, particularly in situations where no *a priori* classification of them is presented, are placed into groups or clusters, such that data in a given cluster tend to be similar to each other, and data in different clusters tend to be dissimilar.

3.2.1.1 Background

Many algorithms for clustering have been developed to accomplish this task. Since the need for such analysis is raised in many fields of study, contributions to the field have come from many disciplines, and attempts to summarize different techniques are not easy.

Clustering can be classified in two categories: *hard clustering* and *fuzzy clustering.* The hard clustering algorithm (Duda, 1973) assumes well-defined boundaries between the clusters. In other words, this technique assigns each point to one and only one cluster, with a degree of membership equal to one. This is in contrast to fuzzy clustering in which clusters overlap with each other, and the dependency of each data to each cluster is defined by a membership grade in [0, 1].

Concerning fuzzy clustering, the first technique was suggested by Ruspini (Ruspini, 1967) in which the boundaries between the clusters are not clearly defined. The next significant contribution was conducted by Dunn (Dunn, 1974) who formulated the problem of finding the optimal fuzzy clustering of data points. In 1973, Bezdek (Bezdek,1973) suggested an algorithm called *Fuzzy C-Mean (FCM)* based on the hard clustering algorithm (Duda, 1973), and improved the algorithm in 1980 (Bezdek, 1980). According to Backer (Backer, 1981) who studied the performance of several clustering algorithms, the FCM algorithm was the most popular at that time. A simple and fast method based on look-up tables was introduced by Wang and

Mendel in 1992 (Wang and Mendel, 1992). Later, Wang developed another method called *nearest neighbor clustering* (Wang, 1993). In spite of the speed and simplicity of these methods, they have been found too sensitive to noisy data and prone to generating a rule from a single outlying data point (Chiu, 1994). A more efficient method for clustering was presented by Chiu (Chiu, 1994) called *subtractive clustering.* Subtractive clustering is a modified form of the *Mountain Method* that has been proposed by Yager and Filev (Yager and Filev, 1992). It can provide similar degree of accuracy and robustness with respect to noisy data in comparison with more complex methods, while significantly reducing computational complexity.

3.2.1.2 Mountain Clustering

Yager and Filev (Yager and Filev, 1992) proposed an algorithm for approximate estimation of the cluster centers. The algorithm is similar to what a human does in visually forming clusters.

The first step is to form a *discretetization* of the data space R^s (see Figure 11). It is done by forming a grid on R^s. The intersections of the grid lines, which are called node points, provide desired discretetization. The gridding need not be uniform through the space R^s, and in different parts of the space different densities of gridding could be assigned.

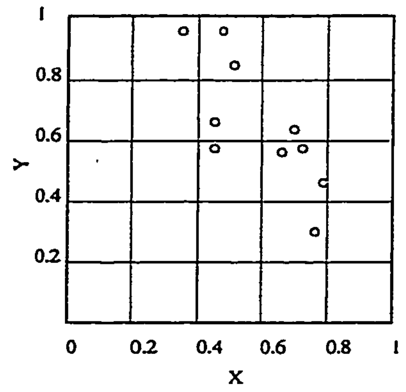

Figure 11: Discretization of data space R^s

The second step is construction of mountain function M. The measure of mountain function for a node point N_i is estimated based on the distance of this node point from all data points. Therefore, higher score will be assigned to the nodes that are closer to data points. The following function shows the value of mountain function at the node point N_i

$$M(N_i) = \sum_{k=1}^{n} e^{-\alpha(x_k - N_i)}$$

where n denotes the number of data points. At the end of this step we have a function which looks like a mountain and shows the distribution of the data. A grid node with the maximal mountain function value is selected as the first cluster center. Finding the next cluster center is accomplished through the process of destroying the mountain. In destroying the mountain, for each node an amount proportional to its distance to the first cluster center will be subtracted. This is done because the effects of the cluster center just identified must be eliminated. After revising the mountain function of all nodes, we can look for the new peak. The grid node with the maximum revised mountain function will be selected as the next cluster center. The value of the second cluster is used to further reduce the mountain function until the mountain is destroyed.

This algorithm can be used as a supporting method, in order to obtain initial estimation of the cluster centers that are used in another method, or as a stand alone clustering algorithm to estimate approximate, not exact, value of the cluster centers.

3.2.1.3 Subtractive Clustering

Subtractive clustering, unlike mountain clustering which considers intersection of grid lines, considers each data point as a potential cluster center. The measure of potential for a data point is estimated based on the distance of this data point from all other data points. Therefore, a data point lying in a heap of other data points will have a high chance of being a cluster center, while a data point which is located in an area of diffused and not concentrated data points will have a low chance of being a cluster center.

After measuring the potential of every data point, the data point with the greatest potential value is selected as the first cluster center. To find the next cluster center, potentials of data points must be revised. For each data point, an amount proportional to its distance to the first cluster center will be subtracted. This reduces the chance of a data point near the first cluster being selected as the next cluster center. After revising the potential of all data points, the data point with the maximum potential will be selected as the next cluster center.

The potential of data points in the first step, as Chiu suggested (Chiu, 1994) is measured as:

$$P_i = \sum_{j=1}^{n} e^{-\alpha||x_i - x_j||^2} \tag{1}$$

where

$$\alpha = \frac{4}{r_a^2}$$

and r_a is a vector which consists of positive constants and represents the hypersphere cluster radius in data space.

The potential which has been calculated through Equation 1 for a given point, is a function of that point's distance to all other points, and the data point which corresponds to maximum potential value is the first cluster center. Let P_1^* denotes the maximum potential, if x_1^* denotes the first cluster center corresponding to P_1^*,

$$P_1^* = \bigvee_{i=1}^{n} P_i$$

where $\bigvee$ denotes the maximum of all P_is.

To revise the potential values and select the next cluster, the following formula is suggested.

$$P_i = P_i - P_1^* e^{-\beta||x_i - x_j^*||^2}$$

where

$$\beta = \frac{4}{r_b^2}$$

and r_b is a vector which consists of positive constants and is called the hypersphere penalty radius .

$$r_b = \eta r_a$$

r_b must be set greater than r_a to avoid obtaining cluster centers close to each other. Large values of η will cause the potentials of data points near the first cluster center to be reduced greatly, and make them improbable to be selected as the next cluster center. In contrast, small η will cause the obtaining closely spaced cluster centers. Chiu (Chiu, 1994) suggested that 1.5 is a good choice for η.

x_2^* with the potential $P_i = \vee_{i=1}^{n} p_i$ is a candidate to be the second cluster center. In the general form x_k^* with the potential

$$p_i = p_i - p_k^* e^{-\beta||x_i - x_k^*||^2}$$

is the candidate to be kth cluster center; however x_k^* must satisfy the following criteria to be accepted as the cluster center.

```
if $p_k^* > \bar{\epsilon} p_1^*$
  Accept $x_k^*$ as a cluster center and continue.
else if $p_k^* < \underline{\epsilon} p_i^*$
  Reject $x_k^*$ and end the process
else if $\frac{d_{min}}{r_a} + \frac{p_k^*}{p_1^*} \geq 1$
  Accept $x_k^*$ as a cluster center and continue.
else
  Reject $x_k^*$ and set the potential at $x_k^*$ to 0. Select the data point with the next highest potential as the new $x_k^*$ and re test.
endif
endif
```

Subtractive clustering can be used as a stand-alone approximate clustering algorithm in order to estimate number of clusters and their locations. Integrating this method with a linear least-squares estimation procedure provides a robust and fast algorithm for identification fuzzy models from raw numerical data (Chiu, 1994).

3.2.2 System Identification

When the clustering estimation is applied to a set of input-output data, each cluster center can be considered as a fuzzy rule that describes the characteristic behavior of the system.

In the most general form this fuzzy rule, for a multi-input multi-output *(MIMO)* system, consists of multi-antecedent and multi-consequent variables as follows:

$$\text{IF } X_1 \text{ is } \mathsf{A}_i \text{ AND } X_2 \text{ is } \mathsf{A}_2 \text{ AND ..AND } X_n \text{ is } \mathsf{A}_n \text{ THEN } \mathsf{Y}_1 \text{ is } \mathsf{B}_1 \text{ AND } \mathsf{Y}_2 \text{ is } \mathsf{B}_2 \text{ AND .. AND } \mathsf{Y}_m \text{ is } \mathsf{B}_m$$

Theoretically, a system with multiple inputs, and multiple outputs can be reduced to several multiple inputs but single output systems *(MISO)*. Therefore, the fuzzy rule of a MIMO system can also be presented as a set of rules with multi-antecedent and single-consequent such that for a system with m output, each multi-consequent rule is broken into m single-consequent rules. Although, the number of rules will be increased in this approach, it would be more straightforward, and that is why we are more concerned with this approach in this study.

Consider a collection of data in an M-dimensional space, where the first N dimensions correspond to input variables, and $M-N$ dimensions correspond to output variables. The clustering estimation on this M-dimensional data space divides the data into fuzzy clusters that overlap with each other, and the dependency of each data vector to each cluster can be defined by a membership grade in [0,1]. The data vector with membership grade equal to one is called the cluster center. Suppose that a set of s cluster centers $\{c_1^*, c_2^*, ...c_s^*\}$ has been generated through the clustering estimation method. Each cluster center c_i^* can be decomposed to two vectors x_i^* and

y_i^*, such that x_i^* represents the first N dimensions which are the coordinates of the cluster centers in input space, and y_i^* represents the last $M - N$ dimensions which are the coordinates of the cluster centers in output space.

The membership grade of each data vector is defined as follows:

$$\mu_i(x) = e^{-\alpha||x - x_i^*||^2}$$

where x is the input vector.

Each cluster center c_i corresponds to fuzzy rule i, and the cluster identified above by the exponential membership function represents the antecedent of this rule. If A_i notifies the exponential membership function of cluster i, then rule i can be represented as:

$$\text{IF } X \text{ is } \mathsf{A_i} \text{ THEN } \mathsf{Y_i} \text{ is } \mathsf{B_i}$$

where X is the input variables vector, Y_i is the ith output variable and $\mathsf{B_i}$ is a singleton defined as a linear or quadratic combination of input variables.

When B is defined as a linear combination, the model is called a first order model and when B is a quadratic combination, the model is called a second order model. For the first order model that we are concerned about in this study, B is:

$$\sum_{j=1}^{N} p_{ij}x_j + p_{i0}$$

where, p_{ij} is the coefficient of x_j in rule i.

Employing traditional fuzzy IF_THEN rules, the first order model would be as follows:

r_1: IF X is $\mathsf{A_1}$ THEN $\mathsf{Y_1(X)} = \sum_{j=1}^{N} p_{1j}x_j + p_{10}$

r_2: IF X is $\mathsf{A_2}$ THEN $\mathsf{Y_2(X)} = \sum_{j=1}^{N} p_{2j}x_j + p_{20}$

$\vdots$

r_s: IF X is $\mathsf{A_s}$ THEN $\mathsf{Y_s(X)} = \sum_{j=1}^{N} p_{sj}x_j + p_{s0}$

For a given x_o, the output of the model y_0, is computed as:

$$y_0 = \frac{\sum_{i=1}^{s} \mu_i(x_0) Y_i(x_0)}{\sum_{i=1}^{s} \mu_i(x_0)}$$

This equation can be converted into the linear least-squares estimation problem by the following definition:

$$\beta_i = \frac{\mu_i(x_0)}{\sum_{j=1}^{s} \mu_j(x_0)}$$

So

$$y_0 = \sum_{i=1}^{s} \beta_i Y_i(x_0)$$

When there are n data vectors:

$$y_1 = \beta_{11}(\sum_{j=1}^{N} p_{1j}x_j + p_{10}) + \ldots + \beta_{1s}(\sum_{j=1}^{N} p_{sj}x_j + p_{s0})$$

$$y_2 = \beta_{21}(\sum_{j=1}^{N} p_{1j}x_j + p_{10}) \ldots + \beta_{2s}(\sum_{j=1}^{N} p_{sj}x_j + p_{s0})$$

$$\vdots$$

$$y_n = \beta_{n1}(\sum_{j=1}^{N} p_{1j}x_j + p_{10}) \ldots + \beta_{ns}(\sum_{j=1}^{N} p_{sj}x_j + p_{s0})$$

This is a least square estimation and can be represented as:

$$Y = AP$$

where Y is a matrix of output values, A is a constant matrix, and P is a matrix of parameters to be estimated. A necessary condition for $||Y - AP||^2$ to be minimized is that, P be:

$$P = (A^T A)^{-1} A^T Y$$

Now, the system is identified. However, insignificant input variables interfering in the process of clustering and system identification could lead to a faulty model of the system. Therefore, it is essential to eliminate insignificant input variables before clustering and system identification. The following chapter introduces major techniques to identify significant and influential input variables, and employs these techniques in order to select the most dominant inputs of the stock price predictor model.

Chapter 4

Input selection

To model the stock market using fuzzy system modeling, similar to model any other system, first, the significant input variables of the system should be identified. This phase, which is called *input selection*, is to find the most dominant input variables that affect the output among a finite number of input candidates. For input selection four major techniques are suggested.

4.1 Combinatorial Approach

Sugeno and Yasukawa (Sugeno and Yasukawa, 1993) proposed a method in which:

1. All possible combinations of input candidates are considered.

2. For each combination, two fuzzy models are built based on two different sets of data, set A and set B

3. A performance index called *regularity criterion* is calculated.

4. A combination of input candidates is chosen, which has a minimum value of the regularity criterion.

The regularity criterion, originally suggested by Ihara (Ihara, 1980), and is defined as follows:

$$RC = \left(\frac{\sum_{i=1}^{k_A}({y_i}^A - {y_i}^{AB})^2}{k_A} + \frac{\sum_{i=1}^{k_B}({y_i}^B - {y_i}^{BA})^2}{k_B}\right)/2$$

where k_A and k_B are the number of data of sets A and B, ${y_i}^A$ and ${y_i}^B$ are the output data of the sets A and B, y^{AB} is the model output for the set A input estimated by the model identified using the set B data, and y^{BA} is the model output for the set B input estimated by the model identified using the set A data.

The following example illustrates a combinatorial approach: Consider the following nonlinear system with two inputs, x_1 and x_2, and a single output y.

$$y = ((1 + x_1^2 - 10sin(x_1x_2))^2$$

Set A						Set B					
No.	x_1	x_2	x_3	x_4	y	*No.*	x_1	x_2	x_3	x_4	y
1	0.53	2.05	6.86	7.93	57.99	21	2.49	1.71	1.44	4.14	259.82
2	0.13	1.11	5.6	0.4	0.19	22	2.11	1.61	7.95	3.3	63.05
3	2.39	0.1	1.57	2.01	18.2	23	2.79	1.84	6.27	0.45	323
4	2	1.12	5.02	3.76	8.11	24	1.73	0.31	6.97	2.39	1.27
5	0.95	1.07	6.56	1.15	43.61	25	0.39	0.53	5.1	0.98	0.84
6	0.42	1.98	5.58	6.8	39.38	26	2.42	0.06	6	6.71	29.12
7	0.68	0.41	0.6	4.02	1.77	27	0.98	1.84	1.05	5.9	60.16
8	2.95	1.31	0.13	4.42	264.97	28	0.31	1.35	5.91	3.64	8.6
9	2.35	2.44	4.61	7.18	137.45	29	1.55	1.22	6.74	1.05	36.56
10	0.92	2.72	7	0.7	17.04	30	2.36	2.2	2.58	0.16	238.89
11	2.87	0.89	1.93	0.24	13.27	31	0.18	0.13	2.5	7.18	0.62
12	0.57	0.89	4.98	6.27	12.32	32	2.08	2.03	2.96	6.44	200.79
13	0.11	1.59	4.2	3.56	0.61	33	0.36	2.28	4.83	0.48	38.33
14	1.66	2.67	3.53	4.98	179.43	34	1.24	2.61	5.06	3.09	12.3
15	1.88	1.74	1.12	5.09	34.46	35	2.71	2.41	3.76	0.94	35.19
16	2.22	1.96	6.25	1.87	231.1	36	0.37	0.89	4.89	1.25	4.32
17	2.83	1.94	1.74	7.25	259.08	37	0.54	1.21	0.73	4.78	22.79
18	2.36	1.61	1.75	0.93	160.56	38	2.9	2.16	1.28	2.03	92.28
19	2.47	1.78	4.9	3.24	276.26	39	1.49	2.79	4.34	5.47	138.96
20	1.74	0.31	6.92	0.24	1.13	40	1.52	0.99	7.96	0.63	44.55

Table 1: Input-output data of nonlinear system

From this system equation, input-output data points are acquired (Table 1). x_3 and x_4 as dummy inputs are added to check the validity of the identification method.

Now there are four input candidates, x_1, x_2, x_3 and x_4. Among them the actual inputs affecting the output y must be identified. $2^4 - 1$ combination of input candidates can be counted: four cases if the system has only one input, six cases if it has two inputs, and so on.

The combinatorial approach suggests dividing the data into two sets, A and B, as represented in Table 1 At each stage of the identification, two models are built for two data sets A and B. In a hierarchy algorithm, the combinatorial approach begins with a fuzzy model with one input which make four models: one model for each particular input. Among the one input models, RC of each model is measured and the model that minimize RC is selected. This step identifies one input among all candidates as a significant input.

At the next step, among the remaining three input candidates, one input is added to the input selected at the previous step. Our fuzzy model has two inputs at this step. The second input is selected according to the value of RC, as was done in the first step.

The process is continued until the performances of the models improve by adding new input candidates to existing models. If all values of RC are bigger than the minimal RC at the former step, the search is terminated.

The result for this example is shown in Table 2 . As is shown, x_1 is selected at the first step. x_2 is chosen at the second step, and in the third step, the process is terminated, since both the values of RC for the third input x_3 and x_4 are bigger than the minimal RC in the second step.

The tree represented in Figure 12 illustrates the algorithm. Each node of the tree corresponds to a subset of input candidates. Only one node at each level is selected. Nodes connected by dotted lines are not evaluated. For r_0 input candidates, at most $r_0(r_0+1)/2$ nodes out of $2^{r_0}-1$ nodes should be evaluated. In other words $r_o(r_0+1)/2$

	Input Candidates	RC	
Step 1	x_1	0.7822	○
	x_2	0.9765	
	x_3	11.5087	
	x_4	11.3407	
Step 2	$x_1 - x_2$	0.6201	○○
	$x_1 - x_3$	1.6446	
	$x_1 - x_4$	6.1935	
Step 3	$x_1 - x_2 - x_3$	0.6772	
	$x_1 - x_2 - x_4$	0.7861	

Table 2: Input selection of nonlinear system

fuzzy models must be built and tested in order to identify actual inputs among r_0 input candidates.

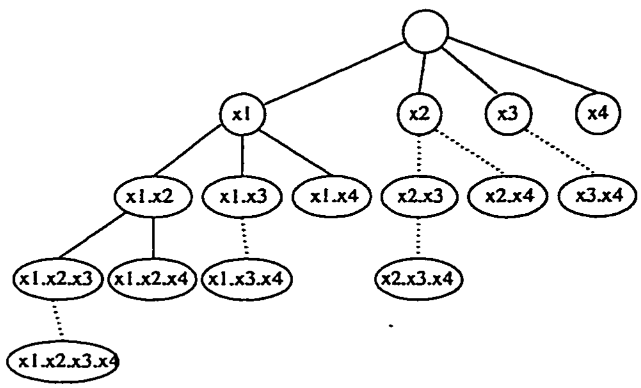

Figure 12: Search tree for input selection

4.2 The Takagi Approach

Takagi and Hayashi (Takagi and Hayashi, 1991) proposed a fuzzy reasoning neural network to identify significant inputs. In this approach for r_0 input candidates, a possible maximum of $r_0(r_0+1)/2$ neural nets should be trained. Significant inputs are identified by eliminating each potential input and checking the performance index. If eliminating an input variable does not change the performance index, then the input variable is not significant.

4.3 Fuzzy Curves

Lin and Cunningham (Lin and Cunningham, 1994) proposed a method to identify the significant input variables. If the input candidates are called x_i $(i = 1, 2, ..., r_o)$, and the output variable is y, then for each input candidate x_i:

1. All data points in $x_i - y$ space are plotted.

2. For every point in $x_i - y$ space, a fuzzy membership function is drawn. The fuzzy membership function is defined as follows:

   $$\mu_{ik}(x_i) = e^{-(\frac{x_{ik}-x_i}{b})^2}$$

   where b is typically about 10% of the length of the input interval of x_i.

3. For each input variable, a *fuzzy curve* c_i is produced by *centroid defuzzification.*

   $$c_i = \frac{\sum_k^m \mu_{ik}(x_i).y_k}{\sum_k^m \mu_{ik}(x_i)} \quad (2)$$

   where m is the number of training data points, and μ_{ik} is the input variable fuzzy membership function for x_i corresponding to the data point k, $k = 1, 2, ..., m$.

In this method, each pair of μ_{ik} and the corresponding y_k provides a fuzzy rule for y; therefore a fuzzy rule is constructed for each sample point as follows:

$$\text{IF } x_i \text{ is } \mu_{ik}(x_i), \text{ THEN y is } \mathsf{y_k}$$

Next, the defuzzified outputs are derived from the set of rules using Sugeno's reasoning formulation(Equation 2). As a result a fuzzy curve will be produced in the input-output plane, and this procedure is repeated for all input candidates, one at a time. Significant input variables are supposed to have a wider range for their fuzzy curve, while insignificant input variables produce a narrow range fuzzy curve. In other words, if the fuzzy curve for an input candidate is flat, this input has no effect in the output data, and obviously is not a significant input. In the contrast, if the range of a fuzzy curve c_i is about the range of the output data y, then the input candidate x_i has a real effect in the output variable. The fuzzy curve indicates that the output is changing when x_i is changing. Therefore, the importance of the input variables x_i can be ranked according to the range covered by their fuzzy curves c_i.

Figure 13 illustrates fuzzy curves for data points of Table 1.

The ranges of fuzzy curves are 0.49936 for c_1, 0.496 for c_2, 0.30804 for c_3, and 0.16999 for c_4. It follows that x_1 is most significant input, x_2 is second, x_3 is third, and x_4 is fourth.

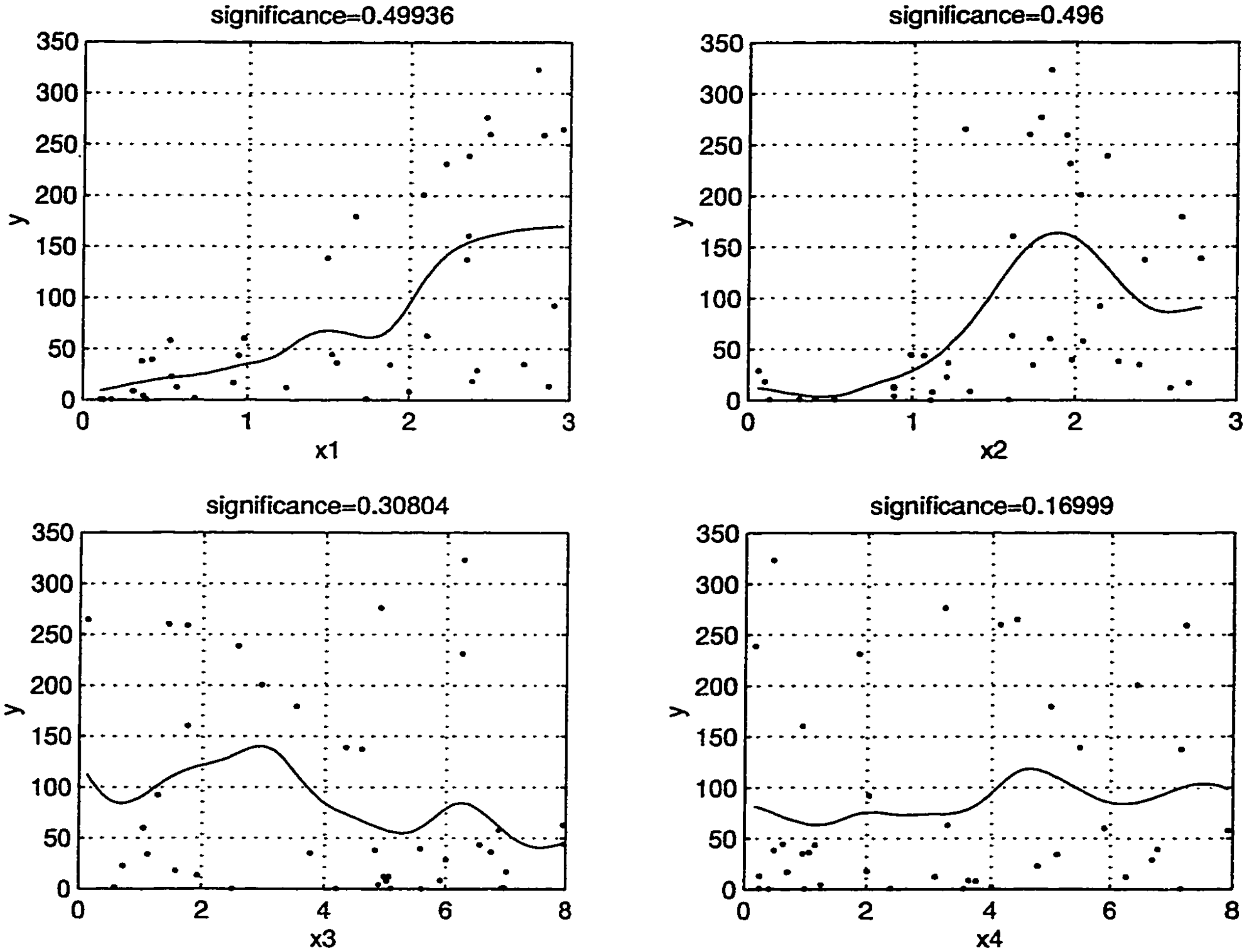

Figure 13: Fuzzy curves c_1,c_2,c_3,c_4

4.4 The Emami Approach

Emami (Emami *et al.*, 1998) proposed an approach in which a quantitative index is used to measure the significance of a potential input. The quantitative index π_j is defined as :

$$\pi_j = \Pi_{i=1}^{n} \frac{\Gamma_{ij}}{\Gamma_j}$$

where Γ_{ij} is the width of the *core* of the membership function of input candidate j in rule i, that is the range in which, the membership function of input candidate j in rule i is one, Γ_j is the width of its *support*, that is the entire range of the input candidate j, and n is the number of rules.

A smaller value of π presents more significant input variables, and vice versa.

This quantitative index is defined based on fuzzy modeling. In fuzzy models, the relationship between input and output is defined through several fuzzy IF-THEN rules in the form of

IF U_1 is B_{11} AND U_2 is B_{12} AND ....AND U_r is B_{1r} THEN V is D_1

AND

$\vdots$

AND

IF U_1 is B_{n1} AND U_2 is B_{n2} AND ....AND U_r is B_{nr} THEN V is D_n

In each rule, all input membership functions Bij are aggregated by AND. Since 'one' is the neutral element of AND connection, if in the entire range of x_j, $x_jB_{ij}(x_j)$ is 'one' , then x_j has no effect in the ith rule. Consequently, for each input candidate the range in which its membership function is 'one' can be an index of how effective that input is in the output.

4.5 Input Selection for Stock Price Prediction Model

Candlestick analysis has been founded based upon the open, high, low and close price of a time period, when the time period can be a day, a week, a month or any other possible duration. Therefore, the open, high, low and close prices are input candidates. But the main problem concerns length of time in which price data should be considered. In other words, when the n most recent periods of price data are potential inputs, how many periods should be selected as actual inputs in order to have an effective model?

Answering this question, fuzzy curve and quantitative index are utilized to test the significance of 40 most recent periods of price data. The combinatorial method and fuzzy reasoning neural network approach are not used in this study, since building $r_0(r_0+1)/2$ fuzzy or neural network models for a system with a large number of input candidates is not practical.

Since candlestick analysis uses the data prices of three most recent periods as inputs, these durations are investigated first.

