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Integrated computational intelligence and Japanese candlestick method for short-term financial forecasting

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ABSTRACT

This research presents a study of intelligent stock price forecasting systems using interval type-2 fuzzy logic for analyzing Japanese candlestick techniques. Many intelligent financial forecasting models have been developed to predict stock prices, but many of them do not perform well under unstable market conditions. One reason for poor performance is that stock price forecasting is very complex, and many factors are involved in stock price movement. In this environment, two kinds of information exist, including quantitative data, such as actual stock prices, and qualitative data, such as stock traders' opinions and expertise. Japanese candlestick techniques have been proven to be effective methods for describing the market psychology. This study is motivated by the challenges of implementing Japanese candlestick techniques to computational intelligent systems to forecast stock prices. The quantitative information, Japanese candlestick definitions, is managed by type-2 fuzzy logic systems. The qualitative data sets for the stock market are handled by a hybrid type of dynamic committee machine architecture. Inside this committee machine, generalized regression neural network-based experts handle actual stock prices for monitoring price movements. Neural network architecture is an effective tool for function approximation problems such as forecasting.

Few studies have explored integrating intelligent systems and Japanese candlestick methods for stock price forecasting. The proposed model shows promising results. This research, derived from the interval type-2 fuzzy logic system, contributes to the understanding of Japanese candlestick techniques and becomes a potential resource for future financial market forecasting studies.

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1. INTRODUCTION

1.1. OVERVIEW

Investment in the world's financial market is a common practice of many institutions, business organizations, and individual households throughout the world. One of the common investments is in the stock market. Each investor hopes that an investment in the stock market will be successful and will increase the value of his or her assets. To aid in this goal, countless financial techniques and applications are currently being developed for forecasting the stock market.

The recent technological advancements of computers, computer applications, and Internet technologies have significantly impacted the financial investment environment. For example, the Internet has made it possible not only for financial service organizations to access market data and information, but also ordinary public investors. In addition, personal computers and applications allow everyone to see the up-to-date price movement of stocks and to create individual investment strategies. The tools available for the only professional traders became accessible to many household investors today. The technology also made it possible to many investors for researching and purchasing various kinds of financial instruments through online. The common stocks are the popular financial instrument, yet a type of derivative product, like options, can also trade through online in real-time. The numbers of investors increased with the spread of accessibility to the technologies. As a result, the financial investment environment is becoming more and more various styles and kinds of investors came into the trading to look for the opportunity, and the rules of trading practice has been changing rapidly. The only rule that has not been changed is that all investors look for the profit from the trading financial instruments.

Today, many financial technical methods are available for investors to improve their profits. One such technical method is the forecasting technique using a computer-based model. Neural networks-based model is one of them. In this technique, investors train a neural network to manipulate a market and use its simulation for investment guides. Financial service organizations are starting to accept the advantages of computer-based financial models to predict the future condition of the market.

Despite the advancements in technology, many traditional forecasting techniques and tools are still valid and widely used today. One of them is candlestick analysis. This technique was developed in Japan in the 1700s for trading and exchanging the commodity rice. This ancient financial technical analysis is a popular technique for predicting the market movement in Japan. Today, financial analysts around the world are becoming aware of the usefulness of this technique and are adapting it into their investment strategies.

It is important to note that Japanese candlestick analysis is an approximate reasoning of forecasting prices in the financial market. The candlestick patterns are too imprecise and complex for static computer models, and they require human-like flexibilities for analysis. A system of fuzzy logic can focus on modeling problems characterized by imprecise or ambiguous information. Therefore, fuzzy logic is a useful tool for understanding and recognizing the candlestick patterns.

The efficiency of the candlestick chart in a fuzzy logic-based hybrid model becomes a desirable advantage in forecasting the market and economy—which many financial organizations would like to have. This combination of candlestick chart analysis techniques and a hybrid model brings benefits to many types of financial research.

1.2. RESEARCH MOTIVATION AND OBJECTIVES

It is time-consuming and expensive for financial institutions to train financial experts and traders to watch all companies listed in all financial markets. There is a limit to what one trader can follow and study. Also, it is difficult to pass on the knowledge of well-trained and experienced experts and traders to newcomers because this process of transferring knowledge is different from simply handing out a how-to manual. Such manuals do not provide experts' insight, comprehension, or skills acquired from experience. In addition, the remaining years before the trained experts and traders retire may be short, and the time needed to regain the investment made in training expenses may be uncertain. To solve these problems, a hybrid intelligent system must be developed to observe the stock market and give appropriate signs for trading decisions. This system also will allow future generations to learn from current traders.

Developing the best intelligent forecasting system that produces the maximum profit is the ideal goal for many researchers and investors. However, this is a difficult task. Some of today's researchers question the efficient market hypothesis that has been a popular theory and indicate that the inefficiencies of the market are clear.

Before developing the forecasting model with Japanese candlestick methods, various available techniques were examined for feasibility in financial forecasting. One is neural network-based forecasting. The observation from the neural network models was that individual neural network architectures have their own limitations; it is necessary to add techniques to overcome these limitations. After this observation, the experiment involving the existing model developed by Disorntetiwat (2000) was performed. His model uniquely represented the behaviors of the international financial markets. However, it also presented several difficulties, one of which was the processing of the input data. His model could not perform well when the market indices rapidly shifted up and down. A detailed analysis found that this committee machine-based model actually does not function well under such market conditions. Then, the possibility arose of applying a new approach within the model, the Japanese candlestick chart technique.

Representing the candlestick chart was a complicated task. Many Japanese traders and investors use the candlestick chart system and analyze the pattern visually. Therefore, the first approach was to process the candlestick patterns like human traders do. The development of candlestick pattern images was successful; however, detecting the images correctly and examining the patterns proved more difficult. The pattern and image recognition application developed by Chafin (1999) was used for this purpose. This application program had performed well with three-dimensional images. All of the candlestick images are simple, two-dimensional images, so processing them was believed to be an easy task. However, the identification of candlestick patterns was not successful. Therefore, new approaches toward identifying candlestick patterns are tested and discussed in this dissertation.

The Japanese candlestick chart technique is new to many well-trained traders. Books discussing this technique describe that the Japanese candlestick patterns show both quantitative information, such as market trend movements, and qualitative information, such as market psychology. In any given financial market condition, it cannot be concluded that an efficient market hypothesis exists. All traders are looking for trading strategies that adapt to market conditions. The Japanese candlestick chart techniques could be the solution for which they are looking. However, they have not yet applied it to their trading strategies and taken advantage of this unique method. Therefore, implementing Japanese candlestick chart techniques in a hybrid intelligent system could become one potential method for trading strategies in the future.

In this research, first the performance and effectiveness of Japanese candlestick chart techniques are investigated. Then, a basic model for this technique is developed to seek the system's optimal method and architecture. Finally, the hybrid forecasting system using the candlestick technique method is presented to evaluate the performance of the system.

This dissertation aims to develop a candlestick chart-based model for stock price forecasting and then to evaluate its effectiveness. This candlestick chart-based model is a hybrid model that combines the efficiency of neural networks and the strengths of candlestick chart techniques. In addition, type-2 fuzzy logic systems process ambiguous candlestick pattern definitions. The performance of this model is compared with other models to evaluate its efficiency. For comparison, stock price data from randomly selected companies are used.

1.3. ORGANIZATION

This dissertation encompasses the following sections. Section 1 provides an introduction of the overall dissertation, including an overview of the research and intelligent systems as well as a list of research objectives. Section 2 presents the literature review, which supports the techniques and methods implemented in the study as well as research from other scholars. Section 3 gives the tools used to develop the study models for the research. Section 4 introduces the Japanese candlestick chart techniques, which gives you the definitions of patterns. Section 5 discusses experimentation of the existing techniques that were possible candidates for the research model. Section 6 describes the systems and data for the study models. Section 7 summarizes the experiments and results from the models. Finally, Section 8 concludes the study and presents possible future work.

2. LITERATURE REVIEW

2.1. DEMAND OF FORECASTING

Since the civilization started in the world, people were curious about future events and related phenomena. They tried to figure out how the future events were linked with the universe and the surroundings. People observed the space and developed the astrology, feng shui, fortune telling, and so on to predict the future of the societies, cultures, and the individual lives.

In today's modern society, people still use the natural phenomena to predict the future. In the mid western states in the United States, people forecast the severity of the winter in each weeks looking at the woolly worms' 13 color bands. The same people also predict the amount of snow from the persimmon's seeds whether they are the spoon shaped or the folk shaped. In Japan, people look at the location of the bird nests on the tree to predict the amount of rain during the rainy season, and the location of the mantis' eggs on the tree to forecast the amount of snow. In China, the government observes the animals' behavior to predict the earthquake.

The society in any countries and cultures search for the answer to many occurrences and incidents. Then, they endeavor to find the correlation with the phenomena so that they understand the way to predict the future.

Forecast is the estimate process of future events. Estimating the unknown situation and predicting the future occurrence are the important activities for reducing the risk of the future plans. The failure of any plan becomes a cost. To minimize the cost, the various kinds of forecasting models are developed.

Weather forecast is one of the popular demands in this area. Lai, Braun, Zhang, Wu, Ma, Sun, Yang (2004) studied the weather forecasting in the east coast of China. They collected several data that related to the weathers from many regions of China to find the correlation of those data. Their model focused on forecasting the temperatures and rainfalls. Hansen and Nelson (1997) developed a model to forecast the state tax revenue in Utah. The estimation of the state revenue is critical for budgeting the maintenance and improvement of the state infrastructure and the state education. The wave forecast model for seas is important for the safety of the shipping transportation (Tuomi and Sarkanen, 2008). Their new model forecast the several wave conditions and extended the length of forecast from the current forecasting models. The new model improved the overall forecasting system for the naval safety. In the similar study area, Parker of National Ocean Service, NOAA (1986) had conducted the forecasting of the water level and circulation. In the same organization, Salman (2004) presented the forecasting models for maintenance work load for weather forecasting systems and equipment in Alaska. The analysis of forecasting uncertain hotel room demand and revenue management was conducted by Rajopadhye, Ghalia, Wang, Baker and Eister (1999). The model was for forecasting the next day's room demand. However, their model did not create a significant impact on forecasting the room demand in a hotel. After the investigation of their results and errors, the authors concluded they needed further research with other forecasting methods and tools. In 2000, Ghalia and Wang improved the same model for estimating the hotel room demand with addition of flexibility of fuzzy logic systems.

Some of the examples of forecasting models are: The electric energy consumption forecast model (Baczynski and Parol, 2004), the trend analysis for long term financial prediction model (Kuwabara and Watanabe, 2006), semiconductor manufacturing forecast (Chittari and Raghavan, 2006), short term traffic flow forecasting with support vector machine (Sun, Wang, and Pan, 2008), neural network prediction model for a psychiatric purpose (Linstron and Boye, 2005), Occupational disease incidence forecast (Huang, Yu, and Zhao, 2000), and many other kinds of models are studied by scholars and researchers. In any case, they tested their model to find the optimized solution and efficiency to reduce the cost of operations and activities.

2.2. FORECASTING IN FINANCE

Financial service firms, the industry, the government, and individual investors and many other organizations need to manage the finance to operate their businesses. In financial fields, more and more organization dependent on advanced instrument and computer technologies to institute and maintain competitiveness in a global and local economies (Trippi and Turban, 1996). The various financial forecast applications are built to support today's competitive environment.

Financial forecasting like stock market prediction and price movement of stocks and other financial products are complex and dynamic. The numbers of models in the financial forecasting field are developed by researchers and scholars using their knowledge to develop and improve the performance of their models. Many methodology and techniques are applied in their models. However, their models still have various problems and challenges.