Figures 14, 15 and 16 show fuzzy curves for the first, second and third most recent periods of data respectively. t denotes the current period which is the first most recent

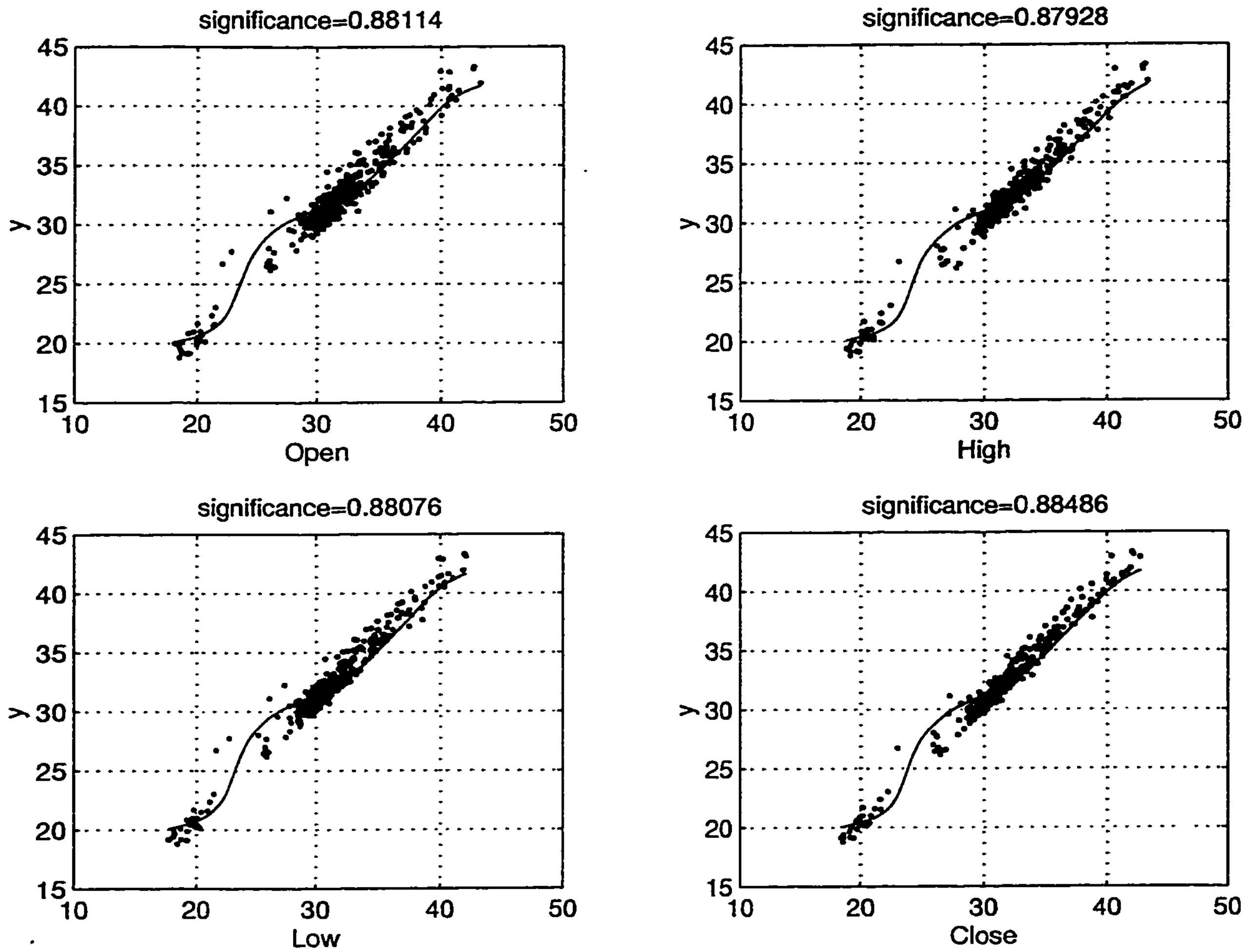

Figure 14: Fuzzy curve for the data price of the first most recent period (t)

period of the market, $t-1$ represents the second, and $t-2$ the third one, in these figures. The upcoming period is shown by $t+1$.

The significance degrees and the curves themselves reveal that the data prices of these periods are quite influential, and have effect on the output. As can be seen, the output changes when these variables change.

To validate this result, the open, high, and low prices are chosen as the output of the system, one at a time, and quantitative indices by the Emami method are

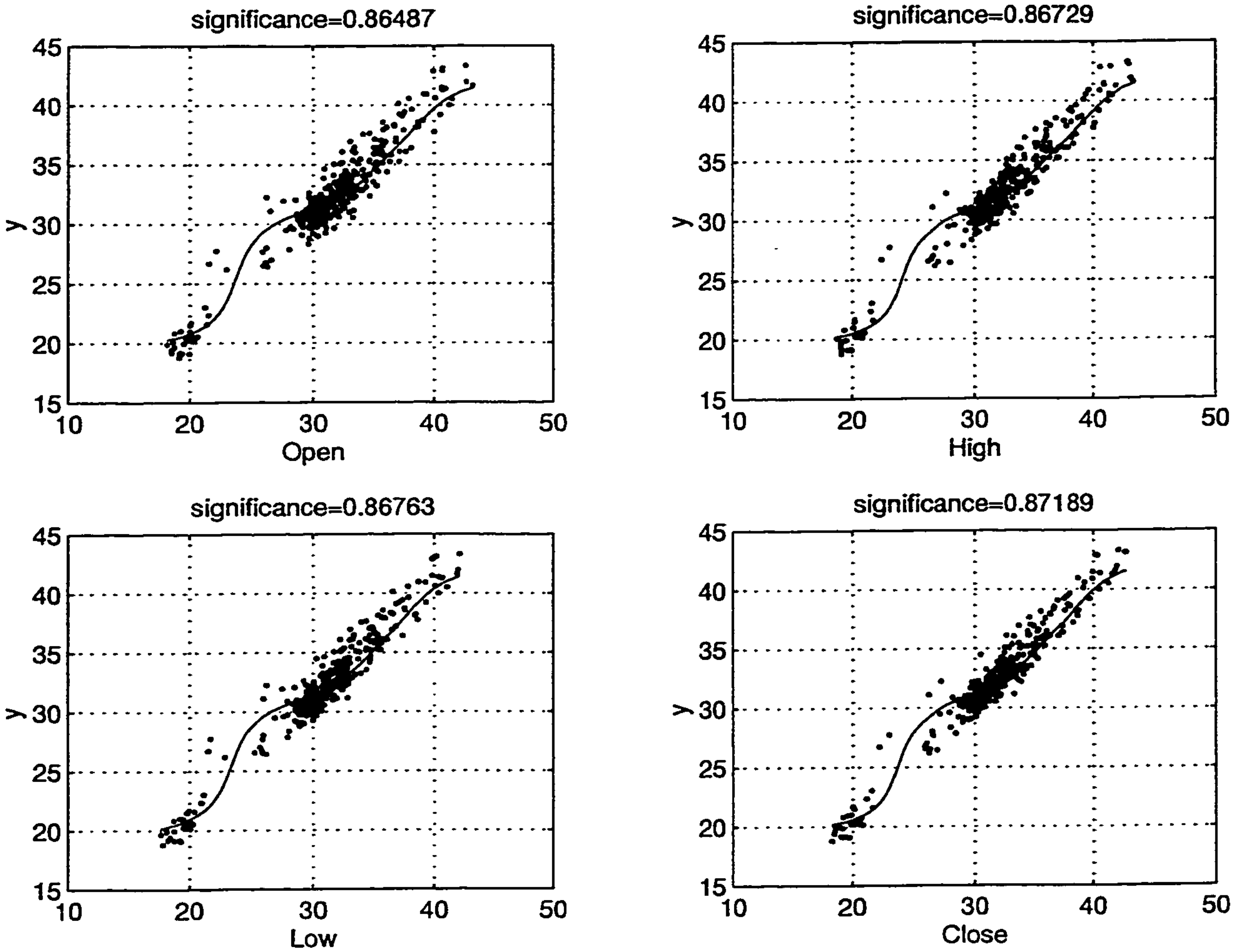

Figure 15: Fuzzy curve for the data price of the second most recent period (t-1)

calculated. The results are summarized in Table 3 on page 58. The Emami method also supports the significance of the open, high, low and close of three most recent periods and recommend them as actual inputs. This study is extended to last 40 periods.

This investigation shows that significance is a decreasing function of time, as Figure 17 reveals. In other words, as we go backwards in time, data prices have less influence on the future movement of the market. These curves verify that data

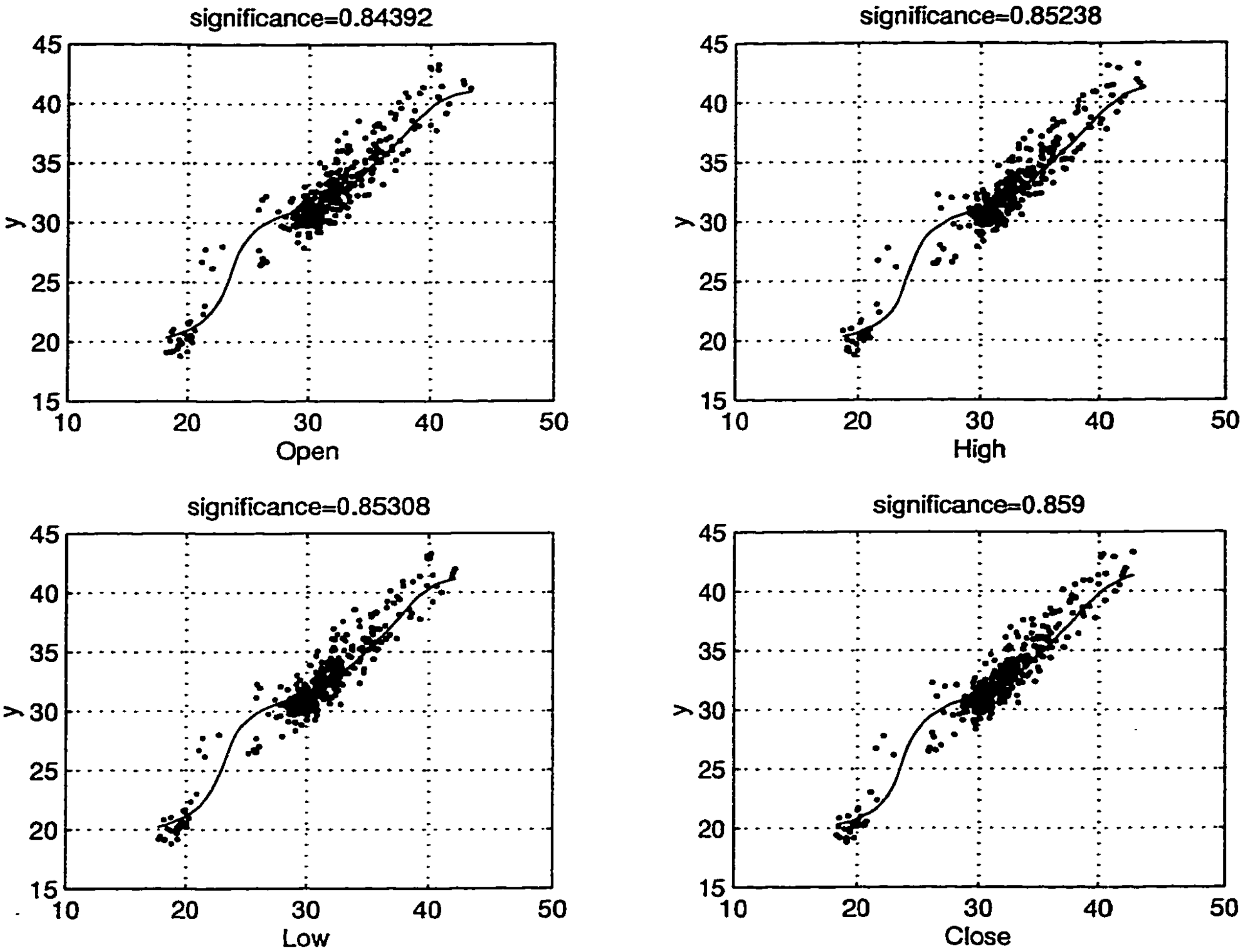

Figure 16: Fuzzy curve for the data price of the third most recent period (t-2)

prices, even from the distant past, are significant inputs and have factual influence on the price movement of the market. However, building a model with a large number of inputs is not practical; therefore, a cutoff point should be determined to restrict the number of inputs. Moreover, Figure 18 on page 59, which show a compression between fuzzy curves of recent past and distant past prices, illustrates that data of recent periods are concentrated, while data of distant periods are scattered around their fuzzy curves, but this observation does not reveal any criteria to determine such

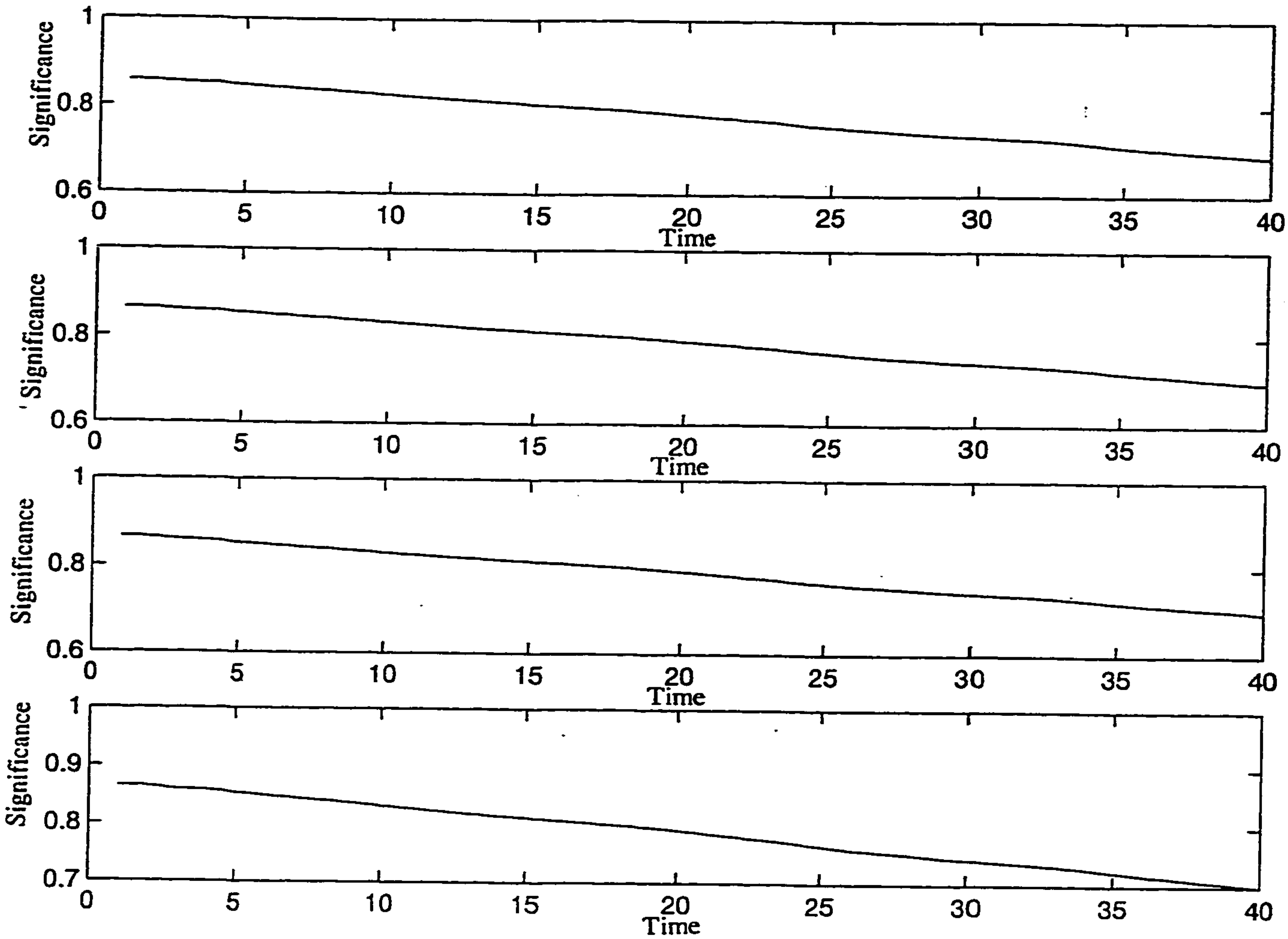

Figure 17: Significance of open, high, low, and close price respectively in the past and distant past periods

cutoff points. However, facts acquired through experiment with candlestick analyses can augment our judgement in order to restrain the number of inputs and determine the cutoff point.

4.5.1 Facts about Candlestick Analysis

As we mentioned in Chapter 2, analyses that can be given by individual candles are not enough to predict future stock price movements. Consequently, data from a single period is not adequate.

In candlestick analysis, to have an accurate perspective of future movement, a sequence of individual candlesticks must be considered. This sequence of individual candlesticks forms a pattern. There are patterns with a single candle line, a double candle line and three or more candle lines. Frequencies of patterns are in reciprocal proportion to the pattern sizes (duration of patterns). The patterns with longer pattern size appear less frequently than the patterns with shorter ones. Through experiments with historical stock data over five and half years (Lee and Jo, 1999) patterns with pattern size one occurred 75% of the time, with size two less than 25%, and with size three about 0.002%.

As we mentioned in Chapter 2, some patterns with size one have different interpretations depending on where they occur. A pattern of size one is called 'Hammer' when it occurs in a downturn market and suggests an upturn move (see Figure 5); the same pattern is called 'Hanging man' when it occurs at the top of an upturn, and suggests a downturn move (see Figure 6). This fact emphasizes that the data of an individual period is not sufficient to give a precise interpretation of the market. This is because one should recognize not only the pattern of size one but also the context in which the pattern occurs. The model should realize that a pattern occurs in an upturn market or a downturn one, so at least the data of two periods should be considered as the system input.

Test results in the same study also show that the relationship between the predicting power and the pattern size is not linear. The patterns with pattern size two have better performance than the ones with pattern size one or three.

Based on the above mentioned observations, considering two periods as inputs should cover more than 99% of patterns which occur in the market. However, as they may be better performance by covering the three-line candlestick, it is tempting to add one more period as the model input.

In this study, inspired by the combination approach, first a model with two periods as inputs was built, then the data prices of a third period were added, but no significant improvement in performance index was observed as a result. On the other hand, elimination of any data price of two most recent periods caused a worse performance index.

Based on the above discussion, data prices of two most recent periods i.e. $t-1$ and t was found to be actual inputs.

Input	Fuzzy Curve	Emami	Fuzzy Curve	Emami
$Open(t)$	0.8811	0.0050	0.8692	0.0050
$High(t)$	0.8793	0.0033	0.8677	0.0033
$Low(t)$	0.8808	0.0038	0.8681	0.0038
$Close(t)$	0.8849	0.0025	0.8725	0.0025
$Open(t-1)$	0.8649	0.0024	0.8517	0.0024
$High(t-1)$	0.8673	0.0026	0.8538	0.0026
$Low(t-1)$	0.8676	0.0023	0.8550	0.0023
$Close(t-1)$	0.8719	0.0021	0.8599	0.0021
$Open(t-2)$	0.8439	0.0024	0.8345	0.0024
$High(t-2)$	0.8524	0.0025	0.8403	0.0025
$Low(t-2)$	0.8531	0.0025	0.8405	0.0025
$Close(t-2)$	0.859	0.0038	0.8443	0.00380

Table 3: Significance and quantitative indices of three most recent periods

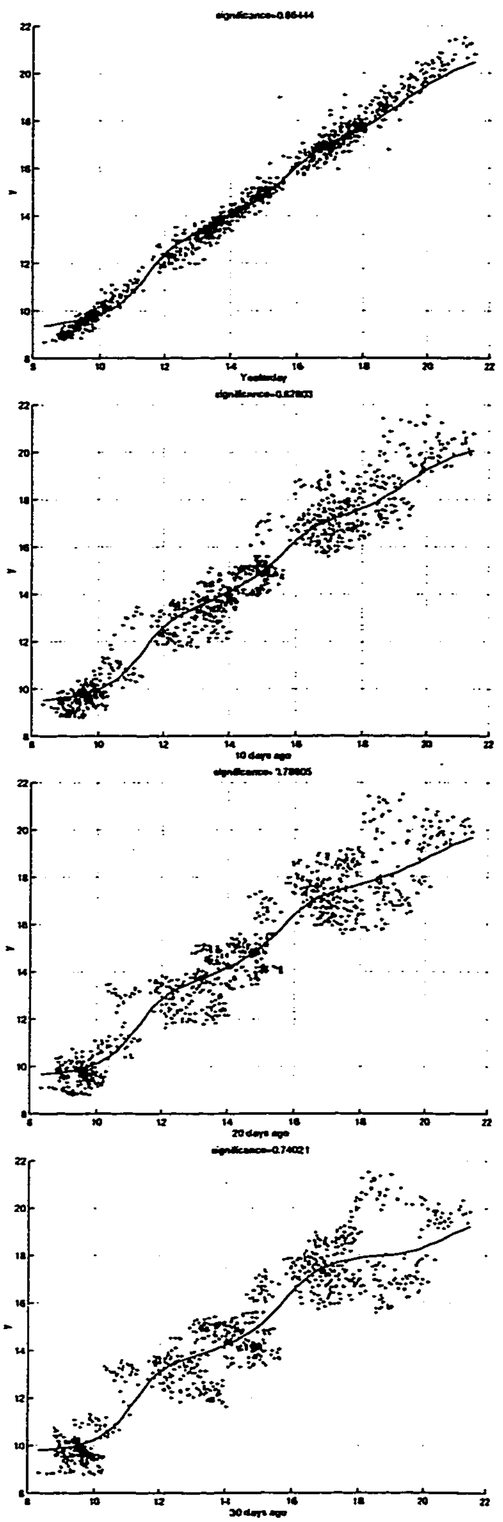

Figure 18: Fuzzy curves of 1, 10, 20, and 30 periods ago

Chapter 5

Experimental Results and Model Validation

5.1 Experimental Results

5.1.1 Short Term Prediction

Input-output data of five different stocks are obtained. Using subtractive clustering, and Sugeno system identification, fuzzy rules are elicited, and employing the obtained rules, the upcoming period is predicted.

Based on the discussion in Section 4.5, the data prices of two most recent periods are inputs of each model, and the open, high, low and close prices of the upcoming period are the output of the model. In practice this MIMO (multi input multi output) model is broken down to four MISO (multi input single output) models: A model with eight inputs and only the open price as output, another model with the same eight inputs but predicting the high price as the output, and so on.

The data prices of a period of 13 months from February 1, 1999 to January 31, 2000 are used as training data, and a set of data points covering the duration of February 1, 2000 to May 30, 2000 are used as testing data.

Since the subtractive clustering is a parametric algorithm, the optimization of the model depends on finding the optimal clustering parameters affecting the clustering method.

In order to find the optimal clustering parameters and select the optimal model, in the first experiment, a parametric search on all clustering parameters has been carried out. For each stock, different values of cluster radius r_a, squash factor η, reject ratio $\underline{\varepsilon}$ and accept ratio $\overline{\varepsilon}$ are examined on their possible range as follows:

$0.1 \leq r_a \leq 1$ step 0.01

$0.2 \leq \eta \leq 2$ step 0.1

$0.1 \leq \overline{\varepsilon} \leq 1$ step 0.1

$0 \leq \underline{\varepsilon} \leq 1$ step 0.05

The best model is selected with respect to the minimum *root mean square (RMS)* on training data. The predicted prices of these models (behavior of the models on testing data set) are found to be faulty and far from the actual prices, showing that the models are overfitting the training data as the error on training data set is minimized. The reason behind this observation, and the issue of overfitting are addressed in Section 5.2.1 that follows.

It is observed that the problem of overfitting usually occurs in the models with the excessive number of rules, because, as the number of rules increases, fuzzy rules reduce to rules with crisp antecedents rather than fuzzy ones, and consequently these rules lose their generalization ability. Therefore, one solution to avoid overfitting could be to consider the training error in conjunction with the number of rules. Table 4 shows the results of one experiment based on this approach. This table depicts the best 1 rule model up to the best 20 rules model, which were found in an enumerative search on the entire range of model parameters. A model with the acceptable number of rules and small training RMS should be selected as the best model in this approach.

Although, the problem of overfitting can be avoided by this approach, this method is somewhat problematic because it is extremely time consuming and suffer from lack of a criterion to specify the acceptable number of rules *a priori*.

As an alternative approach, a well-studied method of model selection is utilized (Devroye, *el al.*, 1996). In this method a new set of data, which is usually called *checking data* or *validation data set* is considered, and model parameters are selected associated with the minimum error on validation data (not training data).

r_a	η	$\bar{\varepsilon}$	$\underline{\varepsilon}$	Testing RMS	Training RMS	Number of Rules
0.7	1.1	0.4	0.4	0.3456	0.3324	1
0.77	1.2	0.3	0.2	0.3411	0.3247	2
0.24	0.5	0.6	0.6	0.366	0.3173	3
0.1	0.8	0.6	0.7	0.3679	0.3111	4
0.76	0.5	0.3	0.3	0.3501	0.3071	5
0.77	0.5	0.3	0.2	0.3949	0.2921	6
0.94	0.5	0.2	0	0.4147	0.2841	7
0.96	0.5	0.2	0	0.4339	0.2766	8
0.75	0.5	0.2	0.2	0.4599	0.2743	9
0.75	0.5	0.2	0	0.5211	0.2668	10
0.96	0.5	0.1	0	0.6473	0.2554	11
0.74	0.6	0.1	0	0.5908	0.256	12
0.72	0.6	0.1	0	0.5139	0.2459	13
0.77	0.5	0.1	0	0.5176	0.211	14
0.72	0.5	0.1	0	0.7429	0.2326	15
0.1	0.6	0.5	0.2	1.1352	0.2415	16
0.1	0.5	0.6	0.2	1.9264	0.2394	17
0.1	0.9	0.4	0.1	4.3394	0.2033	18
0.1	0.8	0.5	0.1	4.0523	0.1923	19
0.13	0.5	0.4	0.2	5.0796	0.176	20

Table 4: Comparison of models with respect to the number of rules

To apply this method an additional data set covering a duration of one month from February 1, 2000 to February 29, 2000 is defined as validation data. Testing data are considered from March 1, 2000 to June 30, 2000 and the best model is selected with respect to the minimum RMS on validation data.

Testing all possible model parameters i.e. r_a, η, $\bar{\varepsilon}$ and $\underline{\varepsilon}$, in order to find the best model is prohibitively time consuming, and requires much effort in order to arrive at the optimal combination of model parameters. However, experiments with different stocks, show that the best model can always be achieved by setting η, $\bar{\varepsilon}$, and $\underline{\varepsilon}$ to reasonable values and changing just the cluster radius i.e. r_a.

For instance, the best model for stock A and B could be obtained with the following model parameters:

Stock A	Stock B
$1 \leq \eta \leq 2$	$1 \leq \eta \leq 2$
$0.5 \leq \bar{\varepsilon} \leq 1$	$0.4 \leq \bar{\varepsilon} \leq 1$
$0.1 \leq \underline{\varepsilon} \leq 0.5$	$0.1 \leq \underline{\varepsilon} \leq 0.4$

These results can be interpreted by considering the fact that, small η will cause the obtaining of closely spaced clusters, and the generating of a rule from a single point. Small accept ratio and large reject ratio also have the same effect and lead to a faulty model which may show a good performance on training data but fail to model new data points. Therefore, to arrive at a good model, squash factor should be set greater than 1, a small value should be selected for reject ratio, and accept ratio must be chosen greater than reject ratio. This is consistent with the Chiu suggestion (Chiu, 1994) for clustering parameters which is:

$\eta = 1.25$

$\bar{\varepsilon} = 0.5$

$\underline{\varepsilon} = 0.15$

Based on this discussion, in this study, the above mentioned combination of model parameters is fixed, and in order to identify the models only different values of r_a are examined. r_a ranges from 0.1 to 1 which means the cluster radius varies from 0.1

to 1 times the width of the data hypercube. In this approach r_a is an approximate specification of the desired resolution of the model. Table 5 shows the best 10 models in order to predict the open price of stock A through this approach. The model specified by $r_a = 0.87$ is selected as the best model. This model creates 3 clusters and consequently 3 rules as shown in Figure 19.

r_a	η	$\bar{\varepsilon}$	$\underline{\varepsilon}$	Testing RMS	Training RMS	Validation RMS	Number of Rules
0.87	1.25	0.5	0.15	0.3375	0.3185	0.2314	3
0.88	1.25	0.5	0.15	0.3376	0.3185	0.2316	3
0.89	1.25	0.5	0.15	0.3376	0.3185	0.2319	3
0.9	1.25	0.5	0.15	0.3377	0.3185	0.2321	3
0.91	1.25	0.5	0.15	0.3377	0.3184	0.2323	3
0.92	1.25	0.5	0.15	0.3377	0.3184	0.2325	3
0.93	1.25	0.5	0.15	0.3378	0.3184	0.2326	3
0.94	1.25	0.5	0.15	0.3379	0.3183	0.233	3
0.95	1.25	0.5	0.15	0.3379	0.3183	0.2332	3
0.96	1.25	0.5	0.15	0.338	0.3183	0.2333	3

Table 5: Comparison of models with respect to the minimum RMS on the validation data

Figures 20 through 23 show a selection of actual and predicted prices of stocks A, B, C, D, and E obtained by the above mentioned model parameters. The complete predicted results of the open, high, low and close price for these stocks are illustrated in Appendix A and the models RMS and hit ratio are summarized in Table 6. In all figures the solid line represents actual price and the dashed line shows predicted price.

Appendix B contains the data price for the above mentioned stocks.

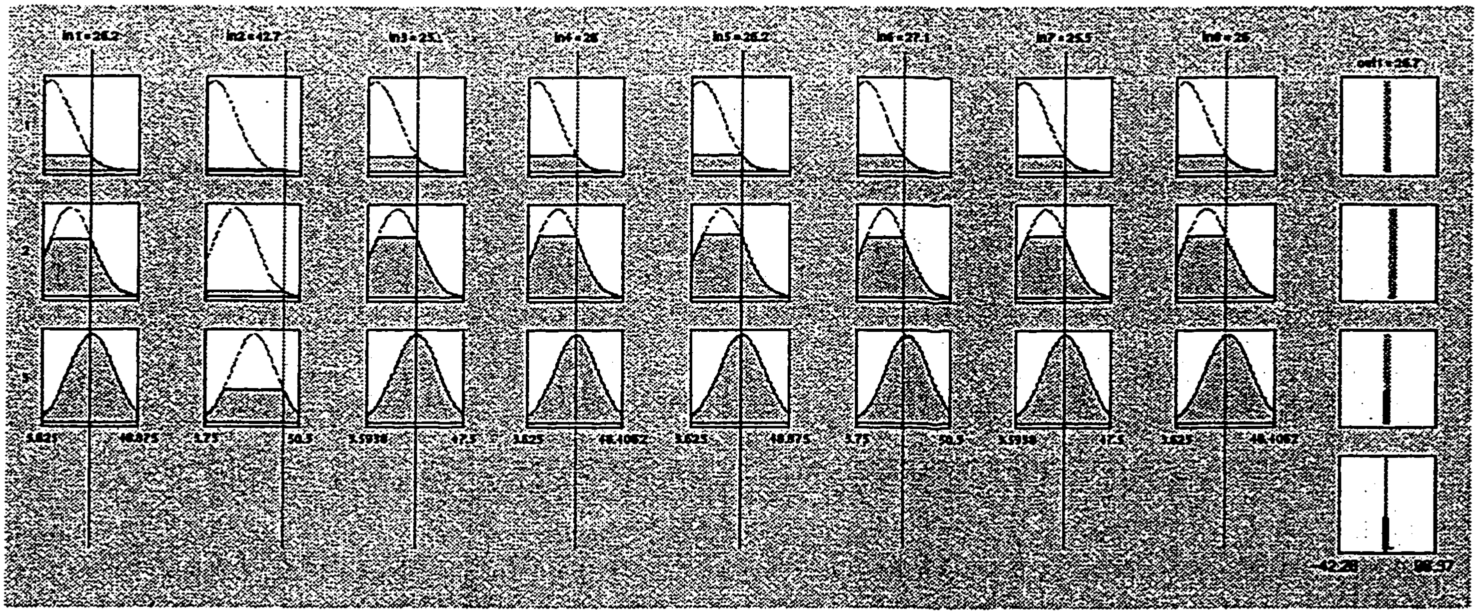

Figure 19: Instance of rules elicited by model

Good performance of the models can be seen; however, the notion of model performance will be discussed in detail in Section 5.2.3.

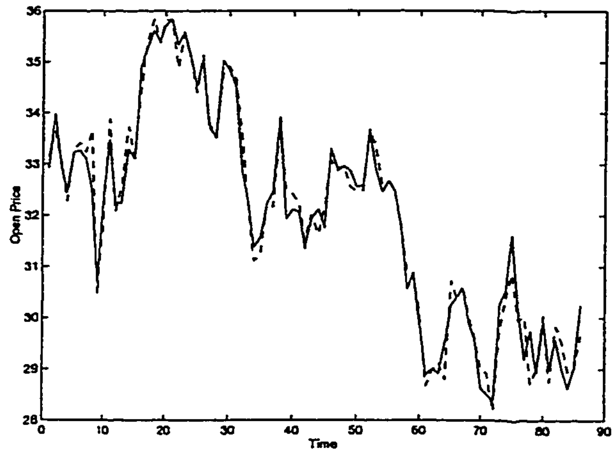

Figure 20: Open price prediction of stock A

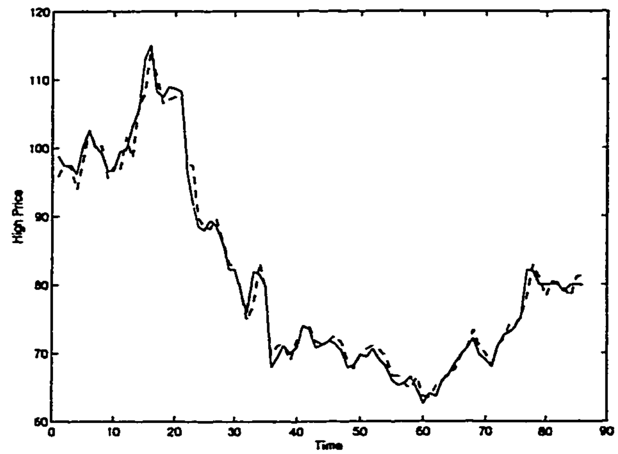

Figure 21: High price prediction of stock B

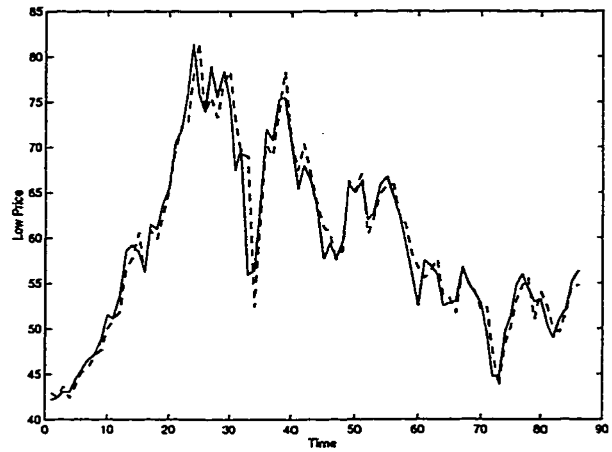

Figure 22: Low price prediction of stock C

5.1.2 Long Term Prediction

Candlestick analysis simply says, stock market prices do not follow random walks, there are certain patterns which occur frequently, and when a pattern is detected, the next market step can be predicted. In other words, when the duration of $t-1$ and t form a certain pattern, a determinate movement can be expected in the period of $t+1$. Candlestick analysis is not restricted to a specific duration. A pattern

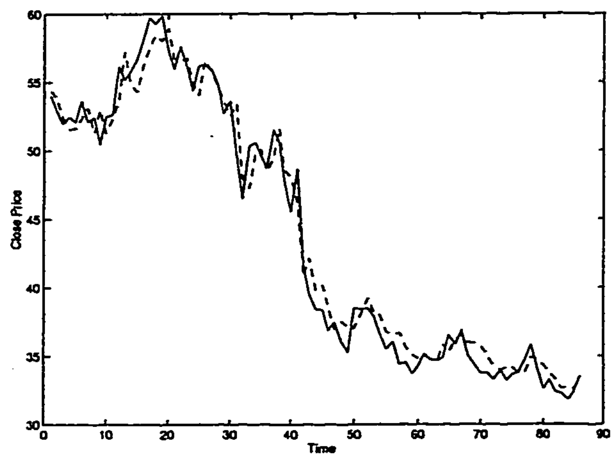

Figure 23: Close price prediction of stock D

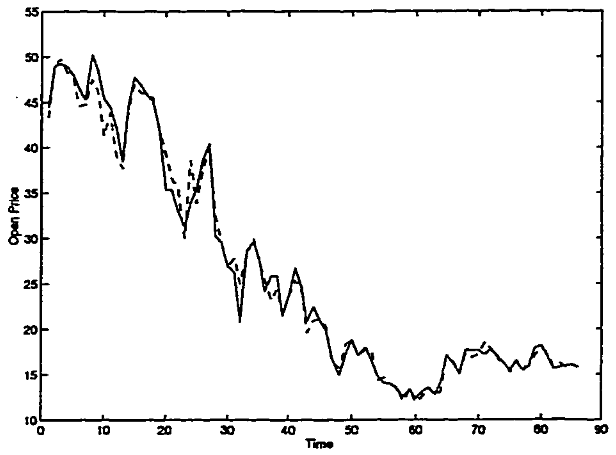

Figure 24: Open price prediction of stock E

appearing in two consecutive days, implies a determined tendency of the market in the upcoming day. If the same pattern occurs in the two consecutive months, the same tendency could be expected in the upcoming month. As a result, theoretically, candlestick analysis is capable of predicting the middle and long term movements of the market.

Since our model uses the same data and concept as candlestick analysis, the same strength is hoped for. Figures 25 and 26 are evidence which confirms such expectation.

	Open		High		Low		Close	
Stock	*RMS*	*HR*	*RMS*	*HR*	*RMS*	*HR*	*RMS*	*HR*
A	0.34	0.95	0.57	0.85	0.52	0.85	0.85	0.69
B	2.18	1	1.53	0.70	1.36	0.65	2.35	0.62
C	1.34	0.83	1.99	0.79	2.27	0.90	3.39	0.64
D	1.03	0.75	0.84	0.66	0.87	0.70	1.35	0.76
E	1.33	0.84	1.46	0.85	1.90	0.69	2.33	0.70
Average	1.24	0.87	1.28	0.77	1.38	0.76	2.05	0.68

Table 6: RMS and hit ratio of stock price prediction models

These figures show the weekly and monthly predictions by the models built in the previous section for stock A.

In this experiment we did not use new data to train the models. In other words, the model that is trained by daily data price is used to predict the price in upcoming weeks, and months. For example, when the data prices of two consecutive days are used as inputs, the output of the model is the price of the upcoming day, while the data prices of two consecutive weeks as inputs imply the price of the next week as output, and so on.

Good performance of weekly and monthly prediction of the model is illustrated in the following figures(Figure 25 and Figure 26).

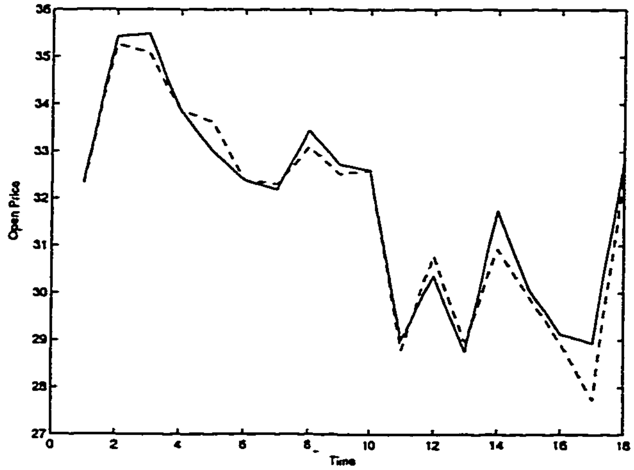

Figure 25: Weekly prediction of stock A

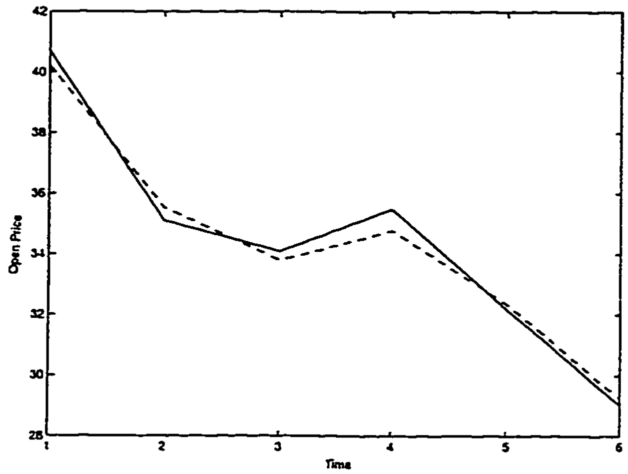

Figure 26: Monthly prediction of stock A

5.1.3 Dynamic Model

A model with the fixed training data set is static, and can be made purposeless with the passing of time. There is always the chance of new features and characteristic appearances in new data. Moreover, new data makes past periods less influential, and not incorporating new data into the training set makes the system ineffective as time passes.

To resolve this problem, we change the training data dynamically. In this approach, new data will be added to both the training data and validation data sets, and the oldest data points will be removed. Next, parameter optimization will be done, and the upcoming period will be predicted via the updated model.

Applying this approach to stock A and B leads to a slightly improved model, However the improvement in a short period may not be considerable. In the duration of three months testing data, a dynamic model which predict the open price, shows about 10% improvement in RMS and 2% of growth in hit ratio. The same experiment in the duration of 10 months training data shows about 15% improvement in RMS and 6% growth in hit ratio in comparison with the static models (see Table 6).

5.1.4 Generalizable Model

The candlestick chart is time independent and field independent, which means it can be applied regardless of particular time and industrial fields, and a pattern appearing in a stock price movement determines its future movement, regardless of the particular stock in which this pattern occurs (Lee and Jo, 1999).

Our model inherits the same features, and this is the most valued strength of this model. Through experiments with four stocks over one time period, it is observed that rules that drawn from a particular set of examples are independent of those examples, and can be generalized and applied to other stocks. Figures 27 through

30 present three-dimensional curves that represent the mapping from *close*(t) (inp8), and *open*(t) (inp5) to *open*($t+1$) (output) for stock A, C, D, and E respectively. Surprisingly, all of them convey the same relation between inputs and the output, and one can be reduced to the others only by a simple scaling. In other words, if, for instance, the data price of stock C are scaled into the range of price of stock A, then the rule that is elicited from A data price can be applied to stock C, and the model trained for stock A can be used to predict stock C.

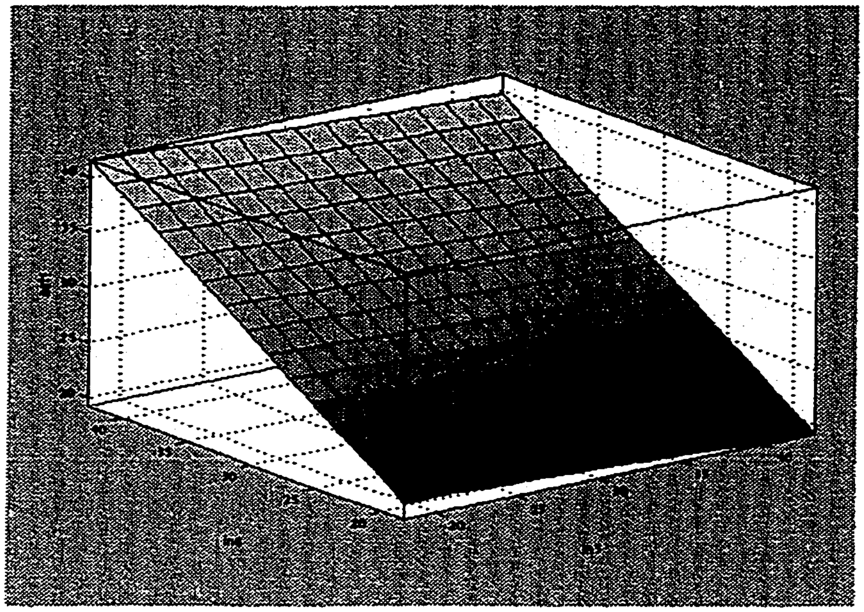

Figure 27: Mapping of *open*(t) and *close*(t) to *open*($t+1$) in stock A

In order to investigate the validity of such expectations, first, data prices of an individual stock should be normalized in a specific range. It is hoped that the model trained by these data prices, will be able to predict the movement of another stock, when input data of the new stock are also normalized in the same range.

Our study confirms such expectations, at least for the four stocks that we studied.

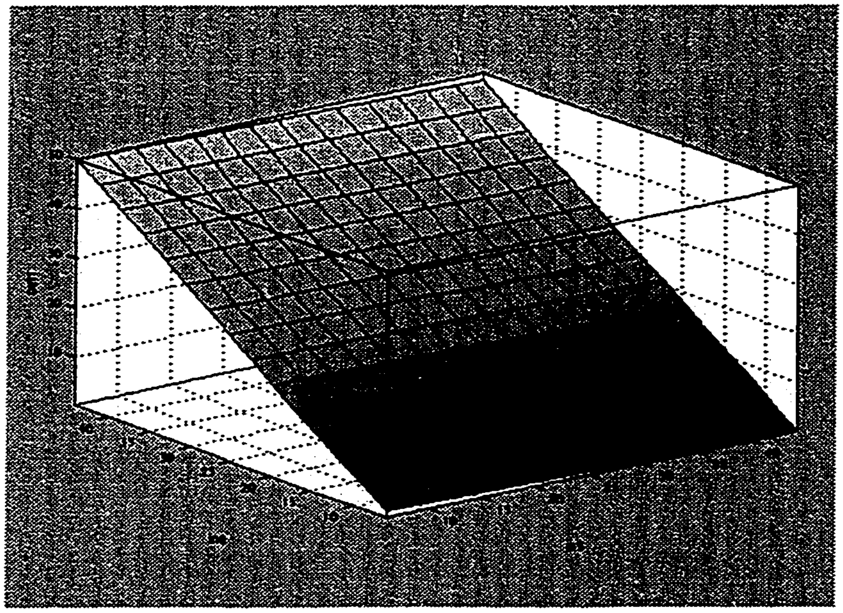

Figure 28: Mapping of *open*(t) and *close*(t) to *open*$(t+1)$ in stock C

Figure 31 shows the prediction of stock B by a model trained for stock A. The same model is employed to predict stock C, and D as illustrated in Figure 32, and 33.

The only problem regarding such a general model is finding a training data set, such that the data set represents all the necessary patterns which may occur in the stock movements.

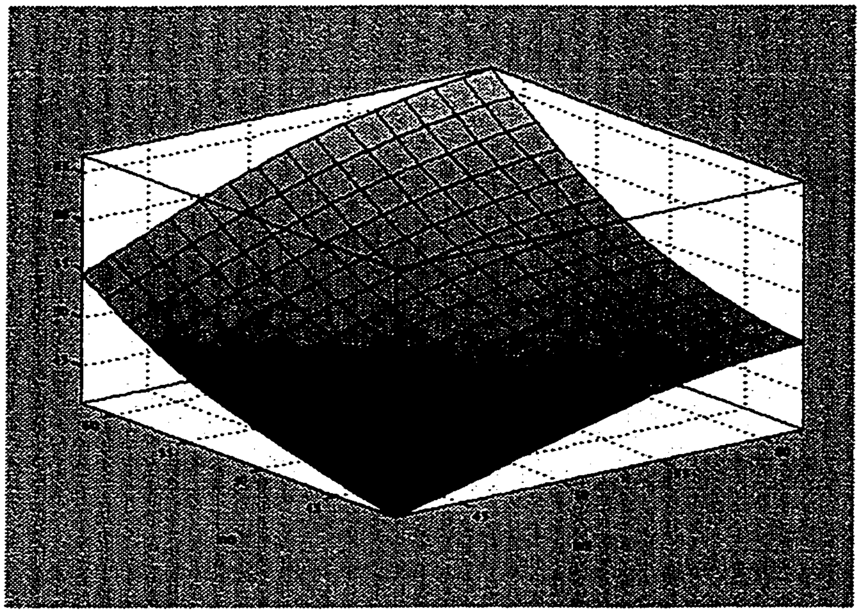

Figure 29: Mapping of $open(t)$ and $close(t)$ to $open(t+1)$ in stock D

5.2 Model Validation

5.2.1 Overfitting Effect

Fuzzy system identification is a parameterized model. One problem with model validation is selecting parameters that show good performance both on training and testing data. In principle, a model is selected to have parameters associated with the maximum performance.

Not surprisingly, the model does not have quite as good performance on the testing data as on the training data. When RMS is the performance index, a zero-error model on training data can always be achieved. However, training-RMS and testing-RMS do not demonstrate a linear relationship. In other words, the smaller values of training

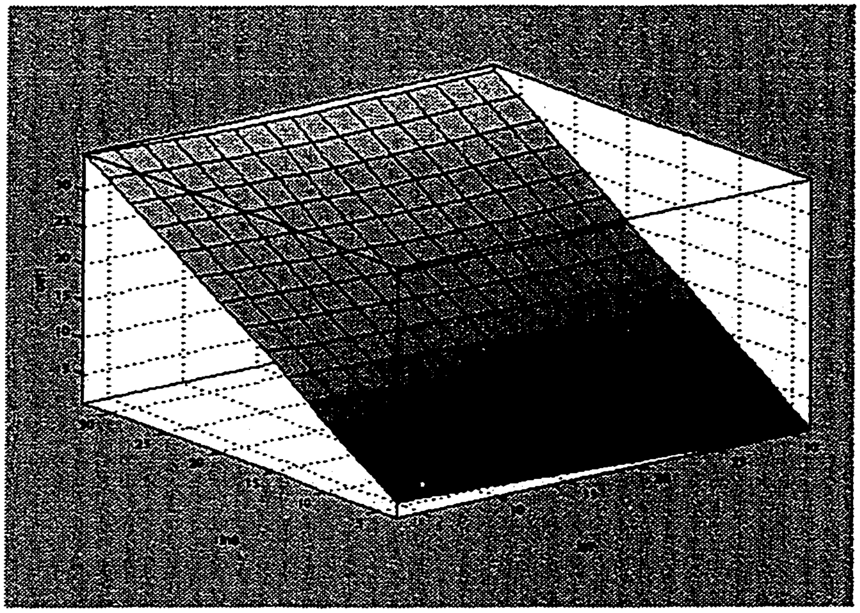

Figure 30: Mapping of *open*(t) and *close*(t) to *open*$(t+1)$ in stock E

data error do not result in the smaller values of testing data error. In practice, up to a certain point, the model error for the testing data set tends to decrease as the training error decreases. After that, attempts to decrease training error make an unexpected increase in error on testing data error. It is shown in Figure 34 on page 77, where the solid line is training error, and the dashed line is testing error.

The basic justification behind this observation is that in the process of minimizing training error, after a certain point, the model begins overfitting the training data set. Overfitting means fitting the model to training data at the cost of losing generality. In the extreme form, a set of n training data points can be modeled with n rules. Such a model follows the training data perfectly. However, these rules are not representative features of the data collections, and that's why they fail to correctly model new data points.

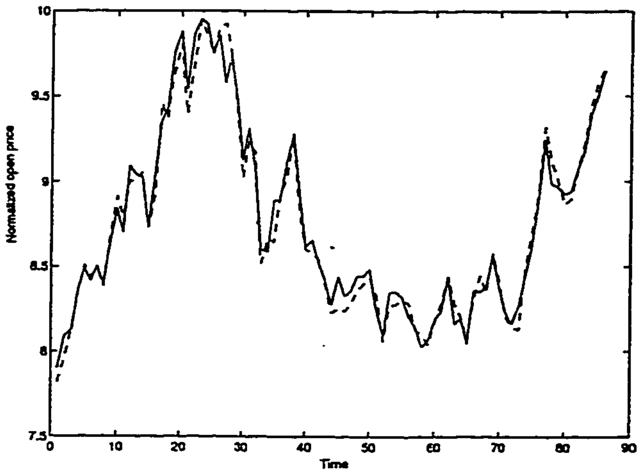

Figure 31: Prediction of B by model A

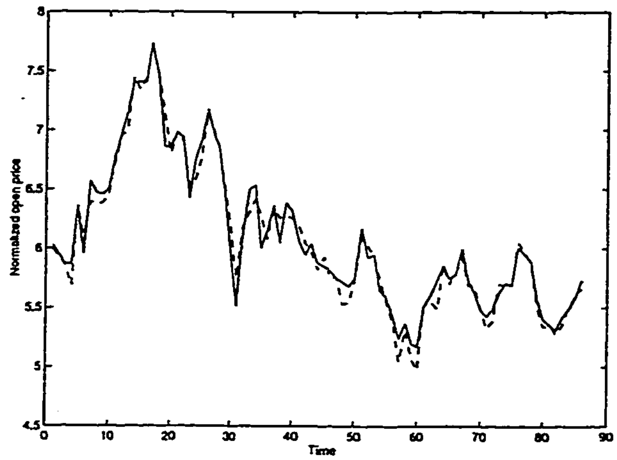

Figure 32: Prediction of C by model A

To avoid overfitting it is essential to use a validation data set which is not known for the model. The optimum model parameters should be selected to have the best performance index associated with this data set which is not necessarily the best performance index associated with the training data set.

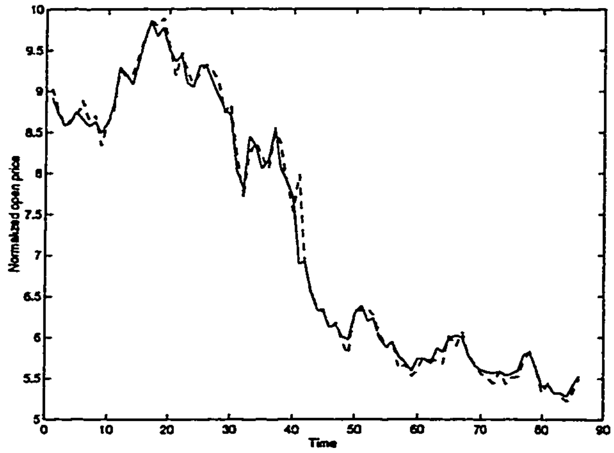

Figure 33: Prediction of D by model A

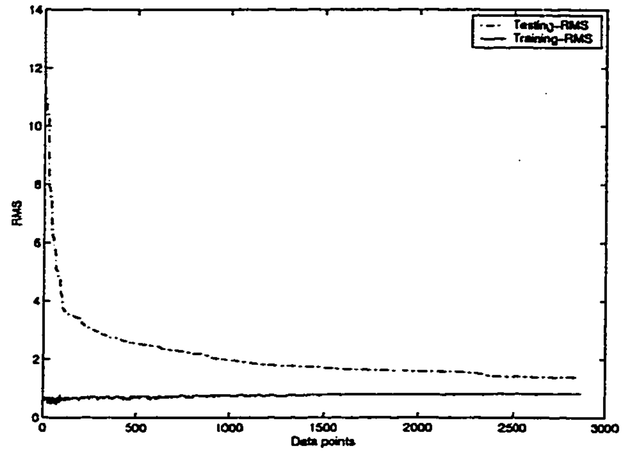

Figure 34: Training and testing error

5.2.2 Length of Training Data

Another problem with model validation is deciding on the length of the training data set, such that the data set represents all the necessary features which determine data movement behavior. If a large amount of data is collected, hopefully this data will represent all necessary features. However, it may incorporate irrelevant characteristics and rules in the model. In our study, accuracy of a model of stock A was compared with two different sets of training data. Model 1 was trained with 10 years data price, and model 2 with that of one year. Both models predicted open price for a duration of three months. The best RMS and hit ratio for Model 1 were found to be 0.48 and 0.91 respectively, while Model 2 showed a better RMS equal to 0.34 and a better hit ratio equal to 0.95. The reason behind this observation is that data from the distant past have no influence on current movements, and considering them among training data could lead to a faulty model of the system.

On the other hand, using a short amount of data runs the risk of resulting in a lack of necessary features.