2.2.1. Statistical Methods for Time Series Forecasting. There are several conventional methods that have been applied to the forecasting models. These models are generally traditional statistical basis. Chang and Tsai (2002a) mentioned about the six traditional statistical models; simple exponential, Holt-Winters smoothing, Regression method, Causal regression, time series method, and Box and Jenkins. These statistical methods are either to execute through means of extrapolating a value at a time based on the equations and formulas of the forecasting models, or to observe the data that fit to the models, or to identify the characteristics of distributions and periodic variations (Chang and Tsai, 2002a). The authors pointed out the dilemma of these methods. For example, the forecasting models with Holt Winters smoothing, Regression method, or Box and Jenkins method normally require numerous observed data to find the corresponding relationships in the data. This nature is not practical for short-term forecasting.

Lee, Yang, and Park (1991) discuss about the autoregressive moving average (ARMA) in their research. The ARMA is a widely accepted method for constructing the short term forecasting models. The procedure of ARMA is achieved with the trial and error basis iterations and tentativeness that depends on autocorrelation function and partial autocorrelation function that introduced by Box and Jenkins in 1976 (Lee, Yang, and Park, 1991). However, the analysis of these patterns is difficult, and many scholars and researchers look for other alternative approaches to build time series forecasting models. Many of these time series forecasting modeling methods need the process of pattern recognition, but they cannot deal with the process of pattern recognition effectively (Lee, Yang, and Park, 1991).

A time series is generally stationary as its generating process is time invariant (Virili and Freisleben, 2000). According to the research of Virili and Freisleben (2000), Medeiros and Veiga (2000, 2005), and so on, the real life economic time series are rarely stationary and non stationary, nonlinear or chaotic behavior cannot be captured by linear statistical time series models. Because the regularities of the financial time series are usually covered with noise and that makes it nonlinear and non stationary behavior (Schwaerzel and Rosen, 1997). They mentioned about the Taylor (1986) concluded that many financial time series forecasting have non-random behavior. Based on the Taylor's testing and examination on his financial time series models, the random walk hypothesis does not appear valid for many financial time series.

Patel and Marwala (2006) also mentioned that if the random walk hypothesis is true, the stock prices on the stock market was set without any influence at all and move purely unpredictable manner. Many statistical time series models are stood on the stationary time series process like exponential smoothing, generalized regression, and ARMA and so on (Li , Liu, Le and Wang, 2005). However, the financial forecasting models have to deal with non-stationary behavior of the financial market. Therefore, artificial neural network received a huge attention for building financial forecasting models.

Several researchers investigated the performance of statistical methods and neural networks. Nagarajan, Wu, Liu and Wang (2005) discussed about the prediction of future price in foreign exchanges. Their research concluded that the neural networks could predict the exchange rates with low mean square errors. They also mentioned that the neural network itself was not suitable for making consistent profits from the trading, but the hybrid model with some statistical methods generated better results. Schwaerzel and Rosen (1997) also discussed about the single neural network system and the ensemble neural network system. Single neural network systems could perform well in many financial forecasting models. However, an ensemble of neural networks will perform better than any individual neural network (Shwaerzel and Rosen, 1997). They demonstrated their model using the currency rate forecasting against the US dollars in daily manner. They compared single neural network and ensemble neural networks, and concluded the ensemble neural network design lowers the prediction errors.

2.2.2. Neural Networks. Neural networks have been widely used for scientific prediction models in the forecasting the future occurrence. The traditional statistical forecasting methods, such as a time series approach and regression analysis, do not fit well in nonlinear behavior models such as stock market forecasting (Xiong, Yong, Shi, Chen, and Liang, 2005). Therefore, neural network techniques have become a popular approach for developing forecasting models in the financial field.

2.2.2.1 Backpropagation. One popular type is the backpropagation approach, and many backpropagation-based models have been developed. However, many of these models share the dilemma that the output of the network lies away from the target (Hagan, Emuth, and Beal, 1996). This is because backpropagation has features such as slow convergence and local minimization (Hagan, Emuth, and Beal, 1996).

Characteristics of backpropagation were studied in Tan and Wittig's (1993) research. They used Ford Motor Company's stock prices to examine the behavior of backpropagation. They discuss how the number of neurons in the hidden layer depends on the researchers. They mentioned Freisleben (1992) suggest a single hidden layer be used where the number of neurons in the hidden layer has a multiple number of inputs minus one. Baum and Haussler (1989) proposed the number of neurons in the hidden layer should be j=me/(n+z), where j is the number of neurons in the hidden layer, m is the number of data points in the training set, e is the error, n is the number of inputs and z is the number of outputs. Baum and Haussler's proposal for the hidden layer is heavily depend on the error rate and was not suite for Tan and Wittig's model (1993).

The momentum and learning rate are the keys for the good results with a backpropagation based models. Tan and Wittig (1993) followed the Freisleben's (1992) suggestion of 0.7. Higher momentum values converge faster, but it becomes unstable after reaching a minimum while smaller momentum values tend to take longer to converge and tend to fall into the local minima frequently (Tan and Wittig, 1993). The learning rate is important factor for the balanced results in terms of accuracy, speed of convergence and stability (Tan and Wittig, 1993). Their model used the learning rate of 0.5 out of the range between 0 and 1.

In their conclusion, they mentioned several elements of backpropagation and their results. One reason was that one of their models' poor forecasting rate maybe the addition of input noise. They say the price data has enough noise already, and the additional noise into the model failed to enhance the learning capability (Tan and Wittig, 1993). For the structure of the backpropagation, a model with less training passes produced the better forecasting results in their case, and the best predictor for the tomorrow's price is the immediate past price. They also mentioned about the activation function. They tested sigmoid function and Gaussian function in backpropagation. They concluded there was no significant advantage using Gaussian function over the sigmoid function (Tan and Wittig, 1993). The authors did not mention the spread of the Gaussian function, and the input data may not be captured well by the Gaussian function in their backpropagation model.

The stock price analysis and prediction was studied by Cheung, Ng, and Lam (2000). One of their models used a backpropagation technique to evaluate the intraday trading and the daily trading. They concluded the backpropagation model was unstable compare to the other models, such as a radial basis function based model. In other words, the results by the backpropagation model could be the best at a moment, but it could be the worst right after the moment. All depends on the input parameters and the numbers of training passes. Backpropagation is one of the popular neural network techniques, yet the performance stability is the issue of building backpropagation based models. Like Tan and Wittig research, Cheung, Ng, and Lam concluded the backpropagation model with fewer training passes produced the better results.

Other researches related to the backpropagation neural networks are: The currency exchange rate forecasting with backpropagation neural networks was studied by Refenes, Azema-Barac, and Karoussos (1992). The problems of backpropagation neural networks were discussed extensively in the paper. Phua, Zhu and Koh (2003) examined the major international stock exchange indices with their model. They experimented using the unique approach of direct use of indices as input data. Forecasting of the bond market from weekly financial data by the backpropagation was studied by Kane and Milgram (1994). The pattern matching method with backpropagation neural network was proposed for detecting the trading points was studied by Chang, Fan, and Liu (2009). The prediction of business cycles was performed by Oh and Han (2001).

2.2.2.2 Recurrent neural networks. Recurrent neural networks have an advantage over handling the data with relationship in time. The feedback feature of the recurrent neural network made it possible to work on the time relations. Khoa, Sakakibara, and Nishikawa (2006) mentioned that recurrent neural networks use not only the input data, but also on their own time lagged values. In their paper, they compared the backpropagation neural network based model and recurrent neural network based models. They tested their models for predicting the Standard and Poor 500 index, and examine the maximizing the profit. Their recurrent neural network was structured simple. They concluded the feature of recurrent neural networks, time capture capabilities, improved the over al results of their prediction model than the back propagation based model. However, the training structure of recurrent neural networks is basically the same as the backpropagation. Therefore, the recurrent neural network trainings have typical dilemma, local minima problem, learning rate settings, the over fitting problems. They tried to avoid the over fitting problem with the early stopping of training.

The study presented by Connor and Atlas (1991) noted some advantages of the recurrent network based models. They built the forecasting model for power load in the Seattle and Tacoma regions in the United States to investigate the performance of the models. They discussed the recurrent neural networks that have the ability to approximate for stochastic process with moving average components, and this was a reason that the recurrent neural networks performed better than feed forward networks.

Roman and Jameel (1996) also compared the backpropagation neural networks with the recurrent neural networks based models. Their model was developed for maximizing the profit from a portfolio of over several stock markets. Like Khoa, Sakakibara, and Nishikawa, the recurrent neural network based model produced the better results than the backpropagation based model. However, Roman and Jameel noted the difference between their two models was not so significant. They assume that the lag time of the recurrent neural networks is only a week, and the one week period may not contain enough information to improve the prediction accuracy large enough against the backpropagation based model.

Stock price pattern recognition by the recurrent neural network methods was examined by Kamijo and Tanigawa (1990). The first section of Tokyo Stock Exchange was used for extracting the stock price patterns. During the three year of testing period, sixteen of particular stock price pattern were correctly extracted by their recurrent neural network models.

Stock price forecasting and river flow forecasting with recurrent network is examined by Pattamavorakun (2007a). The research was mainly for searching the optimal number of hidden nodes for the best forecasting results. The same authors also discussed about the optimal training algorithm for recurrent neural networks in a different paper (Pattamavorakun, 2007b). The river flow data from two different rivers was used in the forecasting model.

More recurrent neural networks related works have accomplished. Forecasting the stock trend of IBM, Apple computer, and Motorola was performed with recurrent neural networks, and tried to search the investment opportunities (Saad, Prokhoroov, and Wunsch, 1996). Recurrent neural network based model was used for forecasting the economic cycle (Chen and Xu, 1998). The forecasting models for the price trend of stock index future (Chi, Chen, Cheng, 1999). Financial prediction and trading via reinforcement learning and soft computing (Li, 2005).

2.2.2.3 Radial basis function neural networks. Radial basis function neural networks are efficient for developing the forecasting models (Chang and Tsai, 2002b; Chen, Cowan, and Grant, 1991; Karayiannis, Balasubaramanian, and Malki, 2003; Xiong, et al., 2005). One reason is that the radial basis function neural network is good at handling the nonlinear system by the simple topological structure of the networks (Yan, Wang, Yu and Li, 2005). The radial basis function neural networks consist of Gaussian radial basis function in the network.

Forecasting the next day closing prices of several international stock exchanges is demonstrated by Patel and Marwala (2006). The Dow Jones Industrial Average, Johannesburg Stock Exchange, All Share, Nasdaq 100 and Nikkei 225 stock average indices were sampled to investigate the performance of their models. They examined both multi-layer perceptron and radial basis function neural networks and discussed the results from both models. Both neural networks are practical for forecasting models because the networks have the capability of classifying the nonlinear relationships and the outstanding universal approximators (Patel and Marwala, 2006). They examined the type of input data and the numbers of hidden nodes for the best performance. At the end, there was no significant comparison between these two neural networks architectures, but the authors opened up the committee machine techniques for the better performance.

The comparison of radial basis function neural networks and backpropagation neural networks was studied by Yan, Wang, Yu and Li (2005). Their models were developed not only for financial forecasting systems, but also for the electric load forecasting systems. The data from the Shanghai stock exchange market was used for financial forecasting. Electric power load data from a city electric power administration was used for forecasting the electric power load. The location of the city was not specified. Both models forecast the next day's values. The results shows that the radial basis function neural networks based model outperformed the traditional backpropagation neural network based models for both stock market forecasting and electric power load forecasting.