In the case of the stock market, Fosback (Fosback, 1976) has proven that there is a strong upward bias to prices before holidays and at the end of each month. Moreover, he has shown that special occasions such as New Year cause dramatic movements in stocks. This is what is often called *the holiday effect.*

Based on the above discussion, and taking 'the holiday effect' into consideration, we considered a duration of 13 months as the training data. A duration of 12 months seems to be the lower bound of a reasonable training duration.

5.2.3 Performance

For any modeling method, it is essential to define performance criteria, and to indicate how performance of the model will be measured. The performance measurement traditionally involves calculation of errors between the actual and the model result. Some of the traditional performance measurements are listed below:

Let:

m_i : the model result

a_i: the actual value

n: the total number of data points

1. MSE : Mean Squared Error

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(a_i - m_i)^2$$

MSE represents the total squared error over n data points.

2. RMS : Root Mean Squared Error

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - m_i)^2}$$

3. MAE : Mean Absolute Error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|a_i - m_i|$$

MAE averages absolute error value over n points.

4. $MAPE$: Mean Absolute Percent Error

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|a_i - p_i|}{|a_i|}$$

5. HR : Hit Ratio

$$HR = \frac{1}{n}\sum_{i=1}^{n} d_i$$

where d_i is equal to 1 if $(a_i - a_{i-1})(m_i - m_{i-1}) > 0$, and is 0 otherwise.

Among them the root mean square (RMS) error is the most popular criterion. The $MAPE$ is another favorite one. However, both of them show a poor validity, both in our application and generally in financial forecasting techniques (Armstrang and Collopy, 1992).

Obviously, in any trading system the main goal is the profitability of the system. More profitable prediction is better prediction, even if it has less accuracy. As Deboeck (Deboeck, 1992) reported, a neural network that correctly predicted the next-day direction 85% of the time, consistently lost money. This was because, although the system correctly predicted market direction when the moves were small, it was wrong on almost every large move, and since transaction costs made the small moves unprofitable, the system was not tradable.

To investigate the relation between accuracy and profit of a system, a simple but very popular trading strategy was studied. This strategy, which is referred to as moving average, or 'buy low sell high', simply suggests that traders sell whenever the price climbs above its moving average, and buy when it drops below. Since the proposed model in this study is able to predict low and high prices, instead of using moving average, the low and high price predictions are used to buy and sell. To be on the safe side, 1% of difference between predicted high and predicted low is calculated as the safety margin. Our system buys when the price drops below the predicted low plus the safety margin, and sells when it climbs above the predicted high minus the safety margin. The relation between profit that is gained through this strategy, and the maximum profit which can be gained (corresponds to actual low and high), is measured as trading performance. We call this new performance index PR.

$$PR = \frac{actual \;\; profit}{maximum \;\; profit}$$

To clarify this, actual and predicted price and profit of a duration of five days for stock B is summarized in Table 7. Figure 35 shows PR, HR, and RMS of a testing data set covering three months of stock B. For a large value of RMS, PR is zero or negative. For a reasonable value of RMS, however, no linear relation can be found between PR, HR and RMS. A smaller value of RMS does not necessarily correspond to a better HR or improved PR.

However, there might be a nonlinear relation between them. To investigate the existence of such a relation, we attempted to build a model that takes RMS and HR as inputs and yields the PR as the output. Although the significance test by the fuzzy curve method showed RMS and HR could be influential inputs of such a system, attempts to train the model in order to estimate PR with new RMS, and

High	Low	Maximum Profit	Predicted High	Predicted Low	Safety Margin	Buy	Sell	Actual Profit	PR
48.75	44.44	4.31	48.39	45.55	3%	45.58	48.36	2.78	0.65
48.00	44.50	3.50	45.76	42.58	3%	0	0	0	0
46.56	41.63	4.94	44.96	41.76	3%	41.79	44.93	3.14	0.64
43.13	37.00	6.13	41.26	38.10	3%	38.13	41.23	3.10	0.51
39.75	35.25	4.50	36.73	33.05	4%	0	0	0	0
36.41	31.75	4.66	36.16	33.17	3%	33.20	36.13	2.93	0.63

Table 7: Maximum profit, actual profit, and PR

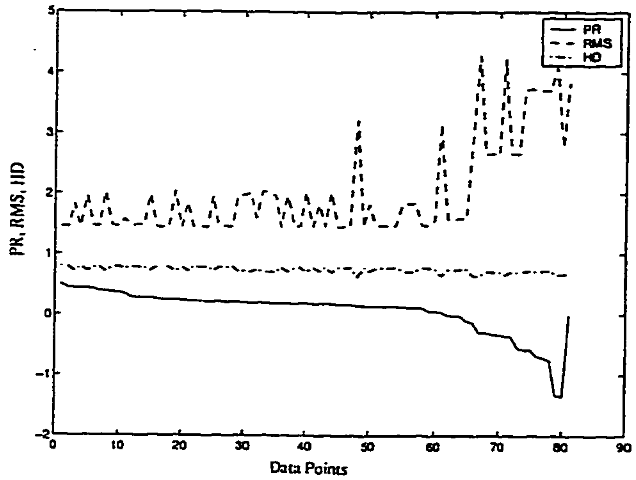

Figure 35: PR, HR, and RMS of stock B

HR were not successful. We can interpret these results as meaning that, RMS and HR are actual and maybe necessary but not sufficient inputs to determine PR.

A convincing explanation is this: Suppose in case A our model predicts the low price below the actual low, and the high price above the actual high, and in case B vice versa, namely the low price above the actual low and the high price below the actual high. RMS and HR in both cases could be equal. However, a trader will lose money in case A and gain money in case B.

There are two lessons to be learned from this. First, standard performance indices such as RMS and HR are poor indicators for trading systems. Second, it is essential to measure the model performance based on the trading strategy associated with the model.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

A subtractive clustering based fuzzy system identification method and the Sugeno type reasoning mechanism are used for stock price prediction. The major concern is to develop a model that can predict future events by taking samples of past events.

Inspired by the key information that the candlestick analysis uses, it is assumed that everything that impacts a market, from economic factors to politics and even trader's beliefs, is distilled down into price. Similar to candlestick analysis, prices of previous sessions of the market are taken as the potential inputs. Different input selection methods are applied to potential inputs, and prices of two most recent periods are found as the most influential inputs. Short term and long term prediction are examined. It is observed that a model which is trained by daily market price data, is capable of being used as a weekly or monthly predictor. Since there is always the chance of new features and characteristic appearance in new data, a model with dynamic training data is introduced. In this model, new data will be added to training data set and the oldest data points will be removed to avoid having an ineffective model as time passes. Through experiments with four stocks over one time period, it is observed that our model inherits the field independent candlestick chart. For the four stocks that we studied, rules that are drawn from a particular stock are independent of that stock, and can be generalized and applied to other stocks. These experiments suggest that our model probably can be used regardless of particular time and industrial fields, and this is the most valued strength of this model. However, to establish this, extra experiments with more stocks must be conducted. Different performance indices are discussed, and it is shown that it is essential to measure the trading model performance based on the trading strategy associated with the model. However, the traditional performance indices are measured for the model. As far as hit ratio is concerned as the performance index, the model shows a very good performance. Our model shows an average hit ratio of 87% in the open prediction, and 76%, 75%, and 67% in the high, low and close prediction respectively (see Table 6).

The main contribution of this thesis is integrating fuzzy modeling and candlestick chart analysis in order to predict the stock price. Candlestick chart analysis is a well-studied method in the area of stock market prediction (Lee and Jo, 1999 ; Chu and Kim, 1993), but it is very difficult to use. To use candlestick chart analysis, one has to:

1. Observe the candlestick patterns which occur frequently in the historical data price.
2. Determine the relation between patterns and the future price movements which is a heuristic knowledge and differs from expert to expert.
3. Evaluate accuracy of the relationship between patterns and the future price movements which is defined by expert's heuristic knowledge.
4. Recognize the patterns in the desired stock data price, and apply its interpretation to the data price in order to predict the future price movement.

Obviously this is a subjective approach. In the other words the whole process depends on the expert's heuristic knowledge which sometimes is not trustworthy enough, and should be evaluated.

Recognizing the patterns is another aspect which requires much effort. Taking this fact into consideration that, a pattern with a long duration, could be constructed by small sub-patterns, and such sub-patterns losing their own meaning, illustrate the complexity of pattern recognition in candlestick chart analysis. The following example illustrates the intricacy of pattern recognition in candlestick analysis.

The *Bullish Harami* pattern composed of a *Big Black* and a white pattern as sub-patterns. A Big Black pattern has a Black pattern as its own sub-pattern. The Bullish Harami pattern implies a rising signal which is different from the meaning of its sub-pattern: Big Black, which implies a falling signal.

It deserves mention that in spite of all these efforts, candlestick analysis can only be used to predict the general tendency of the market which are raising, or falling tendency but can not be used to predict the price.

The model, founded by integration of fuzzy modeling and candlestick analysis in this study, inherits all the advantages of candlestick analysis, but not such less desirable features.

The model is an objective model which can be built and used in the absence of experts. In the other words, rules which governs the market are elicited from raw data automatically, and without having any heuristic knowledge about the market. Moreover, the representation of elicited rules obviates the need of pattern recognition and all the problems associated with that.

Disengaged from the stock price prediction, the model presented in this study contributes a new feature to the conventional fuzzy models. Conventional fuzzy models can be used only under the same conditions as training conditions, but our model is independent from data training features. Our experiments suggest that, a model, which has been trained by daily data price of one stock, can be utilized for weekly and monthly prediction. Furthermore, it can be generalized and be applied to other stocks.

In comparison, we can compare our model with a candlestick analysis based model developed by Lee and Jo (Lee and Jo, 1999). In their model, several aspects, such as recognition of patterns, formulization of pattern definition, rule generation based on the patterns, performance evaluation of the rules, have to be considered, which requires much effort in order to arrive at the optimal model. Moreover, it requires *a priori* knowledge about the market and is impossible to build in the absence of experts and *a priori* knowledge. In our model all of these steps are done automatically, and without any *a priori* knowledge of the market, but only with historical stock data price. The success of this model is evidence that, it is possible to use *soft computing* [1] techniques with a low degree of computational complexity to circumvent the complexity and limitation of traditional approaches.

6.2 Future Work

There are several promising areas for future work. The first promising area involves developing a less accurate (greater RMS) but more profitable model. As is mentioned in Section 5.2.3: a conservative prediction which predicts the low price above

[1] The term soft computing was coined by Zadeh (Zadeh, 1994) for methods that, in term of calculation effort, find imprecise or uncertain solutions at a much lower cost than traditional methods. These include: Fuzzy logic, neural networks, and probabilistic reasoning.

the actual low, and the high price below the actual high, has more chance to be profitable. In Sugeno system identification, rules are elicited through solving the following equation by the least square method (see Chapter 3).

$$P = (A^T A)^{-1} A^T Y$$

A model which solves this equation minimizing positive accumulation error in order to predict the low price and minimizing negative accumulation error to predict the high price, could be a less accurate but possibly more profitable model.

The second avenue concerns the investigation of technical market indicators in order to determine their influence on stock price. It would help to build a model with a selection of inputs which have the most influential effect on the market movements. Three authors (Zweig, 1986; Fosback, 1976; Colby and Myers, 1988) have tested a large number of technical market indicators. However, their methods are rather outdated. The same test could be conducted by the new approach of input selection discussed in Chapter 4 of this thesis.