2.2.2.4 Generalized regression neural networks. One of the networks that consist of a radial basis layer in its network architecture is a generalized regression neural network. The network architecture of this type of neural network has a radial basis layer as the first layer and a special linear layer, usually a perceptron network, as the second layer. The network does not require an iterative training procedure, and it approximates any arbitrary function between the input and output vectors (Yidirim and Cigizoglu, 2002). This generalized regression neural network is useful for function approximation. The networks can approximate a continuous function to an arbitrary accuracy (Demuth and Beale, 2001).

As noted above, generalized regression neural networks are similar to the radial basis function neural networks. The performance of them depends on the application. Heimes and van Heuveln (1998) discussed the strength and weakness of these two neural networks in their paper. The main difference between radial basis function neural networks and generalized regression neural networks is the use of output later (Heimes and van Heuveln, 1998). The output layer of the generalized regression neural networks does the weighted averaging. The output layer of the radial basis function neural networks does the weighted summation.

The generalized regression neural network is best for applications that may need to store all the independent and dependent training data (Heimes and van Heuveln, 1998). Therefore, generalized regression neural networks are good for stock market prediction application. On the other hand, radial basis function neural networks may be preferred to the control systems and computational efficiency applications (Heimes and van Heuveln, 1998).

They also examined the input data and spread. When the input data values become too large, the performance of generalized regression neural networks becomes poor. Likewise the input data values become too small, the performance of generalized regression neural networks become poor. The reason is the generalized regression neural network cannot handle the data in the edge of the data map. To cover the edge of the data map, the large spread can be used. However, the larger spread acts like the averaging the data, and the overall performance of generalized regression neural networks becomes poor again.

Guo, Xiao and Shi (2008) built their generalized regression neural network based forecasting models for Shanghai composite index. They used the closing data of the Shanghai composite index as input data for the networks. The output from the network was the next day's closing price of the Shanghai Composite Index. They examined the spread of the networks and performance. As Heimes and van Heuveln mentioned in their paper, the results from Guo, Xiao and Shi (2008) also showed the same. When the spread becomes larger, the error becomes larger. When the spread becomes smaller, the error also becomes larger. Therefore, it is necessary to find the optimal spread to develop the efficient generalized regression neural networks.

2.2.3. Hybrid Approach. The hybrid approach usually combines two or more methods to overcome the difficulty of solving a problem. There are many forecasting models built with hybrid approach. Many of them are the combination of unique learning algorithms and neural networks or other computational approaches (Castillo and Melin, 2007; Chen, Hsu, and Hu, 2008; Junyou, 2007; Lin, Juan and Chen, 2007; Marzi and Turnbull, 2007; Yunos, Shamsuddin, and Sallehuddin, 2008). Committee Machine is a one of the ways to achieve this goal. The committee machines are good at solving a complex problem to divide into several tasks. If the tasks are still complicated, these tasks can be divided into smaller tasks that are simple and easy to deal with. Then, each expert in the committee machine takes care of the assigned simple task. Solomantine (2005) discussed about the splitting of training set and the combining output for committee machine models in his research.

Ensemble averaging is a simple committee machine approach. The problem is split into several assignments and joined at the end to provide the final solution. The study of stock market movement and the price direction analysis was successful with this technique (Disorntetiwat and Dagli, 2000). In this study, the trend direction of Standard and Poor 500 index and international currencies exchange rate was analyzed. The input data was sorted out based on the categories, high, low, closing prices and so on, and assigned to each expert. Each expert uses the generalized regression neural networks to take care of the data. The results from each expert are combined to make the final solution that was the forecast of next day closing index. The model also applied for forecasting the exchange rate. In both cases, the ensemble averaging technique achieved the successful forecasting results.

The mixture of experts type of committee machine was applied to the price prediction model for power systems in New England (Guo and Luh, 2004). The mixture of experts is that the input space is divided into several regions based on the input data. The model also used a gating network that acts as a negotiator between the experts. For forecasting the price of power systems, both multi-layer perceptron and radial basis function neural networks were investigated. Both neural network architectures performed well with the mixture of experts committee machines for forecasting the price. The actual results demonstrated that they performed better than the single network based model. The authors also discussed about the application of the gating networks. The usage of the gating network made a big difference for the forecasting results. In general, the results produced by the committee machine with gating networks were better than the ones by the ensemble averaging. However, the results produced by the ensemble averaging became better than the one generated by the committee machine with gating networks. The authors analyzed and concluded this occurrence as follow. One is when both models produced relatively close prediction results, and the weight generated by the gating network make it worse the final outcome. The other one is when the model performed well with the change from one network to another network, the weight assignment by the gating network did not react fast enough. This happened twice during the period of experiment data (Guo and Luh, 2004).

2.3. DATA TYPES

The characteristics of the input data types greatly impact the results of forecasting, which faces challenges in finding the rules and mechanisms behind the data (Cristea and Okamoto, 1998). There is always uncertainty concerning random data and predictability. The first section investigates the use of qualitative and quantitative data for prediction models. The second section discusses the impact of the trading volume in forecasting models.

2.3.1. Qualitative Data vs. Quantitative Data. The forecasting model developed by Yoon and Swales (1991) included qualitative data as a part of the input data. This data came from the companies' annual reports. Their model predicts the firms' stock price performance rather than the stock prices themselves. For example, Company A can be classified as a well-performing firm or a poorly-performing firm on the basis of its stock price.

The researchers focused on the presidents' letters to stockholders in the annual reports as a source of qualitative data. The qualitative content analysis technique they used classified and tallied recurring themes that were identified by similar words or phrases (Yoon and Swales, 1991). This qualitative content analysis is popular among the social science fields, and Yoon and Swales adapted the techniques for their model.

Their model had an average 77.5% success rate for categorizing the companies. Unfortunately, Yoon and Swales focused primarily on their model's neural network performance and provided only a limited discussion of the qualitative data and qualitative data extraction from the firms' presidents' letters. However, they stated that qualitative data can provide neglected sources of valuable information to the investors in their research (Yoon and Swales, 1991).

Sagar and Lee (1999) of Singapore also investigated the effect of using qualitative data in their stock price forecasting model. The qualitative data used in their models were retrieved from stock news group articles in Singapore. Their model was developed to predict the next day's stock price of three companies that are listed in the Singapore Stock Exchange (SES).

The news group articles were analyzed with a program, Natural Language Processing (NLP), developed at the University of Durham in the United Kingdom. The NLP program explores the input sentences in free, natural language and stores the meanings as an appropriate representation. The data generated by the NLP program were used with the historical stock data as input data for their neural network-based forecasting models. The author opined that the NLP program's qualitative data extraction was good. However, adding this data did not significantly impact the final forecasting results. The authors concluded that the NLP program's information extraction from the newsgroup articles still had limitations. Improving the results would require improvements in the NLP program. Upon the publication of their research, their forecasting model did not show any better results with the qualitative input data than without it.

Sagar and Lee examined and proved that a correlation existed between newsgroup articles and the movement of stock prices in their models. Their research showed that qualitative information could be integrated as input data for financial forecasting models in the future.

2.3.2. Trading Volume vs. Non-Trading Volume. The impact of trading volume on the forecasting model's performance was explored in Wang, Phua and Lin's study in 2003. The selection of input data is an important factor affecting the accuracy of neural network forecasting, and trading volume is considered a fundamental piece of data (Wang, Phua, and Lin, 2003). The daily stock indices of the S&P 500 and Dow Jones Industrial Average were used as input data for their neural network-based model.

In their study, Wang, Phua and Lin focused on the benefit of using trading volume as one piece of the data input into their stock market forecasting model, especially in tandem with stock prices. They discussed several studies related to trading volume and forecasting. Gallant, Rossi and Tauchen (1992) discussed stock prices and volume, claiming that a relationship exists between the two and that this relationship may be important for stock price establishment. Brooks (1998) discussed market volatility and trading volume in his study. He examined several statistical models, including the one explored in Gallant, Rossi and Tauchen's study. He concluded that those models provide only modest improvements in the results. It remains uncertain whether trading volume improves the forecasting of stock prices (Wang, Phua, Lin, 2003).

The authors also noted that Kanas and Yannopoulos' (2001) study indicated that trading volume is one element for forecasting the market and is practical for long-term forecasting. Wang, Phua and Lin concluded that the implementation of trading volume did not improve short-term forecasting performance.

2.3.3. Data Periods. The forecasting data period is also a noteworthy point. According to Virili and Freisleben (2000), Hatanaka's research (1996) showed that the US economic time series is different from each different time window. They stated that "the shortest post-war series are much easier to analyze and interpret than the full historical record, which includes the first part of the century" (Virili and Freisleben, 2000). The authors noted that the data is rather non-stationary with a more complex time dependency. The data also includes noise and biases, so some kind of trade-off must be considered. Preprocessing the data is important. However, it is not always straightforward, and it is advisable to use all the available knowledge for constructing forecasting models (Virili and Freisleben, 2000).

2.4. FORECASTING METHODS: STATISTICAL VS. NEURAL NETWORK APPROACHES

As mentioned previously, there are numerous methods and tools for forecasting. Researchers and scholars have varying views regarding these methods. In this section, the remarks of many authors are discussed.

Many statistical methods, such as the autoregressive moving average, Box and Jenkins methods, exponential smoothing, and so on, work well with linear and stationary conditions (Li, Liu, Le and Wang, 2005). In other words, the traditional statistical methods have to uncover whether the data system is linear or nonlinear, the appropriate order of functions for prediction, and how to test the fitness of the forecasting model (Chang and Tsai, 2002a).

Schwaerzel and Rosen (1997) indicated that forecasting financial time series depends on strong empirical regularities in observations; however, such regularities are usually masked by noise and exhibit nonlinear and non-stationary behaviors. Many researchers cite the Random Walk Hypothesis, which, in terms of financial forecasting, hypothesizes that the stock market is purely random and unpredictable. In other words, price changes occur without any influence from past prices (Patel and Marwala, 2006). On the other hand, the Efficient Market Hypothesis theorizes that markets incorporate all available information, and price adjustment occurs immediately when new information is available (Patel and Marwala, 2006). If both theories are true, the market would react and balance itself, and there is no advantage in predicting stock performance. Patel and Marwala claim that there is considerable evidence that the Random Walk Hypothesis does not work, and many studies related to this issue have been presented in academia. The authors also suggest that stock prices are largely influenced by investors' expectations, and many investors believe that past prices do affect future prices.

Neural networks become an attractive method because they maintain flexibility and forceful pattern recognition capabilities even when the structure of the data system is not known (Medeiros and Veiga, 2000, 2005). However, Virili and Freisleben note that non-stationary time series can be somewhat problematic for neural networks. Their study shows that, in order to obtain better forecasting results, neural networks may be needed to preprocess the data to remove non-stationary series before those data are applied to the networks. This issue pertains to the generalization capability because neural networks cannot predict accurately the out-of-range data used for data normalization (Virili and Freisleben, 2000; Chang and Tsai, 2002a). Data generalization is the key to overcoming this issue. Many researchers and scholars still prefer neural networks over the traditional statistical methods for forecasting time series models because neural networks have an advantage in mapping noisy, non-stationary, and chaotic time series (Li, Liu, Le, and Wang, 2005).

2.5. MARKET CONDITIONS AND FORECASTING

Many researchers and scholars have concluded that neural network-based models work better than the traditional statistical models because neural networks can deal with the non-stationary nature of the markets. In addition, they prefer certain features of neural networks, such as their nonlinearity, input-output mapping, and adaptivity (Haykin, 1999). However, these features cannot defeat the nature of the market. In reality, there is no universal forecasting model that meets the demands of all kinds of forecasting.