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Appendix A

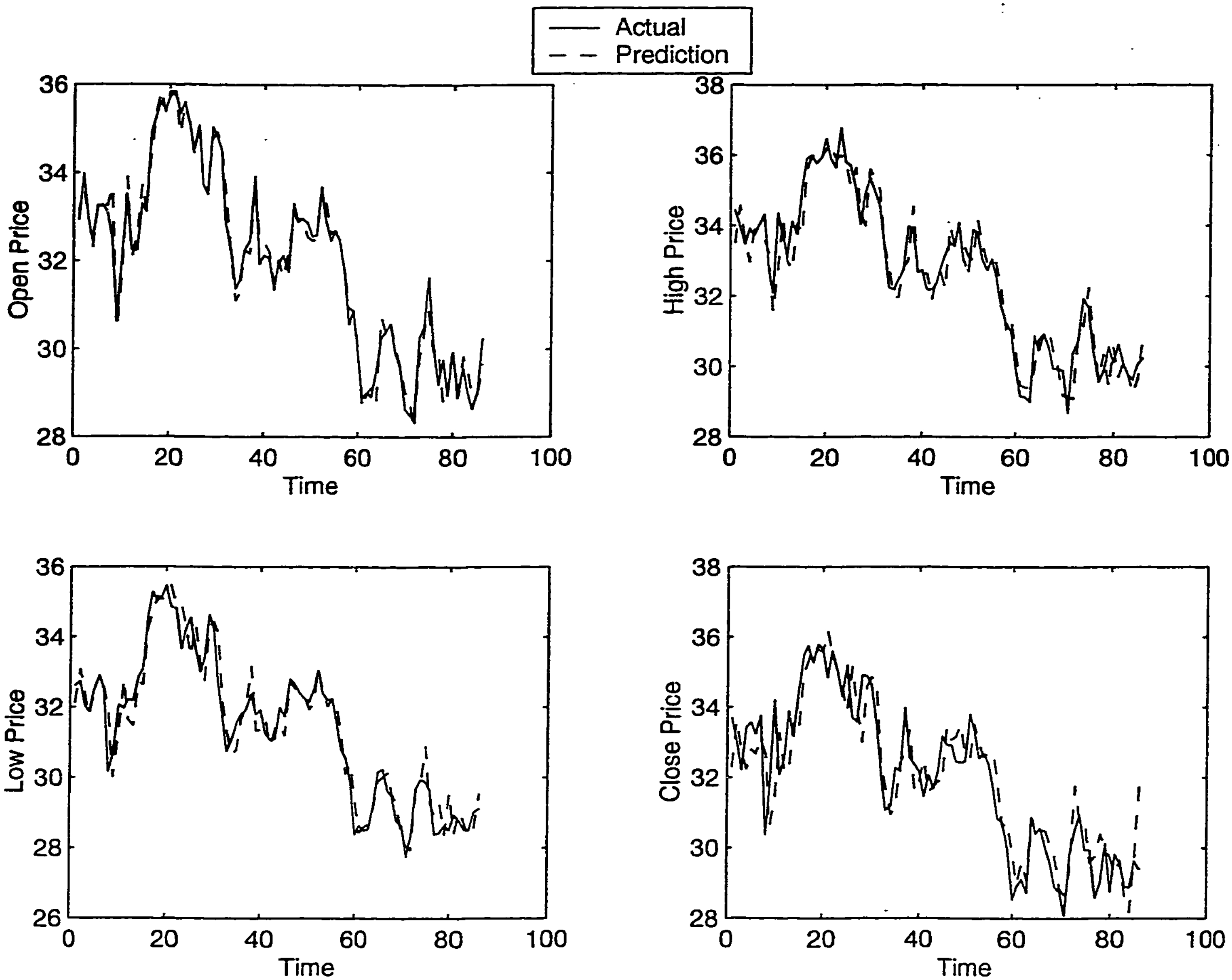

Figure 36: Prediction of stock A

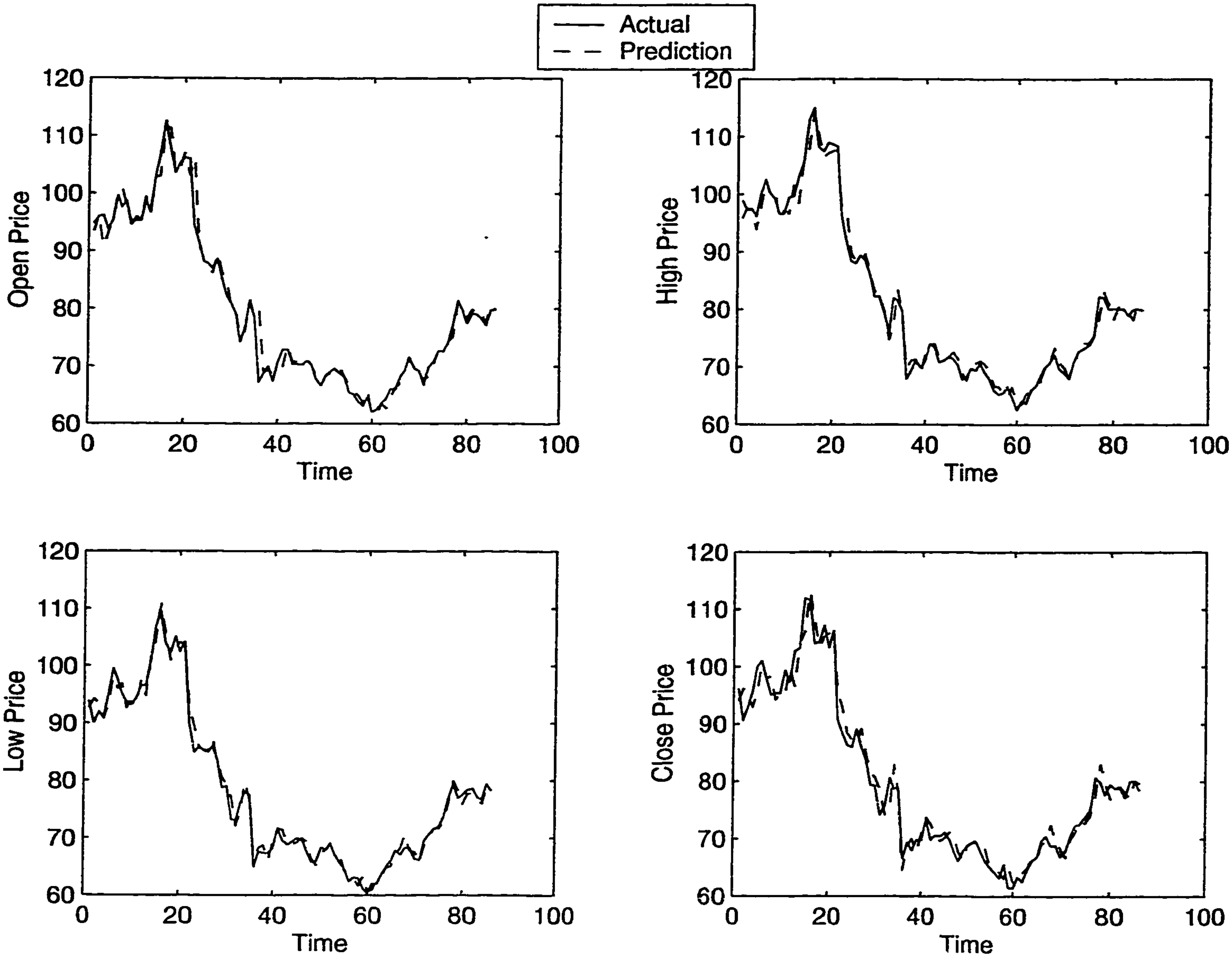

Figure 37: Prediction of stock B

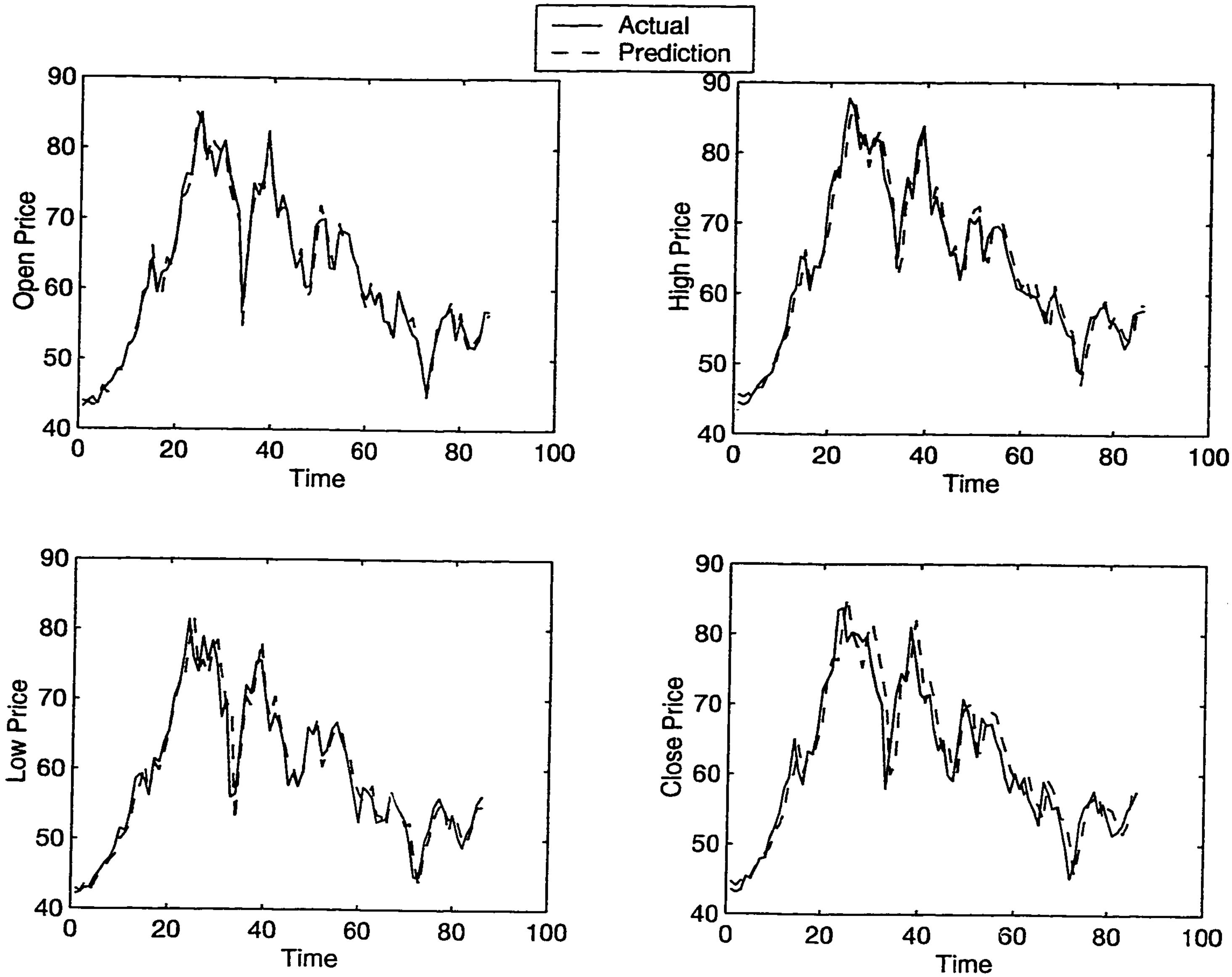

Figure 38: Prediction of stock C

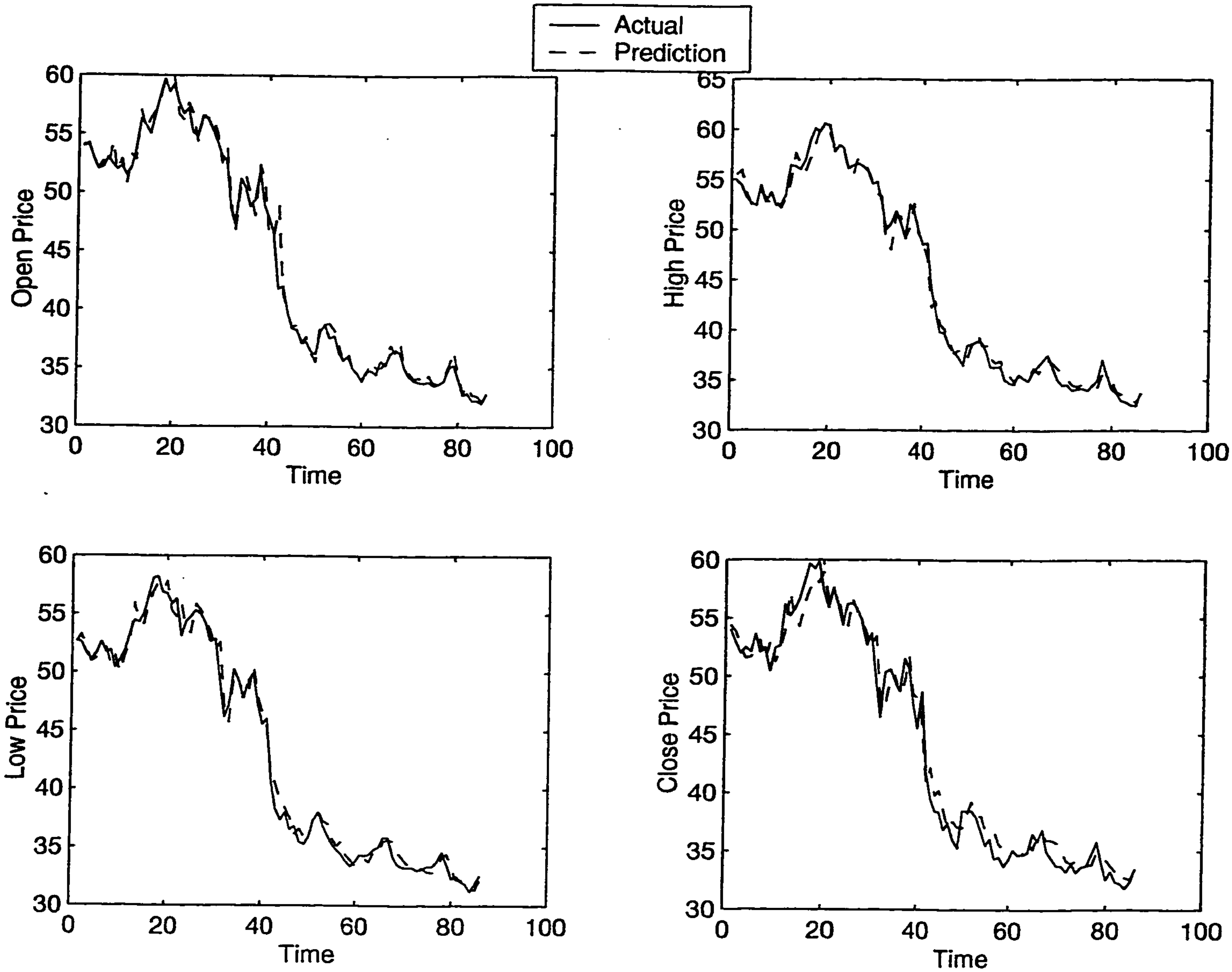

Figure 39: Prediction of stock D

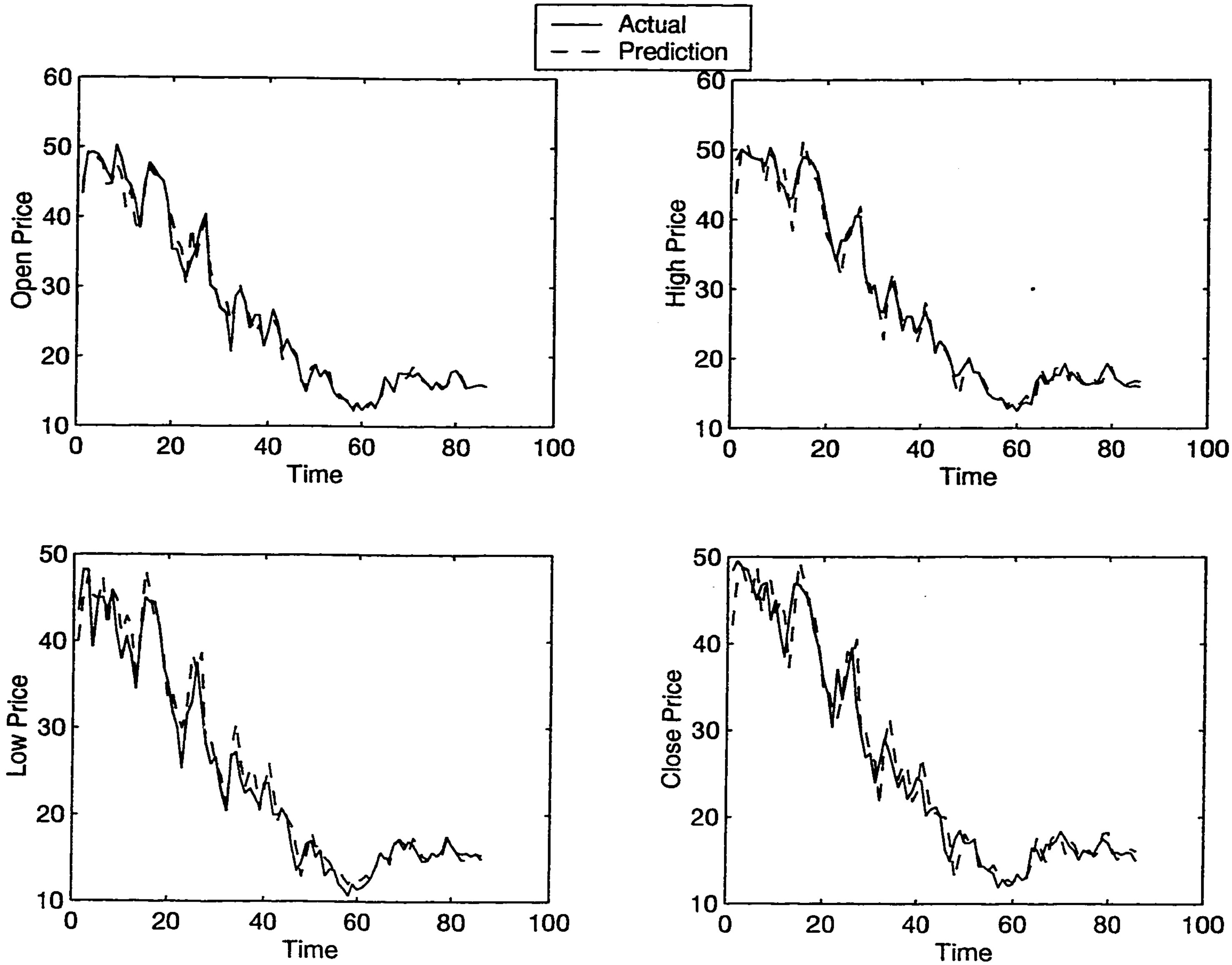

Figure 40: Prediction of stock E

Appendix B

Stock A

Traiding Data

Date	Open	High	Low	Close
1-Feb-99	20.3681	20.5508	20.1854	20.2006
2-Feb-99	19.9571	20.1854	19.8353	19.9266
3-Feb-99	19.8657	20.3376	19.8201	20.3376
4-Feb-99	20.4059	21.2319	20.36	21.2167
5-Feb-99	21.1096	22.0733	21.0025	21.905
8-Feb-99	21.7214	21.8438	21.4767	21.6603
9-Feb-99	21.6909	21.8438	21.5073	21.5685
10-Feb-99	21.339	21.3543	21.079	21.2014
11-Feb-99	21.2014	21.2931	21.1096	21.1402
12-Feb-99	21.1708	21.339	20.6201	20.7272
16-Feb-99	20.3141	20.5436	19.7788	19.7941
17-Feb-99	19.4881	19.7023	19.3198	19.3657
18-Feb-99	19.534	20.1	19.4575	20.0541
19-Feb-99	19.9929	20.4977	19.9776	20.3141
22-Feb-99	20.1459	20.4977	20.1306	20.36
23-Feb-99	20.2988	20.3753	20.0847	20.253
24-Feb-99	20.253	20.5283	20.2224	20.3141
25-Feb-99	20.1918	20.253	19.8858	20.1153
26-Feb-99	20.253	20.253	19.5799	19.8246
1-Mar-99	19.8246	20.3447	19.6717	20.253
2-Mar-99	20.3447	20.4059	19.2128	19.3963
3-Mar-99	19.4575	19.4575	18.6927	18.968
4-Mar-99	18.1114	19.1516	18.0808	19.1516
5-Mar-99	19.8858	19.8858	19.2128	19.6717
8-Mar-99	19.1516	19.7941	19.1516	19.3657
9-Mar-99	18.6927	19.0292	17.5913	18.5397
10-Mar-99	18.4785	19.0904	18.1726	19.0292
11-Mar-99	19.3046	19.5799	18.6927	19.0904
12-Mar-99	19.0904	19.0904	17.7443	18.295
15-Mar-99	18.4785	19.0598	18.3562	18.4785
16-Mar-99	18.6009	18.7233	18.0502	18.5091
17-Mar-99	18.7233	19.3351	18.6621	19.2128
18-Mar-99	19.2128	20.0082	19.1822	19.8858
19-Mar-99	20.2224	20.7425	19.9776	20.7425
22-Mar-99	20.5589	20.926	20.2224	20.253
23-Mar-99	19.947	20.0694	19.3963	19.5799
24-Mar-99	19.6411	20.4671	19.6105	20.0694
25-Mar-99	20.0694	20.8954	20.0082	20.6201
26-Mar-99	20.3141	20.3141	19.6717	19.8246
29-Mar-99	19.8858	20.6201	19.8552	20.4671
30-Mar-99	20.1306	20.1612	19.4575	19.8858
31-Mar-99	19.947	20.3447	19.947	20.1612
1-Apr-99	20.1612	20.1918	19.8858	20.0082
5-Apr-99	20.0388	20.1306	19.8552	19.947

Date	Open	High	Low	Close
2-Aug-99	29.559	30.3264	29.2828	30.1729
3-Aug-99	30.1729	30.664	29.958	30.5412
4-Aug-99	30.4858	32.1179	30.4858	31.5328
5-Aug-99	31.502	31.5944	31.0709	31.1941
6-Aug-99	31.1941	31.3788	30.6398	30.8553
9-Aug-99	30.763	32.5182	30.763	32.3334
10-Aug-99	31.5944	33.1033	31.5944	32.7338
11-Aug-99	32.5182	34.5198	32.0255	34.1811
12-Aug-99	34.2426	34.9201	33.3496	33.3804
13-Aug-99	33.3804	33.3804	32.4566	32.7645
16-Aug-99	33.0109	33.0109	32.4566	32.9493
17-Aug-99	32.9493	33.0417	32.7645	32.8877
18-Aug-99	32.8877	33.1957	32.5798	32.9493
19-Aug-99	32.2718	32.4258	31.7176	32.1179
20-Aug-99	32.1487	33.5036	32.1179	33.3496
23-Aug-99	33.3496	33.3804	32.5182	32.5798
24-Aug-99	32.1795	32.4566	31.1633	32.0563
25-Aug-99	32.2411	32.2411	31.1633	31.3172
26-Aug-99	31.3172	31.656	31.0401	31.1325
27-Aug-99	31.1325	31.5328	30.7937	31.4404
30-Aug-99	31.3172	31.9023	31.3172	31.5944
31-Aug-99	31.656	32.0255	31.4712	31.8099
1-Sep-99	31.9023	31.9331	31.4712	31.9023
2-Sep-99	31.5328	31.8407	31.1941	31.6868
3-Sep-99	31.9639	32.2103	31.5944	31.6868
7-Sep-99	31.6868	32.1487	31.6868	32.0255
8-Sep-99	32.0255	32.3334	31.9023	32.2718
9-Sep-99	32.1487	32.4874	32.1179	32.3334
10-Sep-99	32.3026	32.6414	32.1795	32.4258
13-Sep-99	32.2411	32.2718	31.9331	32.2103
14-Sep-99	32.0871	32.3026	31.9639	32.2103
15-Sep-99	32.2411	32.3026	31.7791	32.1179
16-Sep-99	32.0255	32.0871	31.4404	31.5328
17-Sep-99	32.2718	32.2718	31.9331	32.2718
20-Sep-99	32.0871	32.1795	31.8099	31.9947
21-Sep-99	31.9947	31.9947	30.609	30.763
22-Sep-99	30.7937	31.0093	30.2703	30.5474
23-Sep-99	30.5166	30.5166	29.8391	29.8699
24-Sep-99	29.8699	29.9007	28.8845	29.5004
27-Sep-99	29.562	30.3318	29.3003	30.1163
28-Sep-99	30.1163	30.3934	29.6852	29.9931
29-Sep-99	30.0239	30.301	29.8391	30.0855
30-Sep-99	30.0855	30.8553	29.8391	30.5782
1-Oct-99	30.7014	30.763	29.6236	29.6852

6-Apr-99	19.947	20.1612	19.7023	20.1
7-Apr-99	21.2931	21.5991	20.3447	21.5379
8-Apr-99	21.4155	21.4155	20.8648	21.0484
9-Apr-99	21.1402	21.5073	21.0484	21.4461
12-Apr-99	21.4461	22.2721	21.3849	22.058
13-Apr-99	22.0274	22.9452	21.5685	22.8534
14-Apr-99	22.8228	26.6164	22.7004	26.0657
15-Apr-99	26.0657	27.6566	25.821	26.3411
16-Apr-99	25.9434	26.0657	25.1173	25.7904
19-Apr-99	26.1269	27.9014	26.0045	26.7694
20-Apr-99	26.4329	26.4635	25.5456	25.8822
21-Apr-99	26.0045	26.3411	25.6986	25.7598
22-Apr-99	25.821	26.8918	25.7598	26.1881
23-Apr-99	25.7598	26.647	25.7598	26.4329
26-Apr-99	26.3717	26.4023	25.821	26.0657
27-Apr-99	26.0657	27.5648	26.0657	27.1059
28-Apr-99	27.4119	30.9913	27.3201	30.3488
29-Apr-99	30.3794	32.1233	30.3794	31.6644
30-Apr-99	31.5726	31.8173	29.9817	30.4712
3-May-99	30.4712	30.8383	29.584	29.737
4-May-99	29.6146	30.716	29.5534	30.0123
5-May-99	30.0808	30.0808	29.3441	29.559
6-May-99	29.5283	31.3086	29.0986	31.3086
7-May-99	30.8789	31.5542	30.5105	31.37
10-May-99	31.3393	32.475	31.3086	31.9532
11-May-99	32.8433	32.874	31.4928	31.9532
12-May-99	31.4621	31.6769	30.8482	30.8482
13-May-99	30.7561	30.8789	30.3571	30.4492
14-May-99	30.2036	31.37	30.0501	30.6947
17-May-99	31.1858	31.2472	30.3571	31.0017
18-May-99	30.7561	30.7868	29.7125	30.0808
19-May-99	29.8967	30.6333	29.7739	29.958
20-May-99	29.7125	30.0501	28.4847	28.6382
21-May-99	29.0372	29.6818	28.9144	29.4362
24-May-99	28.9758	30.1115	28.9758	29.6204
25-May-99	29.4976	29.6511	27.8708	27.9015
26-May-99	27.9015	28.9758	27.7787	28.3005
27-May-99	28.2391	28.2391	27.4411	27.8094
28-May-99	27.6252	27.748	26.7351	27.0113
1-Jun-99	27.9936	29.4976	27.748	29.4055
2-Jun-99	29.2214	29.3748	28.6382	29.0986
3-Jun-99	29.0679	29.6204	28.9144	29.3748
4-Jun-99	29.3135	30.4185	29.2828	30.4185
7-Jun-99	29.7125	30.265	29.7125	29.9887
8-Jun-99	30.1115	31.0937	29.958	30.971
9-Jun-99	30.971	31.3086	30.7254	30.9403
10-Jun-99	30.971	32.1067	30.9403	31.7997
11-Jun-99	31.7997	31.8304	30.6333	30.9403
14-Jun-99	30.8175	31.9532	30.8175	31.9225

4-Oct-99	29.7776	30.7322	29.6236	30.7322
5-Oct-99	30.7014	31.5944	30.5166	31.5944
6-Oct-99	31.2864	31.3172	29.4388	30.5474
7-Oct-99	29.6852	30.4242	29.562	30.3626
8-Oct-99	30.301	30.4242	29.7776	30.3626
11-Oct-99	30.3626	31.2249	30.2087	31.0401
12-Oct-99	30.8245	30.8553	30.455	30.6398
13-Oct-99	30.6706	30.7014	29.9931	30.0239
14-Oct-99	30.1779	30.455	29.5004	30.301
15-Oct-99	29.8699	30.6398	29.562	30.301
18-Oct-99	30.1163	30.5782	29.9931	30.0855
19-Oct-99	30.2087	30.4242	29.8083	30.0547
20-Oct-99	30.1779	31.0093	29.8699	30.763
21-Oct-99	30.763	30.7937	30.2087	30.763
22-Oct-99	30.9477	31.0401	30.7014	30.9477
25-Oct-99	30.8245	31.3788	30.7322	30.8553
26-Oct-99	30.9477	31.2864	30.1471	30.1471
27-Oct-99	30.4242	30.455	28.4534	28.9153
28-Oct-99	29.562	29.562	28.4534	28.5766
29-Oct-99	28.5766	29.9623	28.2071	29.9315
1-Nov-99	30.0547	30.4858	29.8391	30.0855
2-Nov-99	30.0547	30.5474	29.9623	29.9623
3-Nov-99	30.2784	30.3402	29.4751	29.506
4-Nov-99	29.5987	29.6914	29.228	29.5369
5-Nov-99	30.402	30.4638	29.815	30.2476
8-Nov-99	30.1858	30.3402	28.7027	29.5987
9-Nov-99	29.7223	30.0004	29.2898	29.6914
10-Nov-99	29.6605	29.6605	29.1971	29.4442
11-Nov-99	29.7223	30.2476	29.7223	30.0931
12-Nov-99	30.4638	30.9273	30.1549	30.8037
15-Nov-99	30.7728	31.6997	30.6492	31.607
16-Nov-99	31.7306	31.8233	31.1435	31.3598
17-Nov-99	31.2362	31.3289	30.8964	30.9891
18-Nov-99	31.3289	31.3289	30.7419	30.9582
19-Nov-99	31.3907	31.6379	31.0509	31.5452
22-Nov-99	31.5452	32.1322	31.298	31.9469
23-Nov-99	31.9469	32.503	31.8851	32.194
24-Nov-99	32.0086	32.0086	31.5143	31.7692
26-Nov-99	32.3794	32.4721	32.194	32.2558
29-Nov-99	32.194	32.2558	31.9777	32.1322
30-Nov-99	32.1322	32.5648	32.1013	32.3794
1-Dec-99	33.1209	33.1209	32.4103	33.0282
2-Dec-99	33.2445	34.9747	33.2136	34.3259
3-Dec-99	34.9129	35.2219	34.5421	35.191
6-Dec-99	35.4072	36.3341	35.3764	35.9016
7-Dec-99	35.3455	36.3032	35.191	35.9943
8-Dec-99	35.9634	35.9634	35.2528	35.4768
9-Dec-99	35.6544	36.3341	35.5308	36.2723
10-Dec-99	36.5813	38.0025	36.4577	37.5082

15-Jun-99	31.9225	32.0453	31.4621	31.769
16-Jun-99	31.6462	32.0453	31.3086	31.8918
17-Jun-99	31.8918	33.0889	31.8918	33.0889
18-Jun-99	33.181	33.3652	32.6899	33.181
21-Jun-99	33.1196	33.1503	30.7561	31.1244
22-Jun-99	31.0017	31.0324	30.265	30.5719
23-Jun-99	30.3878	30.4492	29.8046	30.3571
24-Jun-99	30.3264	31.1551	29.4976	29.6511
25-Jun-99	30.0194	30.9403	30.0194	30.7561
28-Jun-99	31.063	32.0453	30.9403	31.063
29-Jun-99	31.063	31.063	30.4185	30.9096
30-Jun-99	30.9403	31.4314	30.3878	30.3878
1-Jul-99	30.5105	31.1551	29.958	30.9096
2-Jul-99	30.4799	30.8482	30.2036	30.8175
6-Jul-99	30.9403	32.3829	30.9403	31.3086
7-Jul-99	29.958	30.6026	29.7125	30.1422
8-Jul-99	30.0808	31.0017	30.0808	30.664
9-Jul-99	30.664	31.2779	30.6333	30.7561
12-Jul-99	30.8789	30.971	30.2343	30.5412
13-Jul-99	30.2957	30.5105	30.1115	30.4799
14-Jul-99	30.4799	30.6333	30.2036	30.3571
15-Jul-99	30.2036	30.2343	29.7125	29.8353
16-Jul-99	30.8175	30.8789	29.9887	29.9887
19-Jul-99	30.1422	30.2957	29.7432	29.958
20-Jul-99	29.7125	30.1115	29.0372	29.6818
21-Jul-99	29.4669	29.958	29.2828	29.5283
22-Jul-99	29.559	30.2957	29.3135	30.2036
23-Jul-99	30.2036	30.5105	29.2214	29.2214
26-Jul-99	28.9758	29.6818	28.7303	28.7916
27-Jul-99	28.853	30.0808	28.853	29.7739
28-Jul-99	29.5897	30.265	29.3441	30.2036
29-Jul-99	29.7125	29.8967	29.3441	29.559
30-Jul-99	29.4669	29.559	29.0372	29.4055

13-Dec-99	37.0139	37.8172	37.0139	37.4464
14-Dec-99	37.261	38.0952	36.7049	36.9212
15-Dec-99	36.9212	39.0839	36.4268	39.053
16-Dec-99	38.9294	38.9294	37.4464	37.6936
17-Dec-99	38.3733	39.9799	38.3115	38.5278
20-Dec-99	38.5896	38.5896	37.4773	37.9485
21-Dec-99	37.4464	38.0025	37.2919	37.6009
22-Dec-99	38.0643	38.4351	37.7863	37.8481
23-Dec-99	37.8172	39.2693	37.7554	39.1148
27-Dec-99	38.9912	39.4856	38.5896	38.5896
28-Dec-99	39.2384	40.4125	39.1457	39.7945
29-Dec-99	40.7523	40.7832	40.1962	40.4125
30-Dec-99	40.4743	40.7523	39.7018	39.8254
31-Dec-99	39.949	41.2158	39.949	41.0304
3-Jan-00	40.536	41.3085	39.7327	40.0108
4-Jan-00	39.7945	40.4434	39.7018	40.1962
5-Jan-00	40.536	42.7606	40.0417	42.5134
6-Jan-00	42.4516	42.6988	41.9264	41.9573
7-Jan-00	42.5134	42.946	41.8028	41.8337
10-Jan-00	43.0695	43.1313	41.7101	41.7101
11-Jan-00	40.536	41.7719	40.536	41.4629
12-Jan-00	41.3085	41.4629	40.9068	41.0922
13-Jan-00	41.0922	41.1231	40.1962	40.3507
14-Jan-00	40.3507	40.3507	39.1766	39.5474
18-Jan-00	39.8563	39.8563	38.5278	38.5587
19-Jan-00	38.5587	39.053	38.3733	38.6205
20-Jan-00	37.3846	37.6009	35.8398	36.3341
21-Jan-00	36.7049	38.0643	36.3959	37.261
24-Jan-00	37.57	37.7554	35.9634	36.3032
25-Jan-00	36.3032	36.7667	35.4999	35.7471
26-Jan-00	35.778	35.9634	35.0056	35.191
27-Jan-00	35.5926	35.6853	34.6657	34.8511
28-Jan-00	35.2219	35.6544	34.2023	34.3568
31-Jan-00	34.5421	35.0365	34.2332	34.4495

Validation Data

1-Feb-00	34.9747	35.9943	34.7584	35.6544
2-Feb-00	35.5614	37.4836	35.4994	36.9876
3-Feb-00	36.9876	36.9876	35.4064	35.8404
4-Feb-00	35.9645	35.9645	34.6003	34.9723
7-Feb-00	35.1274	35.1274	33.7942	33.7942
8-Feb-00	34.2282	34.2592	32.678	32.7091
9-Feb-00	32.678	33.1121	31.965	32.058
10-Feb-00	32.244	33.5152	32.089	32.492
11-Feb-00	32.9261	34.1042	32.8951	33.5772
14-Feb-00	33.9802	35.9645	33.8252	35.8404

15-Feb-00	35.6234	36.8016	35.6234	36.6465
16-Feb-00	36.5535	37.4216	36.3055	36.5845
17-Feb-00	36.7085	38.4138	36.7085	38.1657
18-Feb-00	38.0107	38.1967	37.2666	37.2666
22-Feb-00	37.0186	37.0496	35.7164	35.9645
23-Feb-00	36.2125	36.2745	35.2824	35.2824
24-Feb-00	35.4684	35.9645	34.5073	34.5693
25-Feb-00	34.5383	35.1274	34.2592	34.8173
28-Feb-00	34.5383	36.8946	34.3213	35.2514
29-Feb-00	35.2204	35.2204	33.5772	33.9802

Testing Data

1-Mar-00	33.9492	35.1274	32.8021	34.6003	1-May-00	32.058	32.182	31.2519	31.4689
2-Mar-00	34.2282	34.3213	32.8641	33.1431	2-May-00	31.3449	32.182	31.0658	32.058
3-Mar-00	32.9261	34.4453	32.616	33.7012	3-May-00	31.9335	32.3692	31.1242	31.6845
6-Mar-00	33.9802	33.9802	32.7401	33.1121	4-May-00	32.1202	32.8361	31.9957	32.1825
7-Mar-00	32.9881	33.4841	32.058	32.213	5-May-00	31.7467	33.1784	31.7467	33.1784
8-Mar-00	32.461	33.9182	31.8719	33.4221	8-May-00	33.3029	33.5208	32.805	32.9295
9-Mar-00	33.2361	33.7322	32.492	33.5772	10-May-00	32.9606	34.081	32.4315	32.4626
10-Mar-00	33.2671	34.0422	32.8951	33.2361	11-May-00	32.8672	33.0228	32.2758	32.4315
13-Mar-00	33.1121	34.3213	32.523	33.7632	12-May-00	32.556	32.7116	32.1513	32.4782
14-Mar-00	32.523	32.7401	30.1667	30.3838	15-May-00	32.5871	33.8943	32.4937	33.8009
15-Mar-00	30.6938	32.089	30.6318	31.7789	16-May-00	33.6453	33.8009	33.0539	33.3341
16-Mar-00	32.213	34.3523	32.058	34.1972	17-May-00	32.8983	33.0539	32.4003	32.556
17-Mar-00	33.4841	33.7322	31.965	32.089	18-May-00	32.4626	32.7427	32.2136	32.6805
20-Mar-00	32.244	33.1431	32.213	32.523	19-May-00	32.6805	33.0539	32.2447	32.3692
21-Mar-00	32.244	34.1042	32.182	33.8872	22-May-00	32.4626	32.5871	31.6222	31.7156
22-Mar-00	33.2981	33.7632	32.8641	33.1741	23-May-00	31.7467	31.7467	30.813	30.8441
23-Mar-00	33.1121	35.0653	33.1121	34.4763	24-May-00	30.564	31.2487	30.564	30.7508
24-Mar-00	34.9103	35.9024	34.5693	35.4994	25-May-00	30.8753	30.9997	29.8793	29.9726
27-Mar-00	35.2824	35.9955	35.2824	35.7474	26-May-00	29.8793	29.9726	28.3853	28.5409
28-Mar-00	35.6234	35.7784	35.0343	35.2824	30-May-00	28.8833	29.1634	28.6343	28.9144
29-Mar-00	35.4064	35.9335	35.1584	35.7784	31-May-00	29.0078	29.1323	28.5098	29.1012
30-Mar-00	35.7164	36.4605	35.4684	35.6544	1-Jun-00	28.9144	29.0078	28.5409	28.7277
31-Mar-00	35.8404	35.9024	34.8483	34.8483	2-Jun-00	29.5058	30.8753	29.1945	30.8753
3-Apr-00	35.3444	35.6544	34.8173	35.5924	5-Jun-00	30.2528	30.4706	30.1594	30.4084
4-Apr-00	35.5924	36.7706	33.6702	35.0653	6-Jun-00	30.4084	30.9375	30.2528	30.564
5-Apr-00	35.1274	35.8094	34.2282	34.3213	7-Jun-00	30.564	30.564	29.6303	30.0038
6-Apr-00	34.5383	35.6854	34.5383	35.1894	8-Jun-00	29.9104	29.9415	29.4747	29.5369
7-Apr-00	35.0653	35.0653	33.6702	33.7012	9-Jun-00	29.568	29.9415	28.7588	28.8911
10-Apr-00	33.7322	34.0422	33.0191	33.5772	12-Jun-00	28.6343	29.8793	28.6343	28.7588
11-Apr-00	33.5152	34.9103	33.3911	34.9103	13-Jun-00	28.5098	28.6966	27.7628	28.0741
12-Apr-00	35.0343	35.3444	34.6313	34.8793	14-Jun-00	28.3853	30.3773	28.3231	29.817
13-Apr-00	34.8483	34.9723	34.2592	34.6313	15-Jun-00	30.2528	30.7508	29.6925	30.5018
14-Apr-00	34.5383	34.5693	32.7401	33.5152	16-Jun-00	30.5018	31.9335	29.9415	30.9375
17-Apr-00	32.8641	33.4221	31.8099	32.058	19-Jun-00	31.6222	31.6845	29.8793	29.9415
18-Apr-00	32.244	32.244	30.7558	31.0658	20-Jun-00	30.1283	30.4395	29.6303	29.9415
19-Apr-00	31.3759	32.182	31.1279	31.1899	21-Jun-00	29.1945	29.568	28.3853	28.5876
20-Apr-00	31.5619	32.492	31.5619	32.275	22-Jun-00	29.7548	29.8793	28.4476	29.0078
24-Apr-00	32.244	32.7401	31.8099	32.182	23-Jun-00	28.9455	30.564	28.6343	30.1283
25-Apr-00	32.461	33.9802	31.934	33.9802	26-Jun-00	29.9415	30.1283	28.5098	28.7588

26-Apr-00	33.9182	33.9182	32.368	32.554
27-Apr-00	31.934	32.678	31.8099	32.368
28-Apr-00	32.12	32.7401	31.934	32.182

27-Jun-00	29.0078	30.6263	28.9455	29.817
28-Jun-00	29.568	30.066	28.7588	29.5369
29-Jun-00	29.0078	29.7548	28.5098	28.8833
30-Jun-00	28.6343	29.6303	28.5098	28.8833