Every forecasting model is unique. Forecasting researchers present many distinctive examples and sole cases to demonstrate the performance of their models. Whether their models use neural networks or traditional statistical methods, they depend on historical data to forecast the future. As Virili and Freisleben (2000) mentioned regarding Hatanaka's study, the data set for forecasting is rarely perfect because it is difficult to believe that the ideal market condition exists. This is why forecasting models fail when market conditions change. To deal with these changes and to overcome forecasting failures, new sets of rules are required. In other words, new forecasting methods could support changes in market conditions and generate new forecasting results.

2.6. JAPANESE CANDLESTICK CHART TECHNIQUES

2.6.1. History of the Candlestick Chart Techniques. The candlestick chart was originally developed by Munehisa Honma in the 1700s. He had been using historical data of exchanging rice in the Dojima Rice Exchange in Osaka to analyze the rice market since the 1600s (Nison, 2001).

During the 1700s, more than 1,300 rice dealers and traders lived in Japan. The Dojima Rice Exchange had already started to trade future contracts during this period, which was the first future contract trading in institutionalized exchange in the world. As expected, rice brokerage became very complex and competitive, and traders needed to have some kind of market analysis and technical strategies to win among the other rice dealers (Nison, 2001).

Munehisa Honma was one of the successful dealers in this period. He studied several factors that affect the price of rice, such as the yearly weather, rice production areas and locations, harvest season, and demand and supply of rice. Also, he collected and analyzed historical data of the price of rice before and after the Dojima Rice Exchange was established. His analytical skills led to the development of candlesticks, and further analysis of candlestick patterns became the foundation of today's candlestick chart techniques (Nison, 2001).

This oldest type of chart system is believed to show the emotion of a market, and it is useful in determining the future trend of a market (Nison, 2001). The western bar chart has four components—open, high, low, and close—as does a candlestick chart. However, the candlestick chart is highly graphical, and the formations and patterns of candlesticks are named based on the market condition at that moment ((Nison, 2001). Since the 1800s, Japanese traders have been using the candlestick chart for their trading, and this has given great weight to the market psychology.

2.6.2. Basic Terms of Candlestick Chart Techniques. The sources of the names, the definitions, and the appearances of candlesticks and their patterns described in this section are based on *Japanese Candlestick Charting Techniques* by Steve Nison (2001), *Candle Power* by Gregory Morris (1992), and other literature from Japan as well as Internet websites. However, because the candlesticks and the candlestick pattern techniques are originally from Japan, the English interpretation of them depends on the authors. Therefore, the Japanese names have been added after the English translation for accuracy. The appearances of the candlesticks and their patterns are typical. Some authors prefer to use the colors red and black instead of white and black when drawing candlesticks. In this dissertation, the latter feature was used to draw the candlesticks.

2.7. FUZZY LOGIC

The idea of fuzzy logic was introduced in *Fuzzy Sets* by Lotfi Zadeh in 1965 (Lin and Lee, 1996). Since then, much fuzzy logic research has been published in various fields of study such as medicine, transportation, manufacturing, economics, and forecasting. The Berkeley Initiative in Soft Computing reported the appearance of more than 237,000 publications with the word "fuzzy" as of March 2011. Some examples of relevant research articles follow. Wang, Tang, Li and Qiu (2009) attempted to apply the fuzzy theory for quality management where precise processing is the main focus. Geng, Liu and Huang (2010) implemented fuzzy logic in their oil drilling prediction model. They concluded that fuzzy logic improved the prediction results better than a neural network-based model. Mondal and Rajan (2004) applied fuzzy logic to process medical images, detecting their edges and reconstructing them. The original fuzzy logic is sometimes referred to as type-1 fuzzy logic. However, this type of fuzzy logic may not handle uncertainties well. The idea of type-1 fuzzy logic was expanded to develop type-2 fuzzy logic, which can handle uncertainties (Zadeh, 1975; Mendel, 2001). The first part of this section focuses on fuzzy logic and forecasting, and the remainder focuses on type-2 fuzzy logic systems.

2.7.1. Fuzzy Logic for Forecasting. Rahamneh, Reyalat, Sheta and Aljahdali (2010) presented a forecasting model for the Amman stock exchange. The results of their fuzzy logic forecasting model were compared with their neural network-based model. Both models produced similar results, but the paper did not provide details about why the results were similar. The possible cause may be due to the limited number of fuzzy rules and inputs in their model. Wang and Zhao (2004) mentioned that fuzzy logic requires more rules for solving complex problems. These two authors developed a rainfall forecasting model for the Zhejian Province in China. Wang and Wang (1993), researchers in a power system industry in China, introduced the usefulness of the fuzzy logic system for short-term forecasting. They suggested that short-term forecasting models should be simple and fast to meet customers' demands. Their paper presents the power system load forecasting model. The power industry needs to forecast daily power load changes for both weekdays and weekends. Several elements affect the power demands; for example, weather changes initiate significant impacts within a short period of time. The authors concluded that their fuzzy logic-based model was more efficient and calculated the forecasting results faster than a conventional backpropagation model. Castillo and Melin (2001) developed a model in which the parameter values for fuzzy membership are calculated by neural networks. The simulation result from their hybrid forecasting model that contains neural networks and fuzzy logic was compared with the result from a traditional statistical model. Their paper indicated that their hybrid approach produced better results because of the training capabilities of neural networks. Also, they concluded that the knowledge representation capability of fuzzy logic was an important advantage for forecasting. Kurniawan (2010) combined neural networks and an interval type-2 fuzzy logic to forecast electrical load. He used a hybrid type of backpropagation algorithm for the training method. Therefore, this model might suffer from the local minima issue. Wang and Wang (1993) mentioned a similar issue in their paper. Kurniawan applied type-2 fuzzy logic to overcome two issues, change of learning rate and variance for backpropagation training. The author implemented interval type-2 fuzzy logic and found the results acceptable. A prediction model for the exchange rate between Mexican pesos and US dollars was presented by de los Angeles Hernandez Medina and Mendez (2006). Their approach is similar to Kurniawan's model except that it uses a singleton interval type-2 fuzzy logic system for backpropagation of neural networks. The output is the daily exchange rate between Mexican pesos and US dollars. Their model trains the exchange rate directly and compares the results with a type-1 fuzzy logic-based model. Bajestani and Zare (2009) presented an interval type-2 fuzzy logic-based forecasting model for predicting the Taiwan Stock Index. Their step-by-step descriptions of constructing their model are very helpful for understanding how they implemented the linguistic values. They noted that type-2 fuzzy logic made it possible to use more observational data for forecasting in a linguistic manner (Bajestani and Zare, 2009).

2.7.2. Type-1 Fuzzy Logic and Type-2 Fuzzy Logic. Type-2 fuzzy logic was introduced by Zadeh in 1975. The basic difference between the two fuzzy logic systems is that the type-1 fuzzy logic system has crisp membership functions, while the type-2 fuzzy logic system has fuzzy membership functions. Membership functions are usually defined by the experts and are based on their intuition and knowledge (Tizhoosh, 2005). Therefore, a problem occurs during the assignment of a membership for type-1 fuzzy logic systems because the intuition and knowledge of experts are not the same. In other words, there is no one crisp or clear answer from the experts. However, the membership functions of type-2 fuzzy logic systems are fuzzy themselves (Mendel and John, 2002). Therefore, type-2 fuzzy logic systems are useful when type-1 fuzzy logic systems are not able to directly model such uncertainties (Tizhoosh, 2005).

2.7.3. Interval Type-2 Fuzzy Logic. Mendel of the University of Southern California, along with his colleagues and students, intensively discussed simplifying type-2 fuzzy logic systems (Karnik and Mendel, 1998, 2001; Mendel, 2001, 2007, 2007; Mendel and John, 2002; Mendel, John, and Liu, 2006; and Wu and Mendel, 2001, 2002). Many researchers study this group's publications regarding type-2 fuzzy logic and regard them as having built type-2 fuzzy logic-based models. Mendel and his research group's approaches to interval type-2 fuzzy logic have become almost common practice for many scholars today.

Mendel (2001) discussed two kinds of approaches for type-2 fuzzy logic systems. One is to construct fuzzy models from nothing. In other words, the model is totally independent from type-1 fuzzy logic. The other approach partially depends on the type-1 fuzzy logic design. Many researchers prefer the latter approach because the partially dependent approaches require less computational costs than the totally independent approaches (Zarandi, Neshar, Turksen, and Rezasee, 2007). There is a trade-off in design flexibility with low computational costs. However, partially dependent type-2 fuzzy logic systems perform better than type-1 fuzzy logic systems (Wu and Tan, 2004). Zarandi et al. (2007) presented the stock market analysis with interval type-2 fuzzy logic. They selected a stock price of an automotive manufacturer and used input data of the opening price, price channel, price changes, and so on to forecast the output data of the closing price. They concluded that the proposed model improved the forecasting results better than a type-1 fuzzy logic-based model. In fact, Wu and Mendel (2002) indicated that forecasting is one of the most appropriate situations in which to apply type-2 fuzzy logic systems.

In this dissertation, the studies by Mendel's group were used as a reference for building interval type-2 fuzzy logic systems. *Type-2 Fuzzy Sets and Systems: An Overview* (Mendel, 2007) is a good introduction to type-2 fuzzy sets and systems. *Uncertainty Bounds and Their Use in the Design of Interval Type-2 Fuzzy Logic Systems* (Wu and Mendel, 2002) provides good descriptions of fuzzy memberships for interval type-2 fuzzy logic systems. *Interval Type-2 Fuzzy Logic Systems Made Simple* (Mendel, John, and Liu, 2004) provides good instructions for constructing an interval type-2 fuzzy logic system-based model. Many of this group's ideas were implemented in the final model presented in this dissertation.

2.8. SUMMARY

This section started with the nature of forecasting, and presented the several financial forecasting tools and techniques that many researchers and scholars are interested in. From this section, it is possible to observe that researchers have been trying to improve their forecasting models to achieve their goals. However, some models have the issues in developing the forecasting models because of the financial market environment. Some researchers develop the forecasting model based on the efficient market hypothesis. Some do not. Today, the efficient market hypothesis is not popular due to the several factors. For example, investment strategies perform well in a certain environment, but the same strategies also perform badly in other environments. Because of this fact, the quantitatively, fundamentally, and technically-based methods tend to fail in a certain environments.

Many forecasting models do not contain the qualitative information that would help about predicting the future. A new approach, the Japanese candlestick techniques is believed to have qualitative information, such as the market psychology. Therefore, Japanese candlestick techniques can become a unique tool for developing financial forecasting models.

Unfortunately, there is not many forecasting researches have been done with the candlestick chart techniques. One reason can be due to the ambiguous definition of candlestick patterns. Fuzzy logic introduced by Zadeh has an ability to handle ambiguous definition of Japanese candlestick patterns.

Since the introduction of fuzzy logic, type-1 fuzzy logic has been successfully applied to develop models. However, it has limited capabilities to handle data uncertainties (Mendel, 2007). Linguistic data is one of them because the words can mean different things to different people (Mendel, 2007). Defining candlestick chart patterns by stock traders and experts is the same aspect. Every trader's candlestick pattern readings are different. Therefore, type-2 fuzzy logic's ability to handle ambiguous information becomes valuable. Type-2 fuzzy logic based-models demonstrate positive effect toward managing uncertain data.

In this section, existing financial forecasting techniques and tools were investigated and explored.