Stock B

Traiding Data

Date	Open	High	Low	Close	Date	Open	High	Low	Close
1-Feb-99	87.7188	87.9688	85.4062	86.4688	2-Aug-99	85.6875	86.9375	84.375	84.8125
2-Feb-99	86.25	86.2812	83.125	83.8125	3-Aug-99	85.875	86.0625	84.375	84.75
3-Feb-99	83.1875	84.9375	83	83.4062	4-Aug-99	85.125	87.1875	84.75	84.9375
4-Feb-99	84.0625	84.1875	79.4375	79.5312	5-Aug-99	85.375	86.375	84.75	85.75
5-Feb-99	80.125	80.8125	77.4375	80	6-Aug-99	86.0625	86.4375	84.9375	85.125
8-Feb-99	81.2812	82.7812	80.8125	82.625	9-Aug-99	85.625	85.8125	83.6875	83.8125
9-Feb-99	82.4688	83.375	79.875	80.0312	10-Aug-99	83.5625	84.0625	81.625	82.9375
10-Feb-99	79.9375	82.1875	79.3125	80.3125	11-Aug-99	84	84.6875	82.3125	84.1875
11-Feb-99	81.375	81.9375	80.1875	81.375	12-Aug-99	83.9375	84.1875	81.625	81.75
12-Feb-99	80.8438	81.8438	78.5625	78.875	13-Aug-99	82.9375	85.625	82.75	84.6875
16-Feb-99	79.875	79.9375	77.2812	78.125	16-Aug-99	85.0625	85.8906	82.3125	84.3125
17-Feb-99	76.4688	77.0625	74.25	75	17-Aug-99	85.4375	85.5	82.9375	84.5625
18-Feb-99	75.4688	75.6875	71.9922	72.875	18-Aug-99	84.4375	86.1875	84.0625	85
19-Feb-99	73.7188	74.625	72.875	73.875	19-Aug-99	84.5625	85.125	83.125	83.8125
22-Feb-99	74.125	74.5	72.375	74.4062	20-Aug-99	84	84.7812	83.0625	83.375
23-Feb-99	76.4688	77.8125	75.25	77.7188	23-Aug-99	84.3125	86.625	83.875	86.4375
24-Feb-99	78.2188	79.6875	76.375	76.4375	24-Aug-99	87.0625	93.5	87.0625	92.1875
25-Feb-99	76.1875	76.875	74.8125	76.75	25-Aug-99	93.625	96	93.1875	95.3125
26-Feb-99	76.1875	76.25	74.75	75.0625	26-Aug-99	95.375	96.375	93.6875	94.625
1-Mar-99	74.7812	76.2812	74.75	75.875	27-Aug-99	95.0625	95.125	92.375	93.25
2-Mar-99	75.9375	77.0625	73.8125	74.2812	30-Aug-99	92.875	93.4375	91.5625	92.25
3-Mar-99	74.5	75.3438	73.5312	74.8125	31-Aug-99	91.8125	93.125	90.125	92.5625
4-Mar-99	75.5625	76.75	74.0625	76.125	1-Sep-99	92.3125	93.4375	91.625	92.375
5-Mar-99	77.375	77.6875	76.5625	77.4688	2-Sep-99	91.5	92.5625	90.6875	91.8125
8-Mar-99	77.75	79.6172	77.5	79.5	3-Sep-99	93.75	96.4375	93.5	95.875
9-Mar-99	79.9375	82.375	79.875	80.9062	7-Sep-99	94.875	96.6875	93.75	94.25
10-Mar-99	81.1562	81.25	79.5938	80.6875	8-Sep-99	93.6875	94.6875	92.0625	92.25
11-Mar-99	80.5	82.2812	79.6562	80.7188	9-Sep-99	92.4375	94.1406	91.7969	94.0625
12-Mar-99	81.3125	81.375	78.4062	80.0938	10-Sep-99	95.0625	95.3125	94	95
15-Mar-99	80.2812	83	78.9375	82.9375	13-Sep-99	94.5	94.8125	93.375	93.875
16-Mar-99	82.75	85	82.125	84.5312	14-Sep-99	93.6875	95.5625	93.625	95.0625
17-Mar-99	84.5312	84.7188	83.375	83.5625	15-Sep-99	95.5	95.75	92.375	92.625
18-Mar-99	83.2188	86.2812	83.0938	86.2188	16-Sep-99	92.875	94.0625	90.625	94
19-Mar-99	86.9375	87.0625	84.9375	85.5938	17-Sep-99	94.375	96.5	93.8125	96.4375
22-Mar-99	86.4688	87.4688	86	86.4062	20-Sep-99	96	97.875	95	97.5625
23-Mar-99	86.3438	87.0625	83.125	83.2812	21-Sep-99	96.5625	96.5625	94.125	94.625
24-Mar-99	83.5	85.9062	81.5625	85.625	22-Sep-99	94.75	96.625	93.6875	96.0625
25-Mar-99	86.5312	90.0312	86.25	89.9688	23-Sep-99	96.875	96.875	90.0156	91.1875
26-Mar-99	89.4688	90.1875	87.875	89.0625	24-Sep-99	90.1875	91.375	88.875	90.9375
29-Mar-99	90.125	92.625	87.875	92.375	27-Sep-99	92	92.9375	90.875	91.4375
30-Mar-99	93.375	93.5	92.25	93	28-Sep-99	91.25	92.6875	89.0625	92.125
31-Mar-99	94.5	94.625	89.125	89.625	29-Sep-99	91.5625	92.125	89.125	89.5
1-Apr-99	91.25	92.875	90.2656	92.6875	30-Sep-99	90	91.6875	88.8125	90.5625
5-Apr-99	94.3125	95.0156	93.5	94.9375	1-Oct-99	90.1875	90.625	88.3125	89.9844
6-Apr-99	95.1875	95.625	93.25	94.0625	4-Oct-99	90.5	92.625	90.25	92.5625
7-Apr-99	94.875	95	91.25	93.3125	5-Oct-99	92.75	93.875	89.5	91.8125
8-Apr-99	93.25	94.625	91	94.5625	6-Oct-99	92.3125	94	92.0625	93.6875

9-Apr-99	94.25	95	93	94.25
12-Apr-99	91.625	93.625	91.375	93
13-Apr-99	93.125	93.125	89.1875	90.125
14-Apr-99	90.8125	91.125	85.875	85.875
15-Apr-99	87.3125	89.875	83.875	88.875
16-Apr-99	89.0625	89.125	85.875	86.625
19-Apr-99	86.875	88.125	80.375	81
20-Apr-99	82.25	84	80	83.125
21-Apr-99	82.125	82.5	80	82
22-Apr-99	85	85.25	83.375	84.9375
23-Apr-99	85	87	83	86
26-Apr-99	87.1875	88.9375	86.75	88
27-Apr-99	88.75	88.75	83.9375	84
28-Apr-99	85.3125	86.5	81.7188	82.125
29-Apr-99	82.375	83.6875	80.4062	82.0625
30-Apr-99	82.75	83.75	79.875	81.3125
3-May-99	81.4375	81.5	78.5625	79.875
4-May-99	80.5	81.8125	77.75	78.0625
5-May-99	79.125	79.875	76.4375	79.125
6-May-99	80.6875	81.125	77.5	77.9375
7-May-99	79.625	80.375	78	79.0625
10-May-99	79.875	80.5	78.25	79.6875
11-May-99	80.75	81.0156	79.4375	79.875
12-May-99	80.75	81	79.25	80.5
13-May-99	81.125	81.75	79.125	79.125
14-May-99	78.875	79.9375	76.625	76.875
17-May-99	77.375	79.5625	77	79.125
18-May-99	79.8125	80.25	77.9375	78.6875
19-May-99	79.875	79.875	77.25	79.3125
20-May-99	79.5625	80	78.375	78.4375
21-May-99	78.5	79	77	77.5625
24-May-99	77.875	77.875	76.0625	77.25
25-May-99	76.75	79.25	76.125	76.25
26-May-99	77.1875	78.5	75.5	78.5
27-May-99	78.25	79.4375	77.5	78.375
28-May-99	78.75	80.875	78.125	80.6875
1-Jun-99	80.625	80.75	78.4375	78.5
2-Jun-99	78.0625	78.625	76.25	78.4375
3-Jun-99	78.375	78.9375	76.125	76.375
4-Jun-99	76.9375	79.6875	76.75	79.5625
7-Jun-99	79.9375	81.0625	79.1875	80.25
8-Jun-99	79.875	82.125	79	79.375
9-Jun-99	80.125	82.625	80	82.3125
10-Jun-99	81.875	82.3125	79.0625	79.875
11-Jun-99	80	80.5	77.5625	78.125
14-Jun-99	78.75	79.6875	77.4375	77.5625
15-Jun-99	78.0625	78.875	76.6875	77.6875
16-Jun-99	79.0625	81.625	78.9375	81
17-Jun-99	80.6875	83	80.5	82.875
18-Jun-99	82.3125	85	82.125	85
21-Jun-99	84.875	89	84.875	88.9375
22-Jun-99	88.4375	88.4375	86.25	86.5

7-Oct-99	93.6875	95.0625	92.6875	93.75
8-Oct-99	93.5	95.1875	92.125	94.9375
11-Oct-99	94.625	95	94.125	94.3125
12-Oct-99	94	94.3125	92.375	92.5625
13-Oct-99	92	93.125	90.3125	91.0625
14-Oct-99	90.875	92.2344	89.6875	90.6875
15-Oct-99	89.5	89.8125	87.3125	88.0625
18-Oct-99	87.1875	88	85.0625	87.875
19-Oct-99	88.25	89.25	85.25	86.3125
20-Oct-99	91.5625	92.375	90.25	92.25
21-Oct-99	90.5625	93.125	90.5	93.0625
22-Oct-99	93.5625	93.875	91.75	92.6875
25-Oct-99	92	93.5625	91.125	92.4375
26-Oct-99	94.375	95.25	92.2656	92.375
27-Oct-99	91.5	91.625	89.6875	90.875
28-Oct-99	90	90.875	89.3125	89.875
29-Oct-99	91.4375	94	91.25	92.5625
1-Nov-99	93.25	94.1875	92.125	92.375
2-Nov-99	92.75	94.5	91.9375	92.5625
3-Nov-99	92.9375	93.5	91.5	92
4-Nov-99	92.3125	92.75	90.3125	91.75
5-Nov-99	91.8125	92.875	90.5	91.5625
8-Nov-99	84.8125	90.75	84.375	89.9375
9-Nov-99	89.75	89.875	86.4375	88.875
10-Nov-99	88.125	89.125	86.4375	87.125
11-Nov-99	88.25	90.4375	88.25	89.625
12-Nov-99	89.75	90	87.0625	89.1875
15-Nov-99	88.25	88.5	86.9375	87
16-Nov-99	86.9375	87.75	85.875	87.3125
17-Nov-99	86.4375	87.0625	85	85
18-Nov-99	84.9375	85.8125	84.5	84.9375
19-Nov-99	84.4375	86.5625	84.375	86
22-Nov-99	89.625	90.375	88.4375	89.8125
23-Nov-99	89.25	91.375	88.375	89.625
24-Nov-99	89.5625	92.25	89.5	91.6875
26-Nov-99	91.625	93.375	91	91.125
29-Nov-99	90.125	92.0625	89.5	90.1875
30-Nov-99	89.75	92.875	89.5625	91.0469
1-Dec-99	91.0625	93.9375	90.875	93.1875
2-Dec-99	93.0625	95.25	92.875	94.8125
3-Dec-99	95.8125	97.125	95.7344	96.125
6-Dec-99	95.25	97.1875	94.75	95.4375
7-Dec-99	94.75	94.875	92.875	93
8-Dec-99	93.125	94.3125	91.6875	91.75
9-Dec-99	92	93.3125	91.4375	92.75
10-Dec-99	93.375	94.125	92.25	93.875
13-Dec-99	93.6094	96.9375	92.75	96.625
14-Dec-99	96.1875	101.125	95.3125	98.6875
15-Dec-99	98.5625	108.75	98.5	108.438
16-Dec-99	109.25	115	108.938	113.688
17-Dec-99	116.625	117.125	113.625	115.25
20-Dec-99	114.812	115	111.188	112.75

23-Jun-99	85.9375	87.375	85.0625	86
24-Jun-99	85.75	86.25	84	84.625
25-Jun-99	85.375	86.4375	84.375	84.9375
28-Jun-99	85.5	86.8125	84.9375	86.75
29-Jun-99	86.6875	88.0625	86	88
30-Jun-99	87.75	90.25	86.75	90.1875
1-Jul-99	89.875	91.5	88.375	91.1875
2-Jul-99	90.875	92.125	90.3125	92
6-Jul-99	92.25	92.9375	89.25	89.5625
7-Jul-99	90.0625	92.3125	89.875	92.3125
8-Jul-99	91.8125	93	90.6875	92.5625
9-Jul-99	92.375	93.3125	92.25	93.25
12-Jul-99	93.1875	94.75	92.375	94.1875
13-Jul-99	93.125	94.0625	92.8125	93.625
14-Jul-99	93.75	95	92.5	94.9375
15-Jul-99	95	95.25	93.75	94.375
16-Jul-99	95.5	99.875	95	99.4375
19-Jul-99	100	100.75	97.8125	98.375
20-Jul-99	96.4375	96.75	92.3125	93.3125
21-Jul-99	93.625	95.3125	93	94.6875
22-Jul-99	94.375	94.5	90	91.0625
23-Jul-99	91.5625	91.75	89.6875	90.25
26-Jul-99	88.875	89.8125	87.625	87.625
27-Jul-99	88.8125	89.75	88	88.8125
28-Jul-99	89.1875	90.5	88.375	90
29-Jul-99	88.6875	88.8125	86.3125	86.9375
30-Jul-99	87.625	88.625	85.5	85.8125

21-Dec-99	112.375	116.625	110.625	115.875
22-Dec-99	116.297	118	115.125	117.562
23-Dec-99	117.25	119.25	116.75	117.438
27-Dec-99	118.438	119.25	116.125	119.125
28-Dec-99	118.75	118.812	117.062	117.5
29-Dec-99	116.938	118.375	116.812	117.938
30-Dec-99	117.875	119.938	117.125	117.625
31-Dec-99	117.5	117.75	116.25	116.75
3-Jan-00	117.375	118.625	112	116.562
4-Jan-00	113.562	117.125	112.25	112.625
5-Jan-00	111.125	116.375	109.375	113.812
6-Jan-00	112.188	113.875	108.375	110
7-Jan-00	108.625	112.25	107.312	111.438
10-Jan-00	113.438	113.688	111.375	112.25
11-Jan-00	111.5	114.25	108.688	109.375
12-Jan-00	108.5	108.875	104.438	105.812
13-Jan-00	104.375	108.625	101.5	107.812
14-Jan-00	107.188	113.938	105.75	112.25
18-Jan-00	111.812	116.5	111.75	115.312
19-Jan-00	110.5	111.5	106	107
20-Jan-00	107.062	109.688	105.875	106
21-Jan-00	107	107.25	103.25	103.75
24-Jan-00	103.797	105.688	100.812	101.25
25-Jan-00	101	103.875	99.5625	102.812
26-Jan-00	102.438	103.5	99.125	99.375
27-Jan-00	99.8906	101.188	97.25	98.75
28-Jan-00	98.125	100.25	97.25	98.25
31-Jan-00	97.625	98.1875	94.875	97.875

Validation Data

1-Feb-00	98.5	103.25	97.6875	102.938
2-Feb-00	102.438	103.938	100.5	100.812
3-Feb-00	102.062	104.188	100.125	103.625
4-Feb-00	104.375	108	104.141	106.562
7-Feb-00	106.812	106.875	104.25	106.625
8-Feb-00	106.438	110	106.438	109.938
9-Feb-00	109.438	109.438	103.875	104
10-Feb-00	103.891	106.562	102.5	106
11-Feb-00	104.875	104.875	99.125	99.9375
14-Feb-00	101.234	101.75	99.0625	99.625

15-Feb-00	99.75	100	98.125	98.5625
16-Feb-00	99.25	100.188	97.125	97.625
17-Feb-00	98.5	99.6875	97.1406	99.625
18-Feb-00	100	100.062	94.875	95.0625
22-Feb-00	95.125	97.125	92.8125	93.8125
23-Feb-00	93.5	95.75	92.0625	94.25
24-Feb-00	94.25	95.875	92	94.75
25-Feb-00	94.6875	94.7031	90.5	91.3125
28-Feb-00	90.25	92.125	88.125	91.5625
29-Feb-00	91.75	91.75	88.875	89.375

Testing Data

1-Mar-00	89.625	94.0938	88.9375	90.8125	1-May-00	72.875	74	71.6875	73.4375
2-Mar-00	91.8125	95.375	91.125	93.375	2-May-00	72.8125	73.5	69.5	69.875
3-Mar-00	94.75	98.875	93.875	96.125	3-May-00	70.375	70.8125	68.8125	70.5625
6-Mar-00	96	97.375	90.125	90.625	4-May-00	70.3125	71.25	69.3125	70.4375
7-Mar-00	96.125	97.5	91.9375	92.875	5-May-00	70.25	71.8125	69.875	71.125
8-Mar-00	93.8125	96.1875	91	95.5625	8-May-00	70.9375	71.375	69.6875	69.8125
9-Mar-00	95.3125	100	95	100	9-May-00	70.1875	70.4375	67.5	67.8125
10-Mar-00	99.5625	102.5	99.5	101	10-May-00	67.75	67.875	65.75	66.1875
13-Mar-00	97.625	100.25	97.5	98	11-May-00	66.625	68.125	65.75	67.875
14-Mar-00	98.625	99.25	95.125	95.125	12-May-00	68.4375	69.75	68.25	68.8125
15-Mar-00	94.5625	96.625	93.6875	95.375	15-May-00	69	69.4375	68	69.375
16-Mar-00	95.9375	96.6875	93.25	95.375	16-May-00	69.5625	70.625	69.0625	69.5
17-Mar-00	95.25	99.5	94.5	99.375	17-May-00	68.875	69.125	67.25	67.6875
20-Mar-00	98.75	99.75	96.5	97.375	18-May-00	68.0625	68.0625	65.875	66.1875
21-Mar-00	96.75	103.125	96.5	102.75	19-May-00	65.375	65.9375	64.5	65.0625
22-Mar-00	102.812	105.625	101.125	103.25	22-May-00	65.125	65.25	62.4375	64.1875
23-Mar-00	106.812	112.875	106.625	111.875	23-May-00	63.875	65.5625	63.0625	63.1875
24-Mar-00	112.625	115	109.562	111.688	24-May-00	63.125	66.5625	63	65.5625
27-Mar-00	107.766	108.25	103.938	104.062	25-May-00	64.5625	64.75	61.125	61.5
28-Mar-00	103.625	107.438	102.375	104.312	26-May-00	62.0625	62.625	60.375	61.4375
29-Mar-00	105.188	108.938	105.125	107.188	30-May-00	62.4375	64.125	62	63.375
30-Mar-00	106.188	108.625	102.5	103.375	31-May-00	63.6406	63.7031	62.0625	62.5625
31-Mar-00	106	108.25	104.125	106.25	1-Jun-00	64.375	66	63.8125	64.5625
3-Apr-00	94.4375	96.5	90	90.875	2-Jun-00	66	66.75	65	66.3125
4-Apr-00	91.5625	92	84.9375	88.5625	5-Jun-00	66.0156	68.375	66	66.875
5-Apr-00	88.25	88.5	85.875	86.375	6-Jun-00	68.1875	69.875	67.8125	69.625
6-Apr-00	87.875	88	85.2656	86	7-Jun-00	69.25	70.75	67.125	70.5
7-Apr-00	87	89.375	85	89.0625	8-Jun-00	71.5625	72.125	68.25	68.8125
10-Apr-00	88.625	88.625	86	86.0625	9-Jun-00	69.625	69.6875	68.3125	68.8125
11-Apr-00	85.125	86.0625	83.5	83.875	12-Jun-00	69	69	66.375	66.875
12-Apr-00	82.125	82.25	78.75	79.375	13-Jun-00	66.75	68	66.125	67.875
13-Apr-00	80.875	82.25	79	79.25	14-Jun-00	69.8125	71	69.5	70.5
14-Apr-00	79.125	79.5	73.25	74.125	15-Jun-00	70.8125	72.6875	70.625	72.375
17-Apr-00	74.25	76	73	75.875	16-Jun-00	72.625	73.125	71.5	72.5625
18-Apr-00	76.5	81.9375	75.875	80.5625	19-Jun-00	72.5625	73.8125	72	73.6875
19-Apr-00	81.4375	81.5	78.125	78.6875	20-Jun-00	73.875	75.25	73.75	74.9375
20-Apr-00	78.625	79.875	77.5	78.9375	21-Jun-00	77	82.1875	76.9375	80.6875
24-Apr-00	67.25	68	65	66.625	22-Jun-00	81.375	82	79.3125	79.875
25-Apr-00	68.75	69.5	67.625	69.375	23-Jun-00	79.9375	80.0625	77	77.6875
26-Apr-00	70	71.125	67.375	68	26-Jun-00	77.5	80.125	77.5	79.5
27-Apr-00	67.4375	69.9375	67.375	69.8125	27-Jun-00	79.25	80.125	78.375	78.8125
28-Apr-00	70.75	71	68.25	69.75	28-Jun-00	79	80.0625	78.625	78.9375
					29-Jun-00	78.25	78.9375	77.0625	77.1875

Stock C

Traiding Data

Date	Open	High	Low	Close
2-Feb-98	6.125	6.2812	6.1016	6.2578
3-Feb-98	6.2578	6.2773	6.1758	6.2344
4-Feb-98	6.2031	6.3477	6.1602	6.2969
5-Feb-98	6.3594	6.3594	6.1211	6.125
6-Feb-98	6.0938	6.2227	6.0391	6.1562
9-Feb-98	6.25	7	6.2227	6.9023
10-Feb-98	6.9688	7.1562	6.8125	6.8125
11-Feb-98	7.0234	7.2148	6.9375	7.1562
12-Feb-98	7.1406	7.3672	7.0938	7.3125
13-Feb-98	7.2812	7.3242	7.125	7.1406
17-Feb-98	7.2031	7.2266	6.9375	7
18-Feb-98	7	7.0625	6.9453	7.0312
19-Feb-98	7.0703	7.3516	7.0469	7.3516
20-Feb-98	7.4062	7.4883	7.3164	7.4648
23-Feb-98	7.5312	7.8125	7.5	7.7422
24-Feb-98	7.7266	7.7344	7.4414	7.4414
25-Feb-98	7.5156	7.6211	7.375	7.4336
26-Feb-98	7.5703	7.75	7.4883	7.7344
27-Feb-98	7.7383	7.7383	7.5664	7.5859
2-Mar-98	7.582	7.6094	7.3477	7.3516
3-Mar-98	7.3516	7.3984	7.0625	7.3203
4-Mar-98	7.25	7.4062	7.0625	7.0625
5-Mar-98	7.125	7.3008	7.125	7.2578
6-Mar-98	7.4062	7.6172	7.3555	7.5938
9-Mar-98	7.6875	7.8906	7.5625	7.7109
10-Mar-98	7.875	7.9023	7.6328	7.6875
11-Mar-98	7.6875	7.8086	7.6289	7.7461
12-Mar-98	7.75	7.8594	7.6641	7.7656
13-Mar-98	7.8359	7.9766	7.8008	7.9766
16-Mar-98	8.0703	8.125	7.9102	8.1094
17-Mar-98	8.1328	8.2344	7.9531	8
18-Mar-98	8	8.0078	7.8906	7.9375
19-Mar-98	7.7188	7.75	7.5781	7.7031
20-Mar-98	7.6641	7.875	7.6328	7.8125
23-Mar-98	7.8125	8.3125	7.7891	8.2344
24-Mar-98	8.4062	8.5547	8.3438	8.4844
25-Mar-98	8.625	8.7344	8.2656	8.3672
26-Mar-98	8.4219	8.4609	8.3281	8.3594
27-Mar-98	8.4375	8.625	8.4297	8.625
30-Mar-98	8.6719	8.7188	8.3672	8.4688
31-Mar-98	8.5625	8.6875	8.5234	8.5391
1-Apr-98	8.6562	9.1562	8.6484	9.1172
2-Apr-98	9.3281	9.4453	9.2031	9.2812
3-Apr-98	9.4375	9.4453	9.1875	9.3125
6-Apr-98	9.3594	9.375	8.8906	9.1094
7-Apr-98	9.0703	9.1016	8.7422	8.8125
8-Apr-98	8.8672	9.1641	8.8203	8.9844

Date	Open	High	Low	Close
3-Aug-98	14.8125	14.9844	14.4062	14.5
4-Aug-98	14.8438	14.875	13.625	13.875
5-Aug-98	14.1875	14.25	12.1875	13.4219
6-Aug-98	13.2656	13.5	12.875	13.1719
7-Aug-98	13.5469	14.1172	13.3125	13.9844
10-Aug-98	13.9531	14.2969	13.8125	14.0938
11-Aug-98	13.7188	13.7422	13.1328	13.3906
12-Aug-98	13.875	13.9609	13.625	13.7109
13-Aug-98	13.5938	13.7891	13.25	13.3203
14-Aug-98	13.4531	13.5312	12.9531	13.2793
17-Aug-98	12.9688	13.3047	12.8906	13.0547
18-Aug-98	13.25	13.9375	13.1953	13.9375
19-Aug-98	14.375	14.375	13.7656	13.9141
20-Aug-98	13.8828	14.2109	13.7734	14.125
21-Aug-98	14.1094	14.1094	13.5547	13.7656
24-Aug-98	13.7891	13.9375	13.4531	13.6016
25-Aug-98	13.875	13.9609	13.6094	13.8438
26-Aug-98	13.5625	13.9062	13.4453	13.8359
27-Aug-98	13.5625	13.7578	12.9297	13.125
28-Aug-98	12.875	13.1406	11.6875	12.0312
31-Aug-98	12.125	12.375	9.9766	10.2422
1-Sep-98	10.0938	11	8.625	10.625
2-Sep-98	11	11.7969	10.75	11
3-Sep-98	10.625	11.25	10.625	10.8438
4-Sep-98	10.9844	11.0625	10.3125	10.75
8-Sep-98	11.875	11.9062	11.4219	11.9062
9-Sep-98	11.9922	12.5	11.75	11.7812
10-Sep-98	11.2266	11.9844	10.9922	11.9844
11-Sep-98	11.75	12.1094	11.375	11.875
14-Sep-98	12.2188	12.4297	12.125	12.25
15-Sep-98	12.2188	12.2266	11.8906	12.1875
16-Sep-98	12.2188	12.9062	12.0625	12.75
17-Sep-98	12.1875	12.5	12.125	12.1875
18-Sep-98	12.2578	12.4297	12.1875	12.2344
21-Sep-98	12	12.875	11.8438	12.7969
22-Sep-98	13	13.4922	12.8203	13.2656
23-Sep-98	13.5312	14.4375	13.4922	14.4062
24-Sep-98	14.3828	15.0938	13.8438	14.0156
25-Sep-98	13.8594	14.5312	13.7969	14.3438
28-Sep-98	14.625	15.0312	14.4062	14.6406
29-Sep-98	14.8281	14.9375	14.375	14.6719
30-Sep-98	13.7656	14.3672	13.7656	13.9531
1-Oct-98	13.5625	13.6562	12.3672	12.5
2-Oct-98	12.4922	13.4375	12.25	13.3984
5-Oct-98	13.25	13.4688	12.1641	12.875
6-Oct-98	13.4141	13.4609	12.1641	12.2031
7-Oct-98	12.0938	12.2266	11.1172	11.5

9-Apr-98	9.2656	9.375	9.1562	9.1875
13-Apr-98	9.1641	9.2812	9.0625	9.1562
14-Apr-98	9.2031	9.4062	9.1875	9.2891
15-Apr-98	9.2578	9.4844	9.2578	9.3828
16-Apr-98	9.3984	9.5469	9.2188	9.4062
17-Apr-98	9.3516	9.3594	9.1562	9.1953
20-Apr-98	9.1875	9.5547	9.1875	9.4922
21-Apr-98	9.4766	9.5781	9.3125	9.3516
22-Apr-98	9.3672	9.4844	9.0312	9.0938
23-Apr-98	9.1094	9.1094	8.8672	8.9062
24-Apr-98	8.9609	9.3594	8.9609	9.3125
27-Apr-98	9.0781	9.1719	8.7812	9.1094
28-Apr-98	9.3906	9.4531	9.25	9.4219
29-Apr-98	9.6875	10.0703	9.625	10.0625
30-Apr-98	10.1875	10.3438	9.9453	9.9922
1-May-98	10.0234	10.4453	9.8906	10.4375
4-May-98	10.6562	11.1484	10.625	11.125
5-May-98	11.0781	11.4922	10.8203	11.1875
6-May-98	10.875	11.0938	10.6875	11
7-May-98	11.2031	11.5312	11.1719	11.2188
8-May-98	11.2109	11.3906	10.8828	11.2656
11-May-98	11.4375	11.4531	10.6875	10.8438
12-May-98	10.8047	10.9766	10.6719	10.9688
13-May-98	11.125	11.25	10.9219	11.25
14-May-98	11.1562	11.2969	10.9531	10.9688
15-May-98	11.0156	11.0156	10.5938	10.6172
18-May-98	10.6172	10.6172	10.1875	10.3906
19-May-98	10.625	10.9922	10.5625	10.9609
20-May-98	11.0938	11.1406	10.7969	10.8125
21-May-98	10.9375	10.9844	10.7734	10.9375
22-May-98	10.8672	10.875	10.5234	10.5781
26-May-98	10.8281	10.8438	10.2578	10.3438
27-May-98	10.0156	10.3438	9.9688	10.3125
28-May-98	10.3281	10.5	10.1094	10.4375
29-May-98	10.5	10.6094	10.3984	10.4141
1-Jun-98	10.3828	10.4062	9.5625	9.8438
2-Jun-98	9.8906	9.9922	9.25	9.6719
3-Jun-98	9.7812	10.0781	9.7344	9.875
4-Jun-98	9.8125	10.2812	9.6328	10.125
5-Jun-98	10.1562	10.4062	10	10.4062
8-Jun-98	10.5	10.6094	10.4453	10.5938
9-Jun-98	10.6016	11.0938	10.5156	11.0781
10-Jun-98	11.1406	11.3438	10.9688	11.1562
11-Jun-98	11.1641	11.25	10.7891	10.875
12-Jun-98	10.875	10.9062	10.4844	10.8906
15-Jun-98	10.75	11.0781	10.625	10.6406
16-Jun-98	10.8125	11.125	10.7031	11.125
17-Jun-98	11.625	11.875	11.5625	11.7344
18-Jun-98	11.8125	12.2344	11.6406	11.7344
19-Jun-98	11.7969	12.125	11.6953	12.0469
22-Jun-98	12.0625	12.7031	12.0312	12.6406
23-Jun-98	12.75	13.3125	12.6953	13.2812

8-Oct-98	10.375	11.1875	10.3125	10.6875
9-Oct-98	10.9688	11.6406	10.3125	11.5391
12-Oct-98	12.125	12.625	11.6719	11.6719
13-Oct-98	11.75	11.7891	11.2734	11.5312
14-Oct-98	11.5156	12.1875	11.4531	11.9531
15-Oct-98	12	13.625	11.9141	13.2109
16-Oct-98	13.2422	13.5	12.5859	12.75
19-Oct-98	12.7266	13.25	12.5859	13.1797
20-Oct-98	13.4922	13.5547	12.875	12.875
21-Oct-98	13.0938	13.5	12.9766	13.375
22-Oct-98	13.3125	14.2422	13.2031	14.2422
23-Oct-98	14.3281	14.7188	14.25	14.3672
26-Oct-98	14.6562	15.1875	14.5781	15.125
27-Oct-98	15.2812	15.5156	14.5859	15.25
28-Oct-98	15.25	15.625	14.75	15.5156
29-Oct-98	15.6797	16.1016	15.3359	16.0391
30-Oct-98	16.0547	16.2109	15.7578	15.9219
2-Nov-98	16.1094	16.9219	16.0391	16.8594
3-Nov-98	16.875	17.0938	16.5156	16.5625
4-Nov-98	17.1094	17.5547	17.0312	17.5312
5-Nov-98	17.3438	17.6562	17.0859	17.4375
6-Nov-98	17.4219	17.6875	17.3125	17.5
9-Nov-98	17.5	18.1094	17.4844	18.0938
10-Nov-98	18.1875	18.625	17.9766	18.0625
11-Nov-98	18.25	18.3672	17.1094	17.1406
12-Nov-98	17.0312	17.9375	17.0312	17.5938
13-Nov-98	17.8125	18.0547	17.2578	17.5
16-Nov-98	17.9375	18.3281	17.7266	18.3281
17-Nov-98	18.1406	19.1094	17.9375	18.8438
18-Nov-98	19.125	21	19.125	20.9375
19-Nov-98	22.25	22.5	20.8125	20.8438
20-Nov-98	21.6875	21.75	20.3281	21.2188
23-Nov-98	22.4375	22.5781	21.7031	22.3125
24-Nov-98	22.8438	23.875	22.5	22.8438
25-Nov-98	23.3438	23.4688	22.7656	23.0625
27-Nov-98	23.6094	23.7188	23.1875	23.7188
30-Nov-98	23.9062	24.0625	21.7812	21.8906
1-Dec-98	20.4062	22.5	20.375	22.4688
2-Dec-98	22.25	22.6094	21.7812	22.0156
3-Dec-98	21.9531	22.5156	20.8125	20.9062
4-Dec-98	21.75	22	21.2031	22
7-Dec-98	22.375	22.4375	21.9375	22.4219
8-Dec-98	22.4219	23	22.1562	22.5938
9-Dec-98	22.9375	23.4688	22.6406	23.2344
10-Dec-98	23.3125	23.4688	22	22.5
11-Dec-98	22.2969	23.0469	22.1094	22.8906
14-Dec-98	22.5	22.6875	22.0938	22.3125
15-Dec-98	22.875	23.3125	22.625	23.1875
16-Dec-98	23.7344	24.3438	23.5781	24.0469
17-Dec-98	23.9688	24.9219	23.9688	24.7812
18-Dec-98	25	26.25	24.9062	26.0625
21-Dec-98	27.125	29.8438	27.0625	29.25

24-Jun-98	13.125	13.5156	12.7344	12.9922
25-Jun-98	13.25	13.5469	13.1016	13.5078
26-Jun-98	13.3438	13.4922	13.25	13.4688
29-Jun-98	13.6875	13.7188	12.9062	12.9062
30-Jun-98	13.0312	13.3438	12.8828	13.1406
1-Jul-98	13.4688	13.875	13.3359	13.8438
2-Jul-98	13.9844	14.1016	13.4219	13.7891
6-Jul-98	13.875	14.25	13.5938	14.1562
7-Jul-98	14.375	14.375	13.5312	13.6094
8-Jul-98	13.3438	13.8438	13.0312	13.8438
9-Jul-98	13.8125	14.4375	13.75	14.2344
10-Jul-98	14.1406	14.2031	13.9062	14.0625
13-Jul-98	14.0312	14.8672	14	14.8594
14-Jul-98	14.9844	15.3594	14.9766	15.0625
15-Jul-98	15.1562	15.2812	14.6406	14.8125
16-Jul-98	14.8594	15.4375	14.5703	15.3281
17-Jul-98	15.3359	16	15.1484	16
20-Jul-98	16.0156	17.0625	16	17.0156
21-Jul-98	17.0312	17.5625	15.6875	16.1953
22-Jul-98	16.2422	16.5938	15.9531	16.3516
23-Jul-98	16.375	16.7422	15.4609	15.6875
24-Jul-98	15.9844	16.6719	14.25	14.8984
27-Jul-98	14.5625	14.7266	13.9141	14.6875
28-Jul-98	14.6875	15.0469	14.2656	14.2812
29-Jul-98	14.5625	14.6406	13.3594	13.4688
30-Jul-98	13.8438	14.75	13.5469	14.7031
31-Jul-98	14.8906	15.2812	14.4844	14.6406

22-Dec-98	30.0312	34.5	28.5781	34.5
23-Dec-98	34.75	35.25	33.5	34.5
24-Dec-98	34.75	34.7656	33.75	34.1562
28-Dec-98	34.875	39.9375	34.75	39.3125
29-Dec-98	39.7812	39.875	36.5	38.6562
30-Dec-98	38.4375	38.5	33.5	36.8594
31-Dec-98	37.2188	40	35.75	38.7812
4-Jan-99	39	39.375	36.7188	37.2031
5-Jan-99	36.75	37.75	36.4844	36.7344
6-Jan-99	36.75	37.9375	36.75	37.25
7-Jan-99	36.25	37.6719	36.25	36.9688
8-Jan-99	37.75	37.9844	36.0938	36.625
11-Jan-99	38.125	41.2812	38.125	41.2812
12-Jan-99	41.75	41.75	37.875	38.4062
13-Jan-99	35.25	37.9844	32.5	36.4375
14-Jan-99	37.25	37.6875	35.7188	36.125
15-Jan-99	36.5	37.3125	36.25	36.625
19-Jan-99	38	38.2188	37.1562	37.625
20-Jan-99	38	38.75	36.7344	37.125
21-Jan-99	36.3125	36.5312	34.75	35.25
22-Jan-99	34.125	36.0625	33.75	35.1094
25-Jan-99	35.9375	36.5	35.125	36.5
26-Jan-99	36.7812	38.75	36.6875	38.75
27-Jan-99	39.625	41.625	39.625	41.375
28-Jan-99	43.1875	44	42.5	43.6094
29-Jan-99	43.9688	44.25	42.625	43.9375

Validation Data

1-Feb-99	44.25	44.375	42.5312	42.7969
2-Feb-99	42.9375	42.9375	41.25	41.875
3-Feb-99	42.0625	43.375	42.0156	43.3594
4-Feb-99	43.125	43.4062	42.1875	42.25
5-Feb-99	42.1094	42.5625	40.3438	41
8-Feb-99	41.5	41.7188	39.25	39.75
9-Feb-99	39.75	39.75	36.3438	36.9844
10-Feb-99	36.8438	37.9844	35.5	37.7188
11-Feb-99	38.3438	41.2344	38	41.1719
12-Feb-99	40.25	40.6094	39.2656	39.625

16-Feb-99	40.9375	41.0625	39.5	39.875
17-Feb-99	40	40.375	38.0625	38.25
18-Feb-99	38.875	39	37.6406	38.9375
19-Feb-99	39	40.3594	38.6406	40.0938
22-Feb-99	40.5625	43.3438	40.3438	43.25
23-Feb-99	44.75	45.9062	43.5	44
24-Feb-99	45.125	45.5	43.5625	43.7812
25-Feb-99	43.5	43.7812	41.75	43.5938
26-Feb-99	44.5	44.875	43	44.4688

Testing Data

1-Mar-99	44.4688	44.9375	43.5938	44.7812
2-Mar-99	45	45.25	43	43.3438
3-Mar-99	44	44.5	42.1562	43.5312
4-Mar-99	43.8125	44.125	42.4375	43.125
5-Mar-99	44.5	44.5625	43.0625	43.4688
8-Mar-99	43.5938	45.625	43.0312	45.4375
9-Mar-99	45.4062	46.625	44.5312	45.0625
10-Mar-99	46.25	46.5938	45.5	46.4062
11-Mar-99	47	48.1875	46.5938	47.9062
12-Mar-99	48.375	48.8125	47.25	48.0625
15-Mar-99	48.9062	51.375	48.75	51
16-Mar-99	51.75	52.9375	51.5312	52.4688
17-Mar-99	52.4688	55.0625	51.125	54.5312
18-Mar-99	54.3125	59.5938	53.6875	58.0625
19-Mar-99	59.375	60.625	58.5625	59.625
22-Mar-99	60	65.25	59.2188	65
23-Mar-99	64.25	64.875	58.5	60.5
24-Mar-99	59.5	60.4688	56.25	58.5625
25-Mar-99	62.25	63.9375	61.5	63.25
26-Mar-99	62.625	63.75	61	62.8438
29-Mar-99	64.1875	66.9688	63.8438	66.1875
30-Mar-99	67.5	74.5	65.5	72.25
31-Mar-99	74.0625	77.5	70.5	73.5
1-Apr-99	76.3438	76.5	72.0312	75
5-Apr-99	76.125	83.5	76	83.4688
6-Apr-99	82.4375	87.75	81.375	83.75
7-Apr-99	85.0625	86.3125	76	79
8-Apr-99	79	80.625	74	80.25
9-Apr-99	79.5	82.625	78.9375	79.9688
12-Apr-99	76	79.9062	75.5312	78.9375
13-Apr-99	79.25	82.125	78.375	79.6562
14-Apr-99	81	81.6875	75	75.4375
15-Apr-99	76.375	76.375	67.5	71.9375
16-Apr-99	73.25	74.375	69.875	69.875
19-Apr-99	71	71.5	56	57.9375
20-Apr-99	57.5	65.125	56.5	64.3438
21-Apr-99	65.25	72.25	63.9688	71.375
22-Apr-99	75	76.5	72	74.3438
23-Apr-99	73.375	73.625	70.8438	73.5
26-Apr-99	75.5	81.25	75.3125	81
27-Apr-99	82.3125	83.5625	75.5	76.5
28-Apr-99	75	78.5	70.5	71.5
29-Apr-99	70.25	71.3125	65.5	70.6875

30-Apr-99	73.3125	73.8125	68	71.375
3-May-99	71	71	66.4688	66.5625
4-May-99	66	68.625	63.4375	63.5625
5-May-99	63.0625	65.5	57.75	64.875
6-May-99	64.5	65.75	59.5	59.875
7-May-99	60.2188	62.0625	57.5938	59.0938
10-May-99	60.5	64.875	59.5625	64.1562
11-May-99	69	70.7188	66	70.7188
12-May-99	69.875	70	65.0312	69.2188
13-May-99	70	71	66.25	66.3125
14-May-99	63.0625	64.75	62	62.625
17-May-99	62.9375	68.0625	62.75	68.0625
18-May-99	68.1875	69.5	65.9062	67.0312
19-May-99	68.25	69.625	66.75	67.25
20-May-99	67.875	68.9688	64.5	64.75
21-May-99	64.6875	65.5	62.5	63.2188
24-May-99	63.2188	63.2188	59.4375	59.75
25-May-99	60	60.8125	56	57.5
26-May-99	58.6875	60.5	52.5312	60.1562
27-May-99	60	60	57.5	58
28-May-99	57.9688	59.875	56.9062	59.625
1-Jun-99	59.625	59.625	56	56.5625
2-Jun-99	55.625	57.9062	52.5312	55.0625
3-Jun-99	55.4375	56	52.8125	52.875
4-Jun-99	53.3125	59.25	53.0312	59
7-Jun-99	59.75	60.25	56.8125	57.5
8-Jun-99	57.625	57.625	55	55.1875
9-Jun-99	55.5	56	54	55.5
10-Jun-99	53.75	54.25	52.75	52.75
11-Jun-99	53	53.875	49.5312	49.75
14-Jun-99	49.25	49.375	44.75	45.25
15-Jun-99	45.1875	48.8125	44.75	47.375
16-Jun-99	49.75	53.5625	49.75	53.25
17-Jun-99	53.25	56.875	51.5	55.3438
18-Jun-99	56	56.75	54.7812	56
21-Jun-99	56.5625	58.0938	56	57.6875
22-Jun-99	57.375	58.3125	54.4688	54.75
23-Jun-99	53	56.25	52.9375	55.875
24-Jun-99	55.6875	55.9375	53.25	53.375
25-Jun-99	54	54.6875	50.5	51.4062
28-Jun-99	52	52.375	49	51.9062
29-Jun-99	51.75	53.375	51.0312	53
30-Jun-99	53.1562	57.125	52.125	55

Stock D

Traiding Data

Date	Open	High	Low	Close	Date	Open	High	Low	Close
1-Feb-99	61.75	62.9167	61.2917	62.375	2-Aug-99	52.8125	52.8125	51.125	51.5
2-Feb-99	62.6667	62.7083	60.25	61.2917	3-Aug-99	52.1875	52.1875	50.25	50.875
3-Feb-99	61.4583	63.4167	60.875	63.3333	4-Aug-99	50.6875	51.1875	49.75	49.9375
4-Feb-99	63.2917	63.2917	60.3333	60.9583	5-Aug-99	50	50.75	49.5	50.6875
5-Feb-99	60.9167	61	58.1667	59.0833	6-Aug-99	50.6875	51.6875	50.375	51.6875
8-Feb-99	59.5	60.8333	58.7083	60.6667	9-Aug-99	51	51.0625	50.375	50.875
9-Feb-99	60.0417	60.4167	57.9167	58.25	10-Aug-99	50.4375	50.625	48.3125	48.9375
10-Feb-99	58.1667	58.2917	56.1667	57.2083	11-Aug-99	49.5	49.5625	48.375	48.4375
11-Feb-99	57.4583	59.0833	55.75	58.7917	12-Aug-99	48.5625	49.125	48.25	48.4375
12-Feb-99	58.3333	58.5833	56.6667	57.25	13-Aug-99	48.875	49.25	48.5625	49.25
16-Feb-99	57.9583	58.1667	55.75	56.4167	16-Aug-99	49.375	49.875	48.25	49.0625
17-Feb-99	56.3333	57.5417	56.0833	56.2083	17-Aug-99	49.75	49.875	48.9375	49.75
18-Feb-99	56.75	57.5	56.4583	57.25	18-Aug-99	49.0625	49.25	48.25	48.625
19-Feb-99	57.25	58.0833	56.75	57.1667	19-Aug-99	48.25	48.4375	47.75	48.1875
22-Feb-99	57.2083	58.25	57.0833	57.7083	20-Aug-99	48	48.0625	46.375	46.875
23-Feb-99	57.9167	58.0833	57.1667	57.2917	23-Aug-99	47.375	47.4375	46.875	47.25
24-Feb-99	57.25	57.4583	56.2917	56.375	24-Aug-99	47.4375	47.8125	46.375	46.625
25-Feb-99	56.3333	56.5833	55.4583	56.3333	25-Aug-99	47.125	49.25	46.9375	49.25
26-Feb-99	56.5	56.7083	54.75	54.75	26-Aug-99	49.625	50.375	49.5	49.9375
1-Mar-99	55	55.9583	54.0833	54.1667	27-Aug-99	50.5	50.5625	47.5	47.5
2-Mar-99	54.6667	55.5	54.375	54.5833	30-Aug-99	48.25	48.3125	45.75	46
3-Mar-99	54.75	55.5833	54.75	55.5833	31-Aug-99	46.4375	46.5	44.25	45
4-Mar-99	56.125	56.7083	55.5	56.2917	1-Sep-99	45.5	47.625	45.375	47.375
5-Mar-99	58.4583	59.0833	57.6667	58.3333	2-Sep-99	46.75	47.25	46.375	47
8-Mar-99	58.4167	59.3333	58.375	58.6667	3-Sep-99	48	48.75	47.8125	48.125
9-Mar-99	58.5	58.5833	57.0417	57.0417	7-Sep-99	48.5	48.8125	47.3125	47.3125
10-Mar-99	56.6667	57.0833	55.25	56	8-Sep-99	46.9375	47	45.6875	46
11-Mar-99	55.9167	56.125	55.0417	55.0417	9-Sep-99	45.5625	46.75	45.5	46.5
12-Mar-99	55.0833	55.0833	54.1667	54.2917	10-Sep-99	47	47.125	45.8125	45.875
15-Mar-99	54.4167	55.3333	54.3333	54.9583	13-Sep-99	45.9375	46.375	45.0625	45.125
16-Mar-99	55.0417	55.5	54.6667	54.9583	14-Sep-99	45.0625	45.25	44.3125	44.5
17-Mar-99	55.125	56.5	54.3333	56	15-Sep-99	44.75	45.25	43.9375	44.5
18-Mar-99	55.5833	55.9583	54.1667	54.75	16-Sep-99	45	45.9375	44.5625	45.5
19-Mar-99	55.25	56	52.6667	53.0833	17-Sep-99	45.4375	45.75	44.9375	45.625
22-Mar-99	53.1667	53.6667	51.5	51.8333	20-Sep-99	46	46.125	45	45.0625
23-Mar-99	51.8333	52.7917	50.5833	51.75	21-Sep-99	44.875	45.625	44.125	44.5
24-Mar-99	52.2917	54	51.9167	53.875	22-Sep-99	44.5625	44.8125	43.75	44
25-Mar-99	54.8333	55.3333	54.0417	54.5833	23-Sep-99	44	44.25	42.25	42.4375
26-Mar-99	54.5417	55.6667	54	55.375	24-Sep-99	42.625	43.125	42	42.625
29-Mar-99	56	56	54.375	54.4583	27-Sep-99	43.125	43.875	42.75	43.625
30-Mar-99	53.7083	54.0833	53.3333	53.5833	28-Sep-99	43.125	44	41.8125	43.75
31-Mar-99	54	54.5833	53	53.2083	29-Sep-99	43.625	44.875	43.25	43.5
1-Apr-99	53.3333	53.75	52.125	52.3333	30-Sep-99	43.625	44.125	42.9375	43.5
5-Apr-99	52.9583	53.0417	51.5	51.625	1-Oct-99	43.9375	44.125	41.5	41.75
6-Apr-99	51.5833	53.5	51.4167	53.4167	4-Oct-99	43	44	42.8125	43.75
7-Apr-99	54.5417	56.75	54.25	56.5833	5-Oct-99	44.25	45.25	44.25	45
8-Apr-99	56.9583	57	55.1667	55.9167	6-Oct-99	44.875	47	44.625	46.625

9-Apr-99	56.0833	57.625	55.8333	57
12-Apr-99	56.8333	59.125	56.125	58.625
13-Apr-99	59.3333	59.6667	58.3333	58.6667
14-Apr-99	58.9167	59.3333	57.0833	57.3333
15-Apr-99	56.875	57.5417	54.5833	55.9167
16-Apr-99	56.75	57	55.5	56
19-Apr-99	56.5625	57.8125	53.5625	53.875
20-Apr-99	53.875	55.25	52.8125	55
21-Apr-99	55.75	57.125	55.125	57
22-Apr-99	58	60	56.75	56.75
23-Apr-99	53.375	54	52.25	53.375
26-Apr-99	54	54.25	52	52.9375
27-Apr-99	54.5	55.6875	52.8125	53
28-Apr-99	53.8125	54.25	53.4375	54.1875
29-Apr-99	54.125	54.1875	53.0625	53.125
30-Apr-99	53.9375	54	50.0625	50.5
3-May-99	51.5	52.1875	51	51.0625
4-May-99	52	52.125	50.875	51.5625
5-May-99	54.9375	57.375	54.5	56.9375
6-May-99	59.25	63	59	61.9375
7-May-99	62	62	60.0625	60.4375
10-May-99	60.625	61.0625	58.0625	59.125
11-May-99	59	59.125	57.5	58.3125
12-May-99	58.9375	60.625	58	60.125
13-May-99	61	61.625	60.375	60.9375
14-May-99	59.5	60.5	58.8125	58.9375
17-May-99	58.9375	59.9375	57.8125	59.625
18-May-99	60.3125	60.3125	58	59.125
19-May-99	58.9375	59.375	58.125	58.5625
20-May-99	58.875	59.5625	58	59.25
21-May-99	59.9375	60.3125	59.25	59.4375
24-May-99	60	60.1875	58.0625	58.1875
25-May-99	58.0625	58.9375	57.4375	57.4375
26-May-99	58.1875	58.25	55.8125	57.25
27-May-99	58	58.4375	55.1875	56.375
28-May-99	56.5	56.6875	55.4375	55.5
1-Jun-99	56	56	54.6875	55.0625
2-Jun-99	55.0625	55.4375	54.4375	55
3-Jun-99	55	55.25	54.125	54.25
4-Jun-99	54.5	54.625	52.5	53.375
7-Jun-99	52.5625	53.75	52.375	53.5
8-Jun-99	53.375	53.9375	52.625	53.4375
9-Jun-99	53.5	54.375	53.3125	53.8125
10-Jun-99	53.125	53.9375	52.8125	53.6875
11-Jun-99	53.75	53.8125	52.625	53.1562
14-Jun-99	53.25	53.4375	52.625	52.9375
15-Jun-99	53.375	54.0625	52.625	52.9375
16-Jun-99	53.5625	54.5625	53.375	54.3125
17-Jun-99	54.3125	54.875	53.5625	54.4375
18-Jun-99	54.375	55.875	54.375	55.625
21-Jun-99	56	56.875	55.8125	56.5
22-Jun-99	56.5	56.75	55.75	56.25

7-Oct-99	47.0625	47.25	46.0625	46.9375
8-Oct-99	47.125	47.75	46.875	47.4375
11-Oct-99	47.625	49.0625	47.5625	48.75
12-Oct-99	48.6875	48.6875	47.75	47.875
13-Oct-99	47	47.5	45.625	45.75
14-Oct-99	45.9375	46.125	44.375	44.6875
15-Oct-99	43.25	44	42.75	43.1875
18-Oct-99	43.1875	44	42.4375	44
19-Oct-99	44.6875	44.75	43.6875	44
20-Oct-99	44.375	44.4375	43.375	43.875
21-Oct-99	43.5	43.6875	42.5625	43.375
22-Oct-99	43.4375	43.6875	42.75	43
25-Oct-99	42.8125	44.75	42.5625	44.6875
26-Oct-99	44.625	44.9375	43.9375	44
27-Oct-99	44.625	44.625	43.4375	44
28-Oct-99	44.75	46.25	44.5	46
29-Oct-99	47.375	47.375	46.4375	46.75
1-Nov-99	47.25	47.8125	47.125	47.3125
2-Nov-99	47.5	47.875	46	46
3-Nov-99	47.5	47.5	46.4375	47.1875
4-Nov-99	47.75	47.9375	47.375	47.9375
5-Nov-99	48.4375	48.625	46.25	47
8-Nov-99	46.375	47.5	46.3125	47.5
9-Nov-99	46.9375	47.0625	45.5625	45.6875
10-Nov-99	45.125	46.5	44.9375	46.4375
11-Nov-99	46.5	47	45	45.75
12-Nov-99	45.75	46.375	45.0625	45.6875
15-Nov-99	45.5	46.625	45.3125	46
16-Nov-99	46.4375	47.625	46.3125	47.5
17-Nov-99	47.3125	48.25	46.875	47.3125
18-Nov-99	47.75	47.875	47.0625	47.5625
19-Nov-99	47.0625	47.375	46.3125	46.5625
22-Nov-99	47.1875	52.25	47	52.0625
23-Nov-99	53	53	50.1875	50.75
24-Nov-99	51.9375	54	51.875	53.1875
26-Nov-99	56.5	58	55.1875	57.4375
29-Nov-99	59.875	61	59.125	60
30-Nov-99	58.625	59.5	55.5625	55.875
1-Dec-99	55.5	56.6875	54.375	55.6875
2-Dec-99	56	57	55.125	56.0938
3-Dec-99	56	57.5625	55.875	57
6-Dec-99	58	58.6875	56.75	57
7-Dec-99	57.625	58.25	57.25	57.875
8-Dec-99	57.875	58	56.8125	57.6094
9-Dec-99	58	58.1875	57.5625	57.8125
10-Dec-99	57.9375	57.9375	56.6875	57
13-Dec-99	57.1875	57.75	55.375	55.5625
14-Dec-99	55.5625	56.0625	55.1875	55.375
15-Dec-99	55.125	55.125	53.75	54.5
16-Dec-99	54.625	54.625	52.75	53.375
17-Dec-99	53.6875	54.8125	53.25	53.625
20-Dec-99	53.9375	54.625	53.5	54.2344

23-Jun-99	56.25	56.25	54.5	55.125
24-Jun-99	54.5625	54.9375	53.3125	54.125
25-Jun-99	54.875	55	54.125	54.625
28-Jun-99	54.625	55.0625	54.25	54.625
29-Jun-99	54.625	55.6875	54.0625	55.625
30-Jun-99	55	55.9375	54.4375	55.8125
1-Jul-99	56.25	57.8125	55.9375	56.625
2-Jul-99	56.9375	57.0625	56.25	56.5625
6-Jul-99	56.5	57.25	56.3125	56.625
7-Jul-99	56.75	58.4375	56.75	58.25
8-Jul-99	57.75	59	57.5	58.5
9-Jul-99	58.0625	58.625	57.0625	57.8125
12-Jul-99	57.25	57.75	56.4375	57.5625
13-Jul-99	56.5625	57.6875	56.5	57.125
14-Jul-99	57.125	57.25	56	56.3125
15-Jul-99	56.8125	56.9375	55.3125	55.375
16-Jul-99	55.3125	55.6875	55.125	55.5
19-Jul-99	55.5	55.875	55.3125	55.8125
20-Jul-99	55.75	55.8125	54.125	54.1875
21-Jul-99	54.75	56	54.1875	55.75
22-Jul-99	55.75	55.9375	54.625	54.75
23-Jul-99	54.625	55.125	53.75	54
26-Jul-99	54	55.25	53.5625	54.875
27-Jul-99	55.375	56	54.8125	55
28-Jul-99	55.3125	55.6875	54.5	54.9375
29-Jul-99	53.5625	54.125	53.125	53.4375
30-Jul-99	53.9375	53.9375	51.75	52.125

21-Dec-99	54.1875	54.75	53.625	54.1875
22-Dec-99	53.9375	54.5	52.5625	52.9375
23-Dec-99	53.375	53.5625	52.375	52.625
27-Dec-99	52.5	52.5	50	50
28-Dec-99	50.5	51.375	50	50.875
29-Dec-99	51.0625	52	50.625	50.625
30-Dec-99	51.125	51.3125	50.25	50.3125
31-Dec-99	50.375	50.8125	49.875	50.8125
3-Jan-00	51	53.4375	50.5625	53.375
4-Jan-00	52.75	53.25	51.25	51.375
5-Jan-00	52	52.375	50.625	50.9375
6-Jan-00	50.75	50.8125	47.5	48
7-Jan-00	49.8125	49.875	47.8125	49.25
10-Jan-00	49.6875	51.6875	49.5625	50.875
11-Jan-00	51.0625	52.25	51.0625	51.8125
12-Jan-00	52.1875	54.625	51.6875	54.625
13-Jan-00	55.0625	56	53.1875	54.5
14-Jan-00	54.3125	55	53.625	54.6875
18-Jan-00	53.5625	54.25	53.1875	53.375
19-Jan-00	52.6875	53.125	52.3125	53.125
20-Jan-00	53.4375	53.75	51.4375	51.6875
21-Jan-00	52.125	52.5625	51	52.0625
24-Jan-00	52.5625	52.75	50.1875	50.5
25-Jan-00	50.5	51.875	49.1875	51.3125
26-Jan-00	51.3125	52.25	50.25	51
27-Jan-00	51.5	51.6875	49.75	50.375
28-Jan-00	50.625	50.75	48	48.875
31-Jan-00	49	53.25	48.5	52.75