3. TOOLS FOR HYBRID COMPUTATIONS

3.1. NEURAL NETWORKS

3.1.1. Background. The first neural network research was done in the 1940s by Warren McCulloch and Walter Pits; they demonstrated that the networks of artificial neurons could compute any arithmetic or logical function (Hagan, 1995). The father of cognitive psychobiology, D.O. Hebb, first introduced the physiological learning rule for synaptic modification, and his study became influential to later work in learning and adaptive computational model development (Green, 2007; Harnad, 1985). In the 1950s, Frank Rosenblatt introduced perceptron networks (Haykin, 1999). Rosenblatt's work on the pattern recognition problem with perceptron was considered to be the first artificial neural network. In the 1980s, the foundation of recurrent networks was discovered by physicist John Hopfield (Haykin, 1999). About the same time, the backpropagation algorithm, which is the most popular learning algorithm today, was introduced by David Ramelhart and James McClelland. Later, the radial basis functions, which are alternatives to multi-layered perceptrons, were developed by Broomhead and Lowe (Haykin, 1999).

3.1.2. Basic Structure of Neural Networks. A neural network is a simple mathematical model composed of biological neurons. Input to the neural network is considered to be the signal received at the neurons. The summation of the inputs and activation function is considered to be the neuron's cell body. Output from the neural network is considered to be the signal out of the axon. Figure 3.1 describes the relationships of these elements.

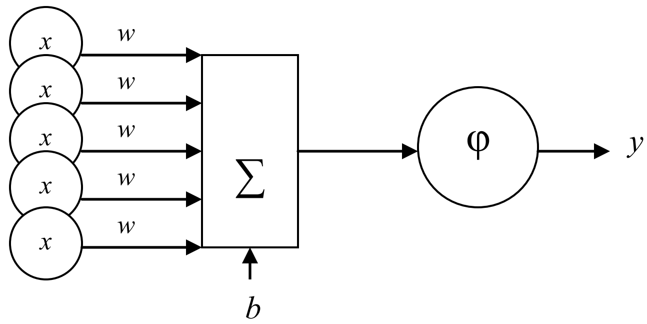

Figure 3.1. Basic Architecture of Neural Networks

In the figure, *x* represents the input, *w* represents the weight, *b* represents the bias, *y* represents the output, ∑ represents the summation, and φ represents the activation function of a neural network. The input of the network is composed of the attributes that are related to the problem and the output solution. The output is the solution to a problem, and it is calculated by the network. The weight is a key element in a neural network, and it represents the relative strength of the input. The weight is adjusted during the network learning. Then, the input multiplied by the weight goes through the summation. Finally, the activation function calculates the level of input and decides the output. The relationship of this activation function can be a linear or non-linear function. In mathematical terms, the above structure is described as

$$y = \varphi \; \Sigma \; x + \;) . \tag{1}$$

Several activation functions exist. For example, the threshold function is a type of linear function, and the sigmoid function is a type of non-linear function. A specific activation function is selected to meet the specifications of a certain problem. Neural networks can be single-layered or multi-layered. The layers between the input and output layers are called hidden layers. A typical structure of a neural network is shown in Figure 3.2.

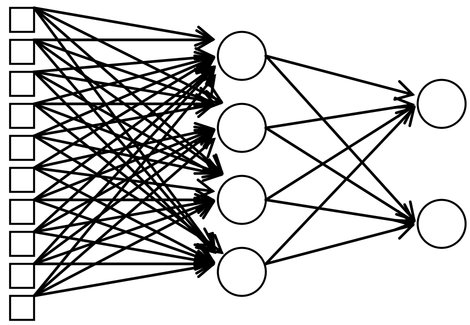

Figure 3.2. Typical Structure of Neural Networks

3.1.3. Learning Process of Neural Networks. The most significant feature of a neural network is its ability to learn and adapt to the environment, thus improving its performance. The learning process of a neural network starts from assigning random weights; the outputs and the target value are the error generated by the networks. Then this process is repeated until the error becomes zero or reaches acceptable values of errors. Many algorithms exist for the learning process. Choosing the learning algorithms depends on the problem to be solved, and each algorithm has advantages of its own (Haykin, 1999).

3.1.4. Strength of Neural Networks. A neural network has several advantages compared with the conventional computation system. The following characteristics are important to neural networks (Haykin, 1999; Trippi and Turban, 1996; Hammerstorm, 1993).

Nonlinearity. A neural network itself is made with an interconnection of non-linear neurons. In addition, nonlinearity means the network expands. Therefore, the input data for a neural network do not need to be formalized.

Input-Output Mapping. A neural network develops input and output map boundaries as its own by training whether the boundaries are linear or non-linear. In other words, the network learns from previous examples to build an input-output mapping for a problem.

Adaptivity. With continuous training, a neural network constantly learns and adapts to the environment. This means that a neural network can handle minor changes in the environment and produce the output accordingly.

Evidential Response. Training networks make it possible to generate the probabilities in rules. Therefore, with training a neural network can select the appropriate output based on the generated probabilities.

Fault Tolerance. Multi-nodes in a network make it possible to run the networks even if a few nodes are damaged. In other words, a neural network will not have a catastrophic failure.

VLSI Implementability. A network can handle noisy, incomplete, or unknown input, and it will produce a reasonable output. In such a case, the network takes less time in per-case processing than the traditional system because the network can handle the available data for a problem all at once.

3.2. COMMITTEE MACHINE

3.2.1. Background. Nilsson's network structure, which a layer of basic perceptron in the first layer and a vote-taking perceptron in the second layer, was the origin of committee machine architecture (Yang and Luo, 2005). A key feature of a committee machine is the principle of divide-and-conquer; a complex task is solved by dividing it into a number of simple tasks, and then combining them to make one final solution (Haykin, 1999). In 1991, a mixture of experts for a complex mapping function was introduced by Jacobs, Jordan, Norman, and Hanton. A mixture of experts consists of a number of supervised modules called experts networks, and a gating network is used as a mediator amoung the expert networks. The role of a gating network can be considered as a classifier (Haykin, 1999).

3.2.2. Structure of a Committee Machine. A committee machine is one of the effective methods used to solve a complex problem. A complicated problem is divided into several simple tasks. The tasks are computed by the individual experts, and the experts generate their own results based on their assigned regions. The combination of results from the experts becomes the final decision for the problem. Two classes of committee machines exist: (1) a static structure committee machine, and (2) a dynamic structure committee machine. Figure 3.3 shows a static structure of a committee machine.

The experts in a committee machine can be incorporated with gating networks, which in turn become a dynamic structure of a committee machine. The gating network is a mediator for the experts, and it usually locates after the experts (Haykin, 1999). Two kinds of dynamic structures exist: (1) a mixture of experts, and (2) a hierarchical mixture of experts. The architecture of a mixture of experts model has one gating network that handles the experts' answers for the assigned tasks. The architecture of a hierarchical mixture of experts has a number of gating networks on several levels to deal with the outputs from the experts at the various stages. Figure 3.4 represents a mixture of experts.

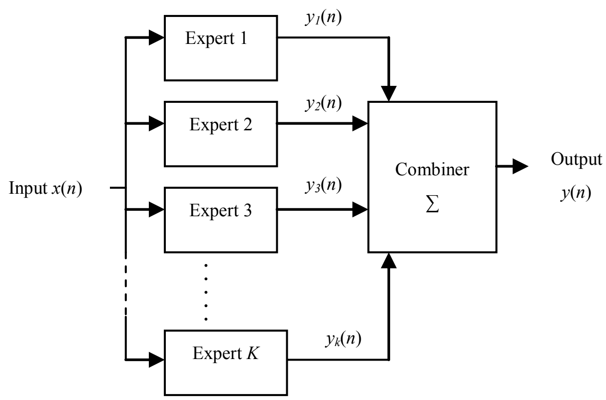

Figure 3.3. Static Structure of a Committee Machine

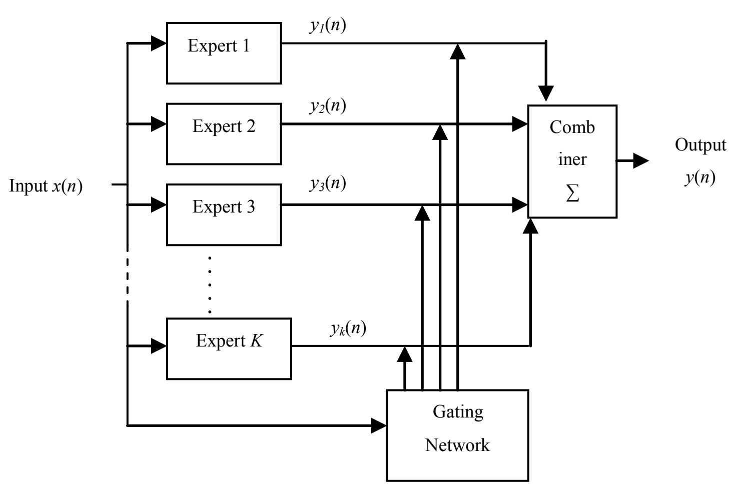

Figure 3.4. Committee Machine with a Gating Network Mixture of Experts

Several layers of gating networks are placed for a hierarchical mixture of experts model. There can be any number of levels in the hierarchy. The principle of divide-and-conquer, in which the input space is divided into subspaces, is the same, and several gating networks are arranged and assigned to the regroupeded and redistributed experts. Figure 3.5 shows an example of a hierarchical mixture of experts with two layers of gating networks.

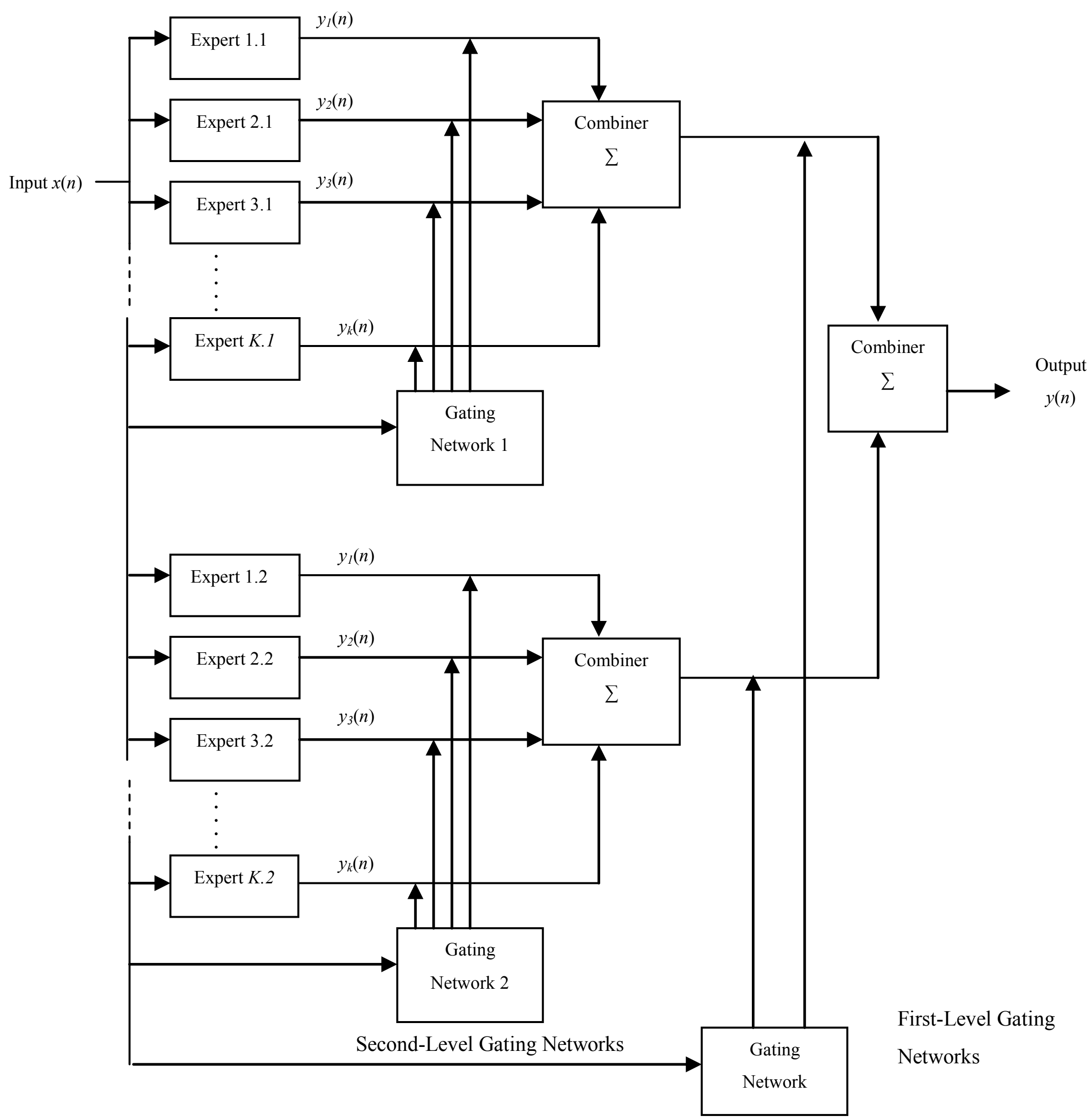

Figure 3.5. Committee Machine with a Gating Network Hierarchical Mixture of Experts