Validation Data

1-Feb-00	51.8125	52.75	51.125	52.5
2-Feb-00	51	53	50.5	51
3-Feb-00	51.625	52.25	50	50.3125
4-Feb-00	51.3125	52	50.25	50.625
7-Feb-00	50.8125	51.625	50.375	51.25
8-Feb-00	51.5	51.5	50.1875	50.375
9-Feb-00	50	50.5	48.8125	48.8125
10-Feb-00	49.25	49.625	48.3125	49.125
11-Feb-00	49.125	49.25	48	48.625
14-Feb-00	49.25	49.25	47.5625	48.375

15-Feb-00	47.75	48.5	47.5	48
16-Feb-00	48.4375	49.9375	48.25	49.5
17-Feb-00	50	50	48.25	49.5625
18-Feb-00	49	49	47.375	47.5625
22-Feb-00	47.5625	47.75	46.25	46.375
23-Feb-00	46.8125	47.25	46.3125	46.875
24-Feb-00	45.9375	46.6875	44.875	44.875
25-Feb-00	46	46	44.5	45
28-Feb-00	44.9375	46.5	44.3125	45
29-Feb-00	45.875	49.875	45.75	49.375

Testing Data

1-Mar-00	50	50	47.5	47.875	1-May-00	47	49	46.3125	49
2-Mar-00	48.75	54.4375	48	54.1875	2-May-00	42.0625	44.375	41.125	41.9375
3-Mar-00	54.625	55.4375	53.25	54.5625	3-May-00	42.25	42.25	38.5625	39.8125
6-Mar-00	54.625	55	53.125	53.5	4-May-00	40	40.125	37.625	38.6875
7-Mar-00	53.5	53.75	52.1875	52.5	5-May-00	38.625	40	38.25	38.625
8-Mar-00	52.5625	53.1875	51.5625	53	8-May-00	38.5	38.75	36.75	37.125
9-Mar-00	52.75	53	52.125	52.625	9-May-00	37.375	38.0625	37.0625	37.6875
10-Mar-00	53.5625	55	53.125	54.1875	10-May-00	37.5	37.5625	35.6875	36.25
13-Mar-00	53	53.3125	52.25	52.625	11-May-00	36.6875	36.75	35.5	35.5
14-Mar-00	52.5	54.25	52.4375	53	12-May-00	36.4375	38.75	36.125	38.75
15-Mar-00	52.8125	53	50.9375	51	15-May-00	38.375	38.875	37.5625	38.6875
16-Mar-00	52	53	51.5	53	16-May-00	38.9375	39.1875	38.25	38.75
17-Mar-00	52.75	54	52.4375	53.1875	17-May-00	37.8125	39	37.125	38.125
20-Mar-00	54.1875	57	53.875	56.75	18-May-00	38	38.0625	36.25	36.875
21-Mar-00	56.875	56.875	55	55.75	19-May-00	36.5	36.5625	35.5	35.75
22-Mar-00	56.375	56.625	54.875	56.375	22-May-00	35.875	36.5625	35	36.3125
23-Mar-00	55.625	57.5	55.5625	57.25	23-May-00	36.25	36.625	34.625	34.625
24-Mar-00	57.25	59.5625	57.125	58.75	24-May-00	35.1875	35.25	34.0625	34.75
27-Mar-00	58.875	60.75	58.6875	60.3125	25-May-00	34.75	34.9375	33.625	33.9375
28-Mar-00	60.3125	60.375	58.8125	59.875	26-May-00	34.125	34.875	34	34.5
29-Mar-00	59	61	57.25	60.25	30-May-00	35	35.8125	34.5625	35.375
30-Mar-00	59.625	60.8125	57.125	57.8125	31-May-00	35	35.4375	34.5	34.9375
31-Mar-00	58	58.1875	56.25	56.3125	1-Jun-00	34.6875	35.1875	34.625	34.9375
3-Apr-00	57.125	58.8125	56.6875	58	2-Jun-00	35.8125	36.1875	35.0625	35.125
4-Apr-00	57.5625	58.5	53.5	56.5	5-Jun-00	35.5	36.75	35.25	36.75
5-Apr-00	55.5	56.5	54.75	54.75	6-Jun-00	36.5	37.25	36.0625	36.125
6-Apr-00	55.1875	56.8125	55.125	56.5625	7-Jun-00	36.75	37.75	36.0625	37.125
7-Apr-00	56.8125	57	55.6875	56.6875	8-Jun-00	36.5625	36.5625	34.4375	35.25
10-Apr-00	56.75	56.75	55.375	56.25	9-Jun-00	35.25	35.3125	33.75	34.625
11-Apr-00	55.75	56.25	54.5625	55.25	12-Jun-00	34.5	34.75	33.5	34
12-Apr-00	54.625	54.9375	53	53.0625	13-Jun-00	34.1875	34.8125	33.5	34
13-Apr-00	53.5	55.125	53.1875	54	14-Jun-00	34	34.25	33.5	33.5
14-Apr-00	53.125	53.25	49.6875	50	15-Jun-00	33.9375	34.375	33.25	34.1875
17-Apr-00	49	50.375	46.5	46.8125	16-Jun-00	34.0625	34.4375	33.3125	33.4375
18-Apr-00	47.625	51	47.5	50.6875	19-Jun-00	33.75	34.1875	33.5625	33.875
19-Apr-00	51.5	52.1875	50.5625	50.9375	20-Jun-00	33.875	34.75	33.5625	34
20-Apr-00	50.8125	51.125	49.625	49.9375	21-Jun-00	34.125	35.25	34	35
24-Apr-00	49.125	49.5	48.125	49.0625	22-Jun-00	35.3125	37.25	34.8125	36.0625
25-Apr-00	49.75	52.875	49.5625	51.875	23-Jun-00	35.5	35.75	33.8125	34.375
26-Apr-00	52.1875	52.1875	50.25	51	26-Jun-00	34.3125	34.3125	32.5	32.8125
27-Apr-00	49.25	50.25	47.5	48	27-Jun-00	32.9375	34	32.75	33.5
28-Apr-00	48.25	48.875	45.875	45.875	28-Jun-00	32.875	33	32.0625	32.375
					29-Jun-00	32.25	32.8125	31.8125	32.25

Stock E

Traiding Data

Date	Open	High	Low	Close
1-Feb-99	4.5938	4.6562	4.375	4.5
2-Feb-99	4.4062	4.4688	4.3281	4.3281
3-Feb-99	4.1719	4.3125	3.9688	4.0312
4-Feb-99	3.9844	4.1562	3.9375	4.1562
5-Feb-99	4	4.0938	3.9844	3.9844
8-Feb-99	4.1875	4.1875	3.625	3.6719
9-Feb-99	3.7188	3.7812	3.625	3.7188
10-Feb-99	3.6875	3.7812	3.6875	3.75
11-Feb-99	3.75	3.75	3.6562	3.6562
12-Feb-99	3.6875	3.75	3.6562	3.7188
16-Feb-99	3.8281	3.8438	3.4062	3.5
17-Feb-99	3.4062	3.5781	3.4062	3.5
18-Feb-99	3.5	3.5625	3.4062	3.4688
19-Feb-99	3.4688	3.5625	3.4219	3.4844
22-Feb-99	3.4688	3.5312	3.4375	3.5
23-Feb-99	3.5625	3.5625	3.3125	3.3906
24-Feb-99	3.4062	3.4062	3.2969	3.3438
25-Feb-99	4.25	4.7266	3.9844	4.4688
26-Feb-99	4.4531	4.4531	4.1562	4.25
1-Mar-99	4.2812	4.3125	4.125	4.1875
2-Mar-99	4.1719	4.3438	4.1719	4.25
3-Mar-99	4.25	4.3125	4.1562	4.1875
4-Mar-99	4.1875	4.25	3.8438	3.8438
5-Mar-99	3.875	4	3.875	3.9062
8-Mar-99	3.9375	3.9531	3.7812	3.8281
9-Mar-99	3.7812	3.875	3.7812	3.875
10-Mar-99	3.875	3.875	3.7188	3.7656
11-Mar-99	3.7656	3.875	3.7188	3.8125
12-Mar-99	3.6875	3.8125	3.5938	3.625
15-Mar-99	3.625	3.75	3.5938	3.75
16-Mar-99	3.7812	3.8125	3.6562	3.8125
17-Mar-99	3.75	3.8125	3.6875	3.7812
18-Mar-99	3.6875	3.9688	3.6875	3.9688
19-Mar-99	3.9375	4	3.8438	3.8438
22-Mar-99	3.8438	4	3.8438	3.875
23-Mar-99	3.8438	4.4062	3.7812	4.125
24-Mar-99	4.125	4.375	4.0938	4.3438
25-Mar-99	4.375	4.375	4.2812	4.3281
26-Mar-99	4.3125	4.3125	3.9375	3.9375
29-Mar-99	4.0312	4.125	3.9219	4.0938
30-Mar-99	4	4.25	4	4.2031
31-Mar-99	4.2031	4.3125	4.1406	4.1406
1-Apr-99	4.1562	4.25	4.0781	4.2188
5-Apr-99	4.2812	4.2812	4.1094	4.25
6-Apr-99	4.2031	4.2656	4	4.25
7-Apr-99	4.125	4.3281	4.125	4.3281
8-Apr-99	4.3594	4.4062	4.3281	4.3672

Date	Open	High	Low	Close
2-Aug-99	10.5312	11.3438	10.4688	10.5312
3-Aug-99	10.6875	10.75	9.7188	9.9844
4-Aug-99	9.75	9.9531	8.625	9
5-Aug-99	8.9375	9.75	8.6875	9.6875
6-Aug-99	9.6875	9.875	8.9062	8.9062
9-Aug-99	8.8516	9.0625	8.3438	8.3438
10-Aug-99	8.2188	8.5938	7.9375	8.375
11-Aug-99	8.4297	9.625	8.4297	9.625
12-Aug-99	9.6562	9.6875	8.6562	8.75
13-Aug-99	9.0312	10.4375	9	10.375
16-Aug-99	10.5625	10.8125	9.7812	10
17-Aug-99	10.25	10.9375	10.125	10.5
18-Aug-99	10.3125	10.6562	10.0625	10.125
19-Aug-99	10.0625	10.3125	9.6875	10.1875
20-Aug-99	10.0625	10.5	10.0625	10.25
23-Aug-99	10.3125	10.875	10.25	10.7812
24-Aug-99	10.75	10.8125	10.5	10.5938
25-Aug-99	10.5938	12.1875	10.5938	12
26-Aug-99	13.875	14.5	12.875	13.4375
27-Aug-99	13.7812	14.2188	12.75	13.1875
30-Aug-99	13.875	13.9375	13.25	13.3125
31-Aug-99	13.5625	16.25	13.3125	16.125
1-Sep-99	15.8125	17.625	14.6875	15
2-Sep-99	14.5625	15.875	13.75	14.875
3-Sep-99	16.3438	16.5625	15.0625	15.625
7-Sep-99	15.75	16.3125	15.5625	15.7188
8-Sep-99	15.6875	15.8125	14.75	15.0625
9-Sep-99	15.3438	16.6875	15.125	16.5
10-Sep-99	17.0156	17.2188	16.625	16.75
13-Sep-99	16.8125	17.9375	16.75	17.4688
14-Sep-99	17.6562	17.8125	17.0625	17.4375
15-Sep-99	17.25	17.6875	16.4062	16.5312
16-Sep-99	16	16	14.75	15.8125
17-Sep-99	16.5	17.375	15.5	17.375
20-Sep-99	17.4375	19.9688	16.875	18.5
21-Sep-99	18.5	18.5938	17.125	17.625
22-Sep-99	17.9062	18	16.75	16.9375
23-Sep-99	17.125	17.375	14.25	14.3125
24-Sep-99	14.3125	14.4688	13.25	13.5312
27-Sep-99	13.7969	14.2188	13.5	13.8125
28-Sep-99	13.875	13.875	13	13.5938
29-Sep-99	13.4844	13.5	12.3438	12.6562
30-Sep-99	12.875	14.0625	12.6875	13.9062
1-Oct-99	13.875	14.25	13.25	13.75
4-Oct-99	13.4375	13.875	13.25	13.8438
5-Oct-99	13.9688	15.125	13.9375	14.75
6-Oct-99	15.2812	16.75	15.25	16.5

9-Apr-99	4.4062	4.75	4.3594	4.625
12-Apr-99	4.3594	4.6562	4.3594	4.6406
13-Apr-99	4.625	4.875	4.625	4.75
14-Apr-99	4.75	4.7812	4.5625	4.75
15-Apr-99	4.7812	4.7812	4.6875	4.7031
16-Apr-99	4.6562	4.75	4.6562	4.7344
19-Apr-99	4.7812	4.7812	4.4375	4.4531
20-Apr-99	4.4375	4.4531	4.3438	4.4531
21-Apr-99	4.4688	4.5625	4.3438	4.5625
22-Apr-99	4.5312	4.7812	4.5312	4.75
23-Apr-99	4.6875	5.3125	4.6875	5.2188
26-Apr-99	5.2812	5.75	5.2188	5.75
27-Apr-99	5.75	5.75	5.3125	5.5312
28-Apr-99	5.4062	5.875	5.2188	5.5469
29-Apr-99	5.2812	5.625	5.2812	5.375
30-Apr-99	5.3125	5.5625	5.2812	5.4062
3-May-99	5.3125	6.1875	5.3125	5.9844
4-May-99	6	6.2812	5.9375	6.0625
5-May-99	6.125	6.1562	5.8438	5.9219
6-May-99	5.875	6	5.7812	5.8438
7-May-99	5.8438	5.9375	5.625	5.9062
10-May-99	5.9688	6.125	5.875	5.9375
11-May-99	5.9375	6.25	5.9375	6.2344
12-May-99	6.25	6.375	6.0625	6.0625
13-May-99	6.0625	6.4531	6	6.1875
14-May-99	6.1875	6.3125	6.1562	6.25
17-May-99	6.2656	6.3125	6.1562	6.25
18-May-99	6.4688	6.4688	5.4688	5.75
19-May-99	5.8125	5.8125	5.1875	5.375
20-May-99	5.5625	5.75	5.5312	5.6875
21-May-99	5.75	5.8438	5.625	5.75
24-May-99	5.8438	5.8438	5.4688	5.5
25-May-99	5.4688	5.5	5.1875	5.2812
26-May-99	5.4688	5.6875	5.4219	5.6094
27-May-99	5.9219	6.2656	5.875	6.1562
28-May-99	6.1562	7	6.125	6.8594
1-Jun-99	6.9688	7	6.625	6.7188
2-Jun-99	6.7188	6.8438	6.5938	6.75
3-Jun-99	6.7344	7.125	6.7188	6.8125
4-Jun-99	6.8438	7	6.7656	6.9375
7-Jun-99	6.875	7.4375	6.875	7.3438
8-Jun-99	7.4219	7.5938	7.25	7.4219
9-Jun-99	7.4531	7.4531	7.0312	7.1562
10-Jun-99	7.0312	7.125	6.625	6.9062
11-Jun-99	6.8906	7	6.75	6.75
14-Jun-99	6.7812	6.7812	6.375	6.5625
15-Jun-99	6.6875	6.9375	6.625	6.9375
16-Jun-99	7	7.5938	6.9688	7.5938
17-Jun-99	7.5781	7.5938	7.4375	7.5156
18-Jun-99	7.5625	7.5781	7.4219	7.4688
21-Jun-99	7.4688	7.6875	7.4531	7.5625
22-Jun-99	7.4375	8.4375	7.4375	8.1562

7-Oct-99	16.9375	17.25	15.25	16.9062
8-Oct-99	16.9062	17	16.125	16.4062
11-Oct-99	16.4375	16.75	14.5938	15.5
12-Oct-99	15.375	16.375	15.25	15.4375
13-Oct-99	15	15.875	15	15.4688
14-Oct-99	15.5	15.6875	15.0625	15.5312
15-Oct-99	14.5	15.5	14.0312	15.1875
18-Oct-99	14.75	14.9375	13.25	13.375
19-Oct-99	14.0625	14.4688	13.75	14.0312
20-Oct-99	14.0312	16.7188	14	15.5625
21-Oct-99	15.3438	16.375	14.625	15.375
22-Oct-99	15.4375	16.1875	15.125	15.125
25-Oct-99	15.5938	15.8125	14.9062	15.5625
26-Oct-99	15.6875	16.0938	15.125	15.1562
27-Oct-99	15.3594	16.625	15.2812	16.625
28-Oct-99	17	18.5938	16.625	18.5
29-Oct-99	19.3125	20.5	18.5	18.625
1-Nov-99	19.5938	23.375	19.5	22.3125
2-Nov-99	23.3125	23.5	20.5938	20.875
3-Nov-99	21.5	22	20.75	21.9375
4-Nov-99	22.7031	22.75	19.1875	20.2812
5-Nov-99	20.5625	21.5	20.5	21.25
8-Nov-99	21.2812	21.75	20.8125	21.3125
9-Nov-99	21.25	21.375	19.9375	20.75
10-Nov-99	20.8125	21.625	20.5	21.5
11-Nov-99	21.625	22.5625	20.875	22
12-Nov-99	23	24	20.9375	21.3125
15-Nov-99	22	22.5	21	21.25
16-Nov-99	21.1562	21.5625	20.625	21.375
17-Nov-99	21.0625	22	20.9375	21.3125
18-Nov-99	21.75	22.7188	21.375	22.4375
19-Nov-99	22.625	22.75	21.25	21.25
22-Nov-99	22.1875	22.25	21.125	21.5625
23-Nov-99	21.3125	21.75	19.4375	20
24-Nov-99	19.9062	20.25	18.5	19.4375
26-Nov-99	19.3438	19.5625	18.125	18.5
29-Nov-99	18.0312	19.2812	17.4375	18.4375
30-Nov-99	20.75	22.875	20.6875	22.4688
1-Dec-99	22.875	22.9375	20	21.1562
2-Dec-99	20.875	22.3125	20.875	22
3-Dec-99	22	22.375	21.75	22.0625
6-Dec-99	22.4375	25.6875	22.125	25
7-Dec-99	27.0625	27.75	25.875	26.6875
8-Dec-99	27.0312	29.2812	26.1562	27.5312
9-Dec-99	27.2188	27.25	23	26.375
10-Dec-99	27	27.1562	26.375	27.0312
13-Dec-99	27	28.3125	26.6562	28.3125
14-Dec-99	28.5	28.75	24.4375	25.875
15-Dec-99	25.8125	26	24	24.6875
16-Dec-99	24.8438	26	24.625	25.5
17-Dec-99	26.5	26.8125	24.75	24.9688
20-Dec-99	25.5312	26.0938	25.0938	26.0938

23-Jun-99	8.125	8.2188	7.7812	8.0625
24-Jun-99	8.0625	8.1406	7.875	7.875
25-Jun-99	7.875	8.0312	7.6562	7.7812
28-Jun-99	7.7188	8.875	7.7188	8.8125
29-Jun-99	8.9375	9.4688	8.8281	9.2812
30-Jun-99	9.6875	10.75	9.4375	10.125
1-Jul-99	10.5	10.9844	9.9375	10.75
2-Jul-99	10.75	11.2188	10.7188	10.875
6-Jul-99	10.8125	11.125	10.8125	10.9062
7-Jul-99	10.875	10.9062	9.75	9.8125
8-Jul-99	9.3125	10	9.2812	9.9688
9-Jul-99	9.9688	9.9688	9.3125	9.5
12-Jul-99	9.5312	9.9062	9.25	9.8281
13-Jul-99	9.625	10.5469	9.4688	10.25
14-Jul-99	10.2188	10.4688	10.0625	10.4062
15-Jul-99	10.4375	11.9688	10.0625	11.4531
16-Jul-99	11.5	12.1562	11.125	11.8438
19-Jul-99	12.4375	12.4688	11.75	12.0312
20-Jul-99	12.125	12.2188	11.5469	11.6562
21-Jul-99	11.5938	11.7188	10.9688	11.375
22-Jul-99	11.0938	11.3125	10.7969	10.9688
23-Jul-99	11.1562	11.1562	10.4219	11.0781
26-Jul-99	10.7812	11.0156	10.3438	10.75
27-Jul-99	10.75	10.8438	9.875	10
28-Jul-99	10.125	10.5	10.0625	10.3906
29-Jul-99	10.1875	10.3125	9.875	10.1875
30-Jul-99	10.0312	10.625	10.0312	10.625

21-Dec-99	26.2188	26.6875	25.75	26
22-Dec-99	25.9375	26.0625	24	25.125
23-Dec-99	25.5625	26.0625	24.125	24.1875
27-Dec-99	24.25	25.125	24.1875	25.0625
28-Dec-99	24.6875	26.125	24.6875	25.4375
29-Dec-99	26.0312	26.1875	24.375	25.3438
30-Dec-99	25.7812	25.7812	24.4375	24.875
31-Dec-99	24	24.875	23.5625	24.3125
3-Jan-00	25.875	25.875	24.3125	25.6875
4-Jan-00	25.75	26	24.5938	25.4375
5-Jan-00	24.6875	25.625	24	25.5312
6-Jan-00	25.5	27.5	25	25.875
7-Jan-00	26.5625	27.5	25.9062	27.2188
10-Jan-00	29.5625	31.5	28	30.5
11-Jan-00	31.4375	31.5625	29.5	29.9375
12-Jan-00	29.75	31.0625	29.5	30.625
13-Jan-00	31.0625	31.3125	30.125	30.9375
14-Jan-00	31	32.5	31	32.25
18-Jan-00	32.5	32.5	31.4375	32.4062
19-Jan-00	32	33.1875	30.5	31.25
20-Jan-00	31.1562	31.875	29.9062	31.0625
21-Jan-00	31.3125	31.3125	28.625	29.75
24-Jan-00	29.25	31.0625	26.1875	28.375
25-Jan-00	27.5625	28.4688	26.5	27.4375
26-Jan-00	28	28.375	27.25	27.5
27-Jan-00	27.5	27.8125	27.0625	27.25
28-Jan-00	27.8125	28.0625	25.6875	25.9688
31-Jan-00	25.9375	26.125	21.1875	24.5

Validation Data

1-Feb-00	24.125	26.25	24.125	25.375
2-Feb-00	25	28	25	26.625
3-Feb-00	27.5	28.1875	27.25	27.9688
4-Feb-00	27.9219	30.0625	27.875	29.1875
7-Feb-00	30.5	31	29	30
8-Feb-00	30.0625	30.125	28.5938	29.0625
9-Feb-00	30	30.0625	28.8125	29.3125
10-Feb-00	29.3125	31.5	28.9688	31.5
11-Feb-00	32.25	35.5	32.25	34
14-Feb-00	36.4375	36.9062	34	35.75

15-Feb-00	36.375	36.6875	31.9375	34.6875
16-Feb-00	34.625	34.9375	32.3125	34.375
17-Feb-00	35.3125	35.5	32.25	33.3438
18-Feb-00	34.0938	34.75	33.9062	34.375
22-Feb-00	34.5938	35	32.9375	34.125
23-Feb-00	34.75	37.5625	34.3125	37.125
24-Feb-00	37.625	39.125	37.5312	38.25
25-Feb-00	39.75	44.875	39.375	42.0312
28-Feb-00	43.5	43.75	40.5	43
29-Feb-00	44.125	46.0625	43.3125	45.3125

Testing Data

1-Mar-00	48.875	50.5	47.5	48.4062
2-Mar-00	48.875	49	44	44
3-Mar-00	44.4688	48.5625	43.5625	48.4688
6-Mar-00	49	50	48.25	49.5
7-Mar-00	49.25	49.4375	48.1875	48.7188
8-Mar-00	48.9375	48.9375	39.375	48.5
9-Mar-00	48	48.6875	45	46.875
10-Mar-00	46.5	48.5	45	45.0625
13-Mar-00	45.25	47.6875	43.5	46.75
14-Mar-00	50.25	50.25	45.5	47
15-Mar-00	48.5	49	41	42.75
16-Mar-00	45.375	45.4375	38	45
17-Mar-00	44.4375	44.625	40.5	41.125
20-Mar-00	42.125	42.75	38.5	38.5
21-Mar-00	38.4375	43.125	34.5	43
22-Mar-00	44.75	47	40.625	46.875
23-Mar-00	47.75	49	45	46.8125
24-Mar-00	46.875	48.75	44.4375	46
27-Mar-00	45.75	48	44.5	45.125
28-Mar-00	45.0625	46.5625	41.625	41.6875
29-Mar-00	42.125	43.125	37	39.5
30-Mar-00	35.3125	39.75	35.25	35.875
31-Mar-00	35.3125	36.4062	31.75	34.25
3-Apr-00	33	34	30	30.375
4-Apr-00	31.3125	37	25.375	37
5-Apr-00	33.875	37	31.5	33.5625
6-Apr-00	35.375	37.9375	32.9375	36.5
7-Apr-00	38.5625	40.5	37.5	39.5
10-Apr-00	40.4375	40.4375	33	33.1875
11-Apr-00	30.25	32.375	28.25	29.6875
12-Apr-00	29.5	29.5	25.875	26.875
13-Apr-00	26.9375	30.5	26.625	27.3125
14-Apr-00	26.2812	26.9375	23	24
17-Apr-00	20.75	26.625	20.5	26.375
18-Apr-00	28.625	29.625	26.75	29
19-Apr-00	29.625	31	27.25	27.5625
20-Apr-00	27.9375	28	24.25	25.5
24-Apr-00	24.125	24.125	22.5	23.5
25-Apr-00	25.875	26.0625	23	24.7656
26-Apr-00	25.875	26	21.9375	22.125
27-Apr-00	21.5	23.75	20.8125	23
28-Apr-00	23.625	25	23.625	24.5625
1-May-00	26.75	26.75	23.625	24.125
2-May-00	24.625	24.625	20	20.1875
3-May-00	20.8125	21.375	20	20.9375
4-May-00	22.4375	22.5	20.5	21.125
5-May-00	20.875	21.75	19.5	20.125
8-May-00	19.75	20.25	16.125	16.25
9-May-00	16.75	17.5	13.5625	14.9375
10-May-00	15	17.75	14.5	17.5
11-May-00	17.375	18.875	16.625	18.4375
12-May-00	18.8125	19.9375	17	17
15-May-00	17.125	18	15.125	17
16-May-00	18	18	15.875	17.4375
17-May-00	16.5	16.5	13	14.3125
18-May-00	14.8125	15	13.75	14.3125
19-May-00	14.0625	14.375	13.625	13.9375
22-May-00	14	14.125	12	13.5
23-May-00	13.375	14.1875	11.4375	11.9375
24-May-00	12.5	12.8125	10.6875	12.8125
25-May-00	13.375	13.375	12	12.0625
26-May-00	12.375	12.5	11.375	12.3125
30-May-00	13.0625	13.4375	11.625	13.4375
31-May-00	13.5625	13.75	12.125	12.75
1-Jun-00	12.8125	13.4375	12.75	13.0625
2-Jun-00	14.25	16.6875	14.0625	16.4375
5-Jun-00	17.125	17.625	15.625	16.25
6-Jun-00	16.3125	16.375	15	15
7-Jun-00	15.0625	17	15	16.875
8-Jun-00	17.6875	17.6875	16.75	16.8125
9-Jun-00	17.625	17.625	17.0625	17.25
12-Jun-00	17.6875	19.25	16.125	18.3125
13-Jun-00	17.1875	17.75	16.9375	17.5
14-Jun-00	17.75	17.75	16.5	16.625
15-Jun-00	16.875	16.9375	15.5	16.125
16-Jun-00	16.125	16.375	14.625	15.125
19-Jun-00	15.4375	16.25	14.75	16.1875
20-Jun-00	16.4375	16.5	15.625	15.875
21-Jun-00	15.4375	16.375	15.25	15.75
22-Jun-00	15.9375	18	15.875	16.75
23-Jun-00	17.875	19.25	17.5	17.5
26-Jun-00	18.125	18.125	16.5	17
27-Jun-00	17	17.0625	15.75	15.8125
28-Jun-00	15.625	16.625	15.5	16
29-Jun-00	15.75	16.125	15.625	15.6875