A gating network is a mediator for all the experts. Each expert produces the best output in its assigned regions. However, the outputs from the experts are not the final overall output. The gating network investigates the output from each expert, and then the network negotiates the outputs from them. For example, the gating network has a single layer of K neurons, and each of them is assigned to work with a specific expert. The gating network's neurons are non-linear. The overall output y for a mixture of experts is shown in equation (2) (Haykin, 1999).

$$y = \sum_{k=1}^{K} g_k y_k\,, \qquad k = 1,2,....K \tag{2}$$

in which g_k represents the activation functions. This variable is defined as:

$$g_k = \frac{\exp(u_k)}{\sum_{j=1}^{K} \exp(u_j)}, \tag{3}$$

where u_k is the inner product of the input vector $\mathbf{x}$ and synaptic weight vector $\mathbf{a}_k$, as defined in equation (4).

$$u_k = a_k^T x \qquad k = 1,2,...,K \tag{4}$$

The function shown in equation (3) is called the soft-max is part of one of five activation functions. The activation function g_k can be obtained in several ways, including the following five examples (Min and Mitra, 2001):

1. **Sum-norm**: Normalize the gating network parameter, the inner product u_k, by the norm of the sum.

$$g_k = u_k \Big/ \sum_{j=1}^{K} u_j \tag{5}$$

2. **Distance-norm**: Normalize the inner product by the Euclidean norm.

$$g_k = u_k / \|u_k\|_j , \qquad \|u_k\|_j = \sqrt{u_{i1}^2 + \ldots + u_{ik}^2} \tag{6}$$

3. **Average**: Average the inner product divided by the number of neurons *K*.

$$g_k = u_k / K \tag{7}$$

4. **Max-norm**: Normalize the inner product by the maximum u_k.

$$u_k = u_k / \max_j (u_k) \tag{8}$$

5. **Soft-max**: Normalize the inner product by an exponential mapping function.

$$g_{ij} = \exp(u_k) \Big/ \sum_{j=1}^{K} \exp(u_j) \tag{9}$$

As shown above, the activation function in the gating network does not have fixed values, does not learn, and makes decisions by assigning weights to each output generated by the experts (Min and Mitra, 2001).

3.2.3. Learning Process. Input data are distributed to the experts to calculate and generate subspace outputs. Then, the subspace outputs are combined to produce an overall output. To improve the performance of any learning algorithm, a boosting can be used. In a boosting, experts are trained on data sets with entirely different distributions (Haykin, 1999). Three different ways of boosting can be applied to the network: boosting by filtering, boosting by sub-sampling, and boosting by reweighing (Haykin, 1999). The subspace can be divided further into smaller pieces to reduce the subspace complexity. In this case, more experts are assigned to handle smaller pieces.

A gating network is also a key to improving the overall performance of a committee machine. It acts as a mediator among the expert networks so that different experts can get the desired response (Haykin, 1999). In addition, in a hierarchical mixture of experts model, an expert network lower down in the hierarchical tree may fail to perform a job. However, the gating network can help the experts to perform better in the next iteration (Haykin, 1999).

3.2.4. Strength of a Committee Machine. A committee machine can handle a problem that may be impossible to solve in a simple model. It can also solve a complex problem without losing insight of the problem while remaining accurate (Haykin, 1999). This is achieved by the divide-and-conquer strategy that is fundamental to a committee machine.

3.3. FUZZY LOGIC

3.3.1. Background. The original fuzzy logic, type-1 fuzzy logic, was proposed by Lotfi Zadeh in his paper *Fuzzy Sets* in 1965. His concept is good at conducting basic human reasoning and decision making with uncertain information. Many applications based on type-1 fuzzy logic have been utilized successfully (The Berkeley Initiative in Soft Computing [BISC], 2011). The performance of fuzzy logic systems depends on the membership functions, rules, and fuzzy inference systems (Lin and Lee, 1996). However, type-1 fuzzy logic has a limited ability to develop and manage data uncertainties (Mendel, 2007).

Later, in 1975, Zadeh introduced another paper, *The concept of a linguistic variable and its application to approximate reasoning-1*, which extended type-1 fuzzy logic theory to type-2 fuzzy logic theory (Mendel, 2007). Type-2 fuzzy logic can handle uncertainties that type-1 fuzzy logic cannot. In spite of Zadeh's proposal of type-2 fuzzy logic, Mendel's introduction of the footprint of uncertainty established the groundwork of type-2 fuzzy logic (Wang, Wang, Bai, Chen, and Sun, 2010).

3.3.2. Type-1 Fuzzy Logic System. A standard type-1 fuzzy logic system has four elements, a fuzzifier, an inference engine, a rule section, and an output processor. Crisp input data travel through the fuzzifier to become fuzzy input sets. The fuzzy input sets move to the inference engine to produce fuzzy output sets based on rules. The fuzzy output sets move into the output processor section that has a defuzzifier to produce the final output in the form of crisp data. Figure 3.6 shows the diagram of a type-1 fuzzy logic system.

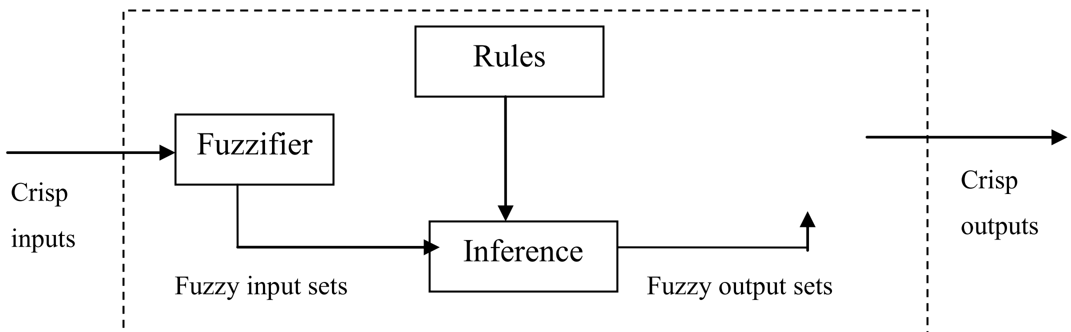

Figure 3.6. Type-1 Fuzzy Logic System

The crisp input data becomes a fuzzy set after moving through a fuzzifier. The type-1 fuzzy set, A, is expressed as

$$A = \{(x, \mu_A(x)) \mid x \in U\}, \tag{10}$$

where $\mu_A(x)$ is a degree of membership function of x in A, and U is a universe of discourse. A fuzzy set is a set without a crisp, clearly defined boundary. A membership function describes how the input space is mapped, and it can contain elements with only a partial degree of membership (Fuzzy, 2009). The rule section is for formulating the data mapping. IF-THEN rules are used for this purpose. During the inference engine process, the input data becomes the output data based on the rules and membership functions. After this process, the fuzzy output sets are defuzzified to produce crisp output data. Figure 3.7 and Table 3.1 describe the data flow direction and inference process.

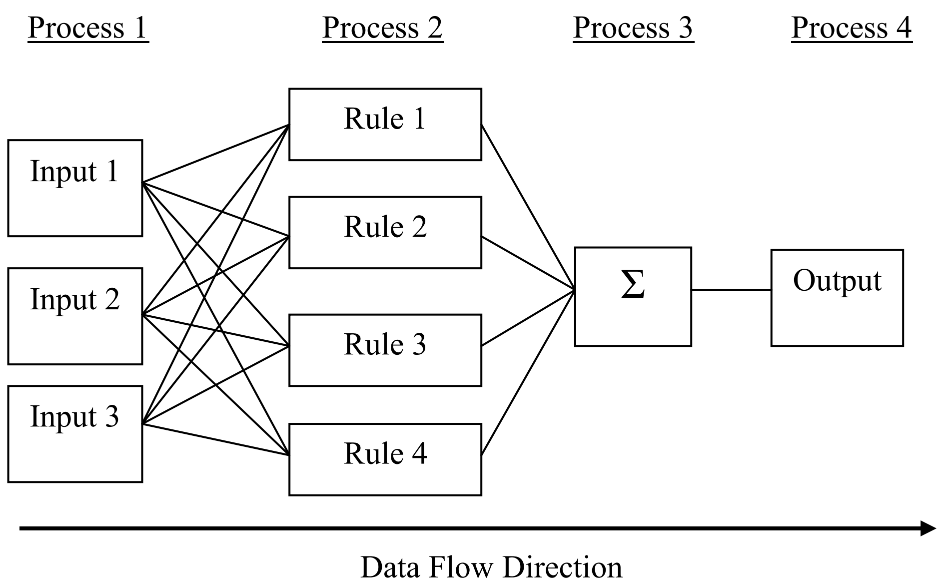

Figure 3.7. Data Flow Direction and Inference Process

Table 3.1. Inference Process Information

	Process Information
Process 1	The input numbers are crisp and limited to a specific range.
Process 2	All rules are evaluated in parallel using fuzzy reasoning.
Process 3	The results from the rules are combined and defuzzified.
Process 4	The output result is a crisp number.

3.3.3. Type-2 Fuzzy Logic System. Type-2 fuzzy logic systems are similar to type-1 fuzzy logic systems. The important difference between the two is the output processing. The diagram of a type-2 fuzzy logic system in Figure 3.8 shows the basic process. Crisp input data sets are fuzzified based on the type-2 membership functions. The fuzzy input data sets are processed in the inference engine with IF-THEN rules to generate type-2 fuzzy output sets. The type-2 fuzzy sets need to convert to type-1 fuzzy output sets via a process called a type reducer. After this process, the type-1 fuzzy output sets are defuzzified to become crisp output sets.

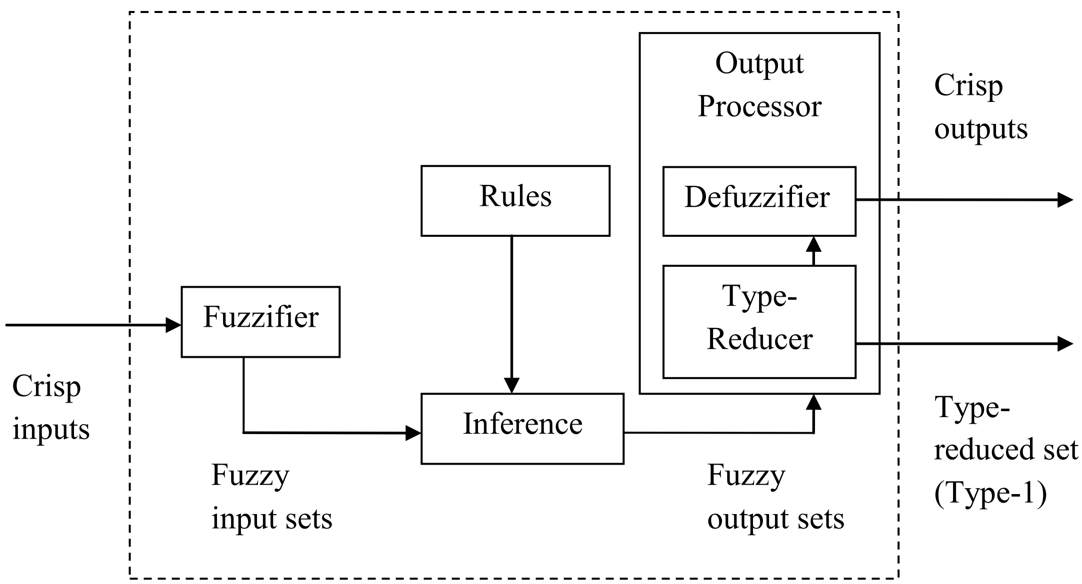

Figure 3.8. Type-2 Fuzzy Logic System

Similar to the type-1 fuzzy set described in equation (10), the type-2 fuzzy set, $\widetilde{A}$, is expressed as (Mendel and John, 2002),

$$\widetilde{A} = ((x,u), \mu_{\widetilde{A}}(x,u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \qquad (11)$$

in which $0 \leq \mu_{\tilde{A}}(x,u) \leq 1$. $\mu_{\tilde{A}}(x,u)$ is a type-2 membership function, where $x \in X$ and $u \in J_x \subseteq [0,1]$. J_x is a primary membership of $\tilde{A}$, where $J_x \subseteq [0,1]$ for $x \in X$. The uncertainty in the primary membership of a type-2 fuzzy set consists of a bounded region of the footprint of uncertainty (FOU). Figure 3.9 shows an example footprint of uncertainty.

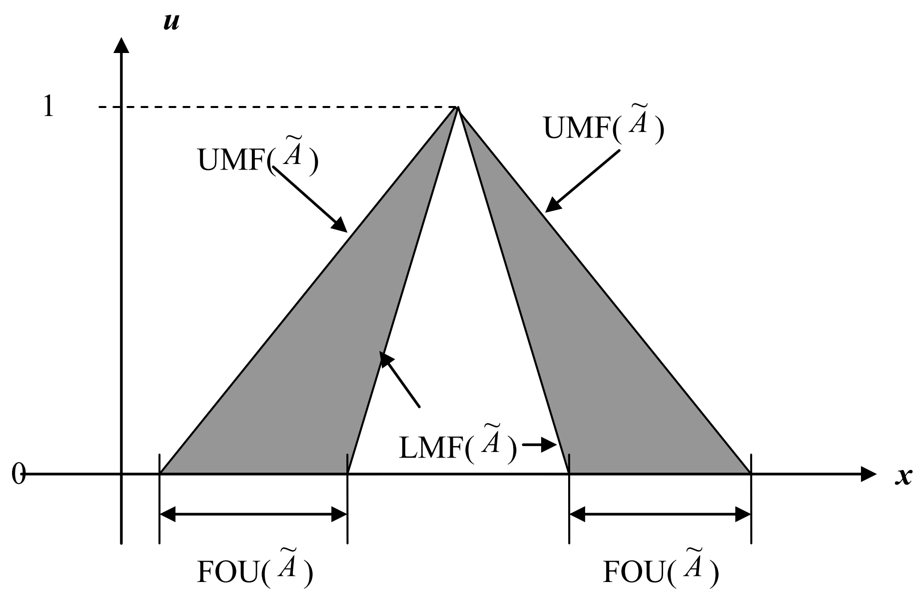

Figure 3.9. Footprint of Uncertainty (FOU) and Membership Functions

The upper membership function (UMF) and lower membership function (LMF) are two type-1 membership functions that form the boundaries of the footprint of uncertainty of $\tilde{A}$.

There are two approaches for type-2 fuzzy logic systems. One is a primary membership function with an uncertain mean. The other is a membership function with an uncertain standard deviation. Equation (12) shows a Gaussian primary membership function with an uncertain mean, and equation (13) shows a Gaussian primary membership function with an uncertain standard deviation.

$$\mu_A(x) = \exp\left[-\frac{1}{2}\left(\frac{x-m}{\sigma}\right)^2\right] \qquad m \in [m_1, m_2] \tag{12}$$

$$\mu_A(x) = \exp\left[-\frac{1}{2}\left(\frac{x-m}{\sigma}\right)^2\right] \qquad \sigma \in [\sigma_1, \sigma_2] \tag{13}$$

A Gaussian primary membership function with an uncertain standard deviation has simpler upper and lower membership functions than a Gaussian primary membership function with an uncertain mean. Upper and lower membership functions for a Gaussian primary membership function with an uncertain mean have to analyze the membership functions segment by segment. The model proposed in this research contains a Gaussian primary membership function with an uncertain standard deviation.

For generating the output, the footprints of uncertainty from the upper and lower membership functions are shown in Figure 3.10. A triangular membership function is shown in this figure for illustration purposes. For the proposed model, the type-2 fuzzy logic system's input and antecedent operations are mainly minimum t-norms, as shown in the figure.

Type-reduction and defuzzification become the last processes. There are many types of this kind of process. For the proposed model with the type-2 fuzzy logic system, a center-of sets defuzzification process (Mendel, 2007) is used, as illustrated in Figure 3.11.

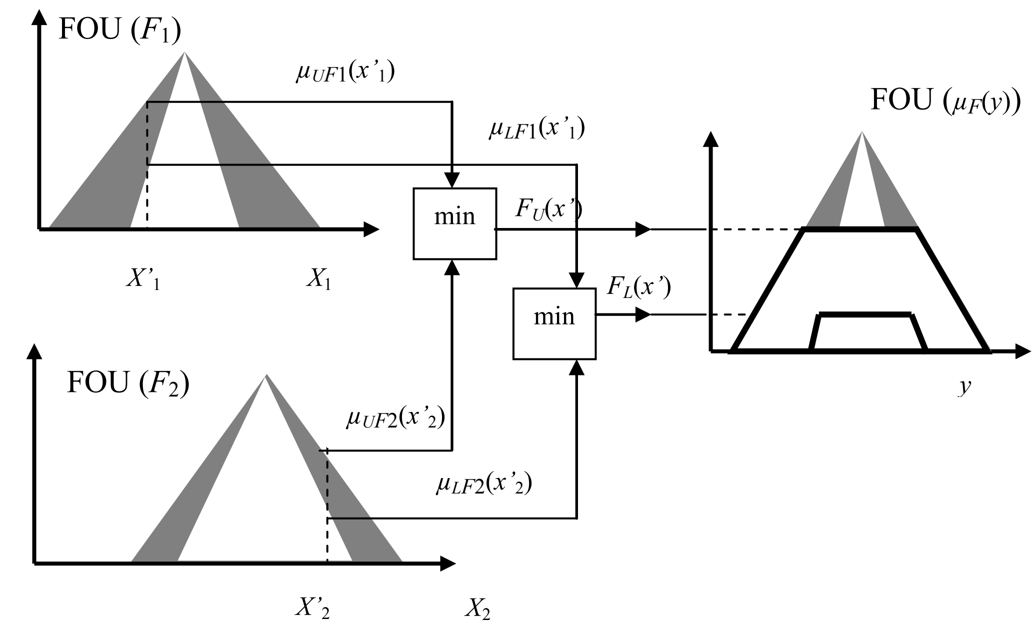

Figure 3.10. Example of Firing Interval to Rule Output FOU

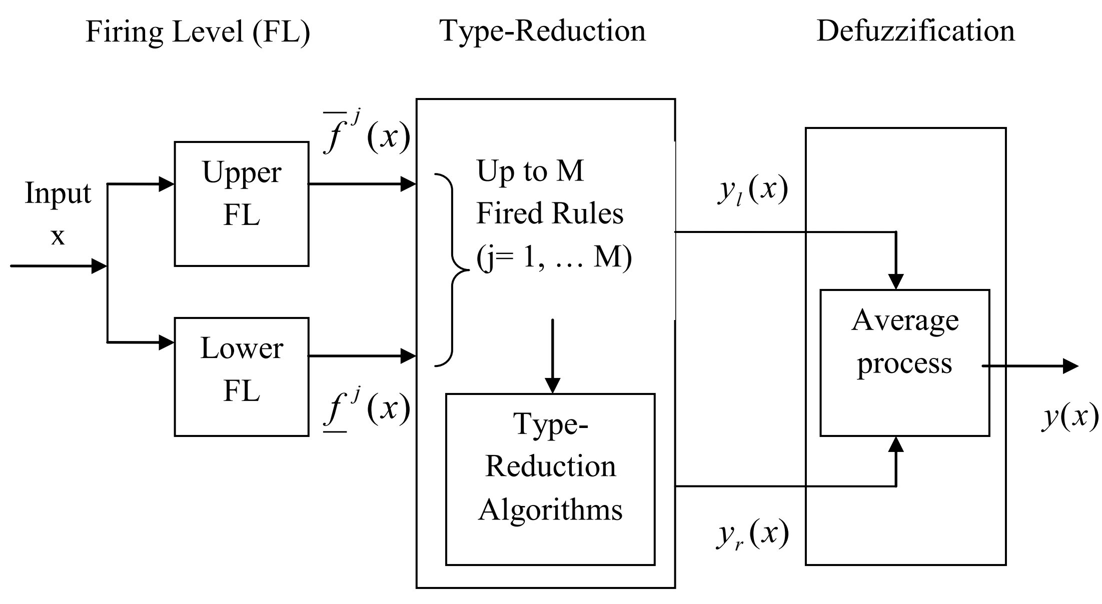

Figure 3.11. Type-2 FLS with Type-Reduction and Defuzzification

3.3.4. Strength of Type-2 Fuzzy Logic. Type-2 fuzzy logic sets are complex and difficult to handle because of their multi-dimensional nature (Mendel and John, 2002). That is, type-2 fuzzy membership grades themselves are type-1 fuzzy sets or higher-level fuzzy sets. However, type-2 fuzzy logic systems are very useful when it is difficult to determine an exact membership function for a fuzzy set because of uncertainties (Karnik, Mendel, and Liang, 1999). Mendel and John (2002) discussed the sources of uncertainties associated with type-1 fuzzy logic systems, indicating that at least four sources of uncertainties exist that type-1 fuzzy logic systems cannot model directly. The main reason is the difference of membership functions between type-1 and type-2 fuzzy systems. In type-1 fuzzy logic systems, membership functions are type-1 fuzzy sets, and in type-2 fuzzy logic systems, membership functions are type-2 fuzzy sets. Table 3.2 shows the four sources of uncertainties in type-1 fuzzy logic systems that Mendel and John mentioned in their paper. Because of these uncertainties, fuzzy logic systems based on type-2 fuzzy sets are robust for directly modeling a broad range of uncertainties that can occur in rule-based fuzzy logic systems (Mendel, 2001). In other words, the type-1 fuzzy logic system is good when the membership of an element cannot be set as 0 or 1 (Karnik and Mendel, 1998).

Table 3.2. Four Sources of Uncertainties

Meanings of the words	The meanings of the words that are used in the antecedents and consequents of rules can cause uncertainty because words mean different things to different people.
Information from a group of experts	Experts in a group do not always agree on information and knowledge used for rule making.
Fuzzy logic system itself	Measurements that activate a fuzzy logic system might be noisy and uncertain.
Data	The data that are used to tune the parameters of a fuzzy logic system might be noisy.

4. CANDLESTICK CHART TECHNIQUES

4.1. BUILDING A CANDLESTICK CHART

The opening, high, low, and closing data are required for drawing candlesticks. Candlesticks can be drawn for any type of trading time frame. When the daily data are used, each individual candlestick shows the market movement for a single day, and the candlestick chart becomes a daily chart. When the weekly data are used, each individual candlestick shows the market movement for a single week, and the chart becomes a weekly chart. Also, for intraday trading, the candlesticks can be 1-minute-based, 5-minute-based, 10-minute-based, and so on for intraday charts.

4.1.1. Standard Candlesticks. A standard candlestick has three elements: a real body, an upper shadow line, and a lower shadow line. First, the difference of the opening price and the closing price is drawn as a rectangle. This rectangle is called the real body of a candlestick. Next, the straight bars above and below this rectangle are called shadow lines. The shadow line above the rectangle is called the upper shadow line, and the upper end of this line becomes the high price. The shadow line below the rectangle is called the lower shadow line, and the bottom end of this line is the low price. All standard candlesticks have a real body, an upper shadow line, and a lower shadow line.

4.1.2. White Candlesticks and Black Candlesticks. The two kinds of standard candlesticks are white candlesticks and black candlesticks. The names of these candlesticks are from the color of the real body or the rectangular part of the candlestick. White candlesticks have an empty rectangle or white color. Black candlesticks have a filled rectangle or black color.

4.1.2.1. White candlestick. When the closing price is higher than the opening price, it becomes a white candlestick, which is drawn with a non-filled rectangular box as shown in Figure 4.1. The bar above the rectangular box is the upper shadow, which represents the difference between the closing price and high price of the trading. The rectangular box is called the white real body. The bar below the rectangular box is the lower shadow, which represents the difference between the opening price and low price of the trading. Normally, a white candlestick is a signal of the bullish sign of the market.

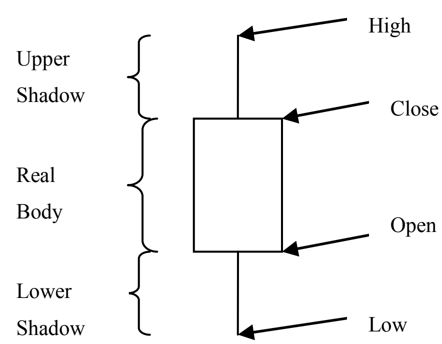

Figure 4.1. White Candlestick

4.1.2.2. Black candlestick. When the closing price is lower than the opening price, it becomes a black candlestick, which is drawn with a filled rectangular box as shown in Figure 4.2. The bar above the rectangular box is the upper shadow, which represents the difference between the opening price and high price of the trading. The rectangular box is called the black real body. The bar below the rectangular box is the lower shadow, which represents the difference between the closing price and low price of the trading. Normally, a black candlestick represents the bearish sign of the market.

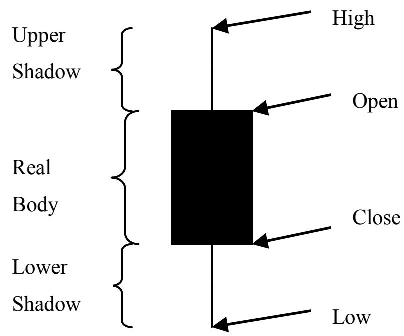

Figure 4.2. Black Candlestick

4.1.3. Non-Standard Candlesticks. Not all candlesticks fall into the standard candlestick category. Some of them have no real body, some of them have no upper shadow line, some of them have no lower shadow line, and so on. When the opening price and closing price are the same, there is no rectangle in a candlestick. In this case, the real body is expressed as a horizontal bar instead of a rectangle. When the high price becomes the same as the opening price for a black candlestick or the closing price for a white candlestick, there is no upper shadow line. Therefore, there is no vertical line above the rectangle. When the low price becomes the same as the opening price for a white candlestick or the closing price for a black candlestick, there is no lower shadow line. In other words, there is no vertical line below the rectangle. Non-standard candlesticks appear when two or more data in the candlestick have the same value. One example is when the opening price and the closing price are the same for the candlestick.

4.2. SINGLE LINE CANDLESTICK PATTERNS

A single line candlestick is one individual candlestick, and a single line candlestick is the foundation of the candlestick chart analysis. A single line candlestick can be a daily candlestick, a weekly candlestick, or a monthly candlestick that depending on the type of data. For example, a daily basis candlestick chart consists of a series of daily-based single line candlesticks that require daily data of the opening, high, low, and closing prices. A weekly basis candlestick chart consists of a series of weekly-based single line candlesticks, that require weekly data of the opening, high, low, and closing prices. In any case, a single line candlestick represents the market condition and situation as well as the psychology of the market at a specific moment. For instance, a single line candlestick for a daily-based candlestick chart tells the daily based market reaction, and a single line candlestick for a weekly basis candlestick chart tells the weekly-based market reaction. The basics of single line candlestick patterns and their applications are described below with their typical appearances of candlesticks. These candlestick patterns become the foundation of the candlestick chart.

4.2.1. Long Candlesticks (*Dai yo sen*/*Dai inn sen*). Long Candlesticks, as shown in Figure 4.3, have a long real body due to the large difference between the opening price and closing price. The real body can be white or black, and it represents the large price movement in trading. A Long White Candlestick has a very strong bullish meaning, and a Long Black Candlestick has a very strong bearish meaning. In Japanese, dai means “large,” yo translates to “positive,” inn translates to “negative,” and sen translates to “line.”

Figure 4.3. Long Candlesticks (White – *Dai yo sen* and Black – *Dai inn sen*)

4.2.2. Short Candlesticks (Sho yo sen/Sho inn sen). Short Candlesticks, as shown in Figure 4.4, have a short real body due to the small difference between the opening price and closing price. The real body can be white or black, and it represents the small price movement in trading. A Short White Candlestick has a weak bullish meaning, and a Short Black Candlestick has a weak bearish meaning. Usually, this candlestick line appears when the market is balancing and adjusting the price. In Japanese, sho translates to "small."

Figure 4.4. Short Candlesticks (White – *Sho yo sen* and Black – *Sho inn sen*)

4.2.3. Long Upper Shadow Candlesticks (*Uwa kage yo sen*/*Uwa kage inn sen*). Long Upper Shadow Candlesticks, as shown in Figure 4.5, have a long upper shadow line because of the large difference between the high price and closing price for a

Long Upper Shadow White Candlestick, and between the high price and opening price for a Long Upper Shadow Black Candlestick. The size of the real body is small because there is a small difference between the opening price and closing price. Usually the length of the upper shadow line is greater than the size of the real body. A Long Upper Shadow White Candlestick represents a weak bullish meaning, and a Long Upper Shadow Black Candlestick represents a weak bearish meaning. These candlesticks appear when the market loses confidence. In Japanese, uwa translates to "upper," and kage translates to "shadow."

Figure 4.5. Long Upper Shadow Candlesticks (White - *Uwa kage yo sen* and Black - *Uwa kage inn sen*)

4.2.4. Long Lower Shadow Candlesticks (Shimo kage yo sen/Shimo kage inn sen). Long Lower Shadow Candlesticks, as shown in Figure 4.6, have a long lower shadow line due to the large difference between the low price and opening price for the Long Lower Shadow White Candlestick, and between the low price and closing price for the Long Lower Shadow Black Candlestick. The size of the real body is small, which means there is a small difference between the opening price and closing price. Usually, the length of the lower shadow line is greater than the size of the real body. Both Long Lower Shadow White Candlesticks and Long Lower Shadow Black Candlesticks represent a strong reversal meaning, and they appear when the market movement changes. In Japanese, *shimo* translates to “lower.”

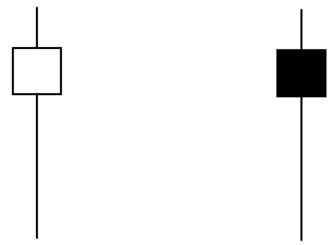

Figure 4.6. Long Lower Shadow Candlesticks (White - *Shimo kage yo sen* and Black - *Shimo kage inn sen*)

4.2.5. Doji Candlestick (Doji). A Doji Candlestick, as shown in Figure 4.7, has no real body because the opening price and closing price are the same. This is a special kind of candlestick, and it seldom appears on the candlestick chart. When a Doji candlestick appears at the top or bottom of the market, this candlestick can give a hint of the market trend reversal. In Japanese, *doji* translates to the “same.”

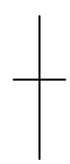

Figure 4.7. Doji Candlestick (*Doji*)

4.3. APPLICATION OF A SINGLE CANDLESTICK

Application of a Single Line Candlestick: In reality, the actual candlestick chart contains more than the above basic candlestick patterns to present the condition of the market at every moment. However, most of them are based on the single line candlesticks in the previous section. In this section, the single line candlestick patterns have similar appearances and description as the basic single line candlestick patterns. The figures below show the typical appearances of the candlesticks. When a real body is shown as a gray color in the figure, the real body can be either black or white. In this case, the size of the real body and the length of the upper and lower shadows become more important than the color of the real body.

4.3.1. Marubozu Candlesticks (Dai yo sen no marubozu/ Dai inn sen no marubozu). Marubozu Candlesticks, as shown in Figure 4.8, have long real bodies with either no shadow line or little shadow lines on both sides of the candle. A White Marubozu denotes a bullish sign of the market or a bearish reversal sign of the market. A Black Marubozu indicates a bearish sign of the market or a bullish reversal sign of the market. In Japanese, *Marubozu* translates to "nothing around the body."

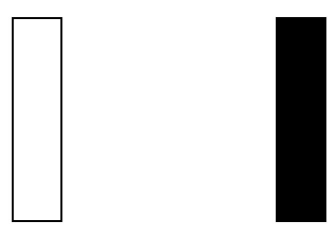

Figure 4.8. Marubozu Candlesticks (White - *Dai yo sen no marubozu* and Black - *Dai inn sen no marubozu*)

4.3.2. Black Closing Marubozu Candlestick (Dai inn sen no ohbike bozu). A Black Closing Marubozu Candlestick, as shown in Figure 4.9, has no shadow line on the closing end of the real body. This happens when the closing price and low price are the same, in other words, when there is no lower shadow but there is a long black real body. This is a sign for the bearish market condition. In Japanese, *Ohbike* translates to "closing" of the market.

Figure 4.9. Black Closing Marubozu Candlestick (Dai inn sen no ohbike bozu)

4.3.3. White Closing Mazubozu Candlestick (Dai yo sen no ohbike bozu). A White Closing Marubozu Candlestick, as shown in Figure 4.10, has no shadow line on the closing end of the real body. This happens when the closing price and high price are the same, in other words, when there is no upper shadow but there is a long white real body. This is a sign for the bullish market condition.

4.3.4. Black Opening Marubozu Candlestick (Dai inn sen no yoritsuke bozu). A Black Opening Marubozu Candlestick, as shown in Figure 4.11, has no shadow line on the opening end of the real body. This happens when the opening price and high price are the same, in other words, when there is no upper shadow but there is a long black real body. This is a sign for the bearish market condition. In Japanese, *yoritsuke* translates to "opening" of the market.

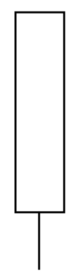

Figure 4.10. White Closing Marubozu Candlestick (*Dai yo sen no Ohbike bozu*)

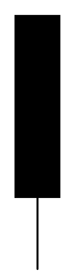

Figure 4.11. Black Opening Marubozu Candlestick (*Dai inn sen no yoritsuke bozu*)

4.3.5. White Opening Mazubozu Candlestick (Dai yo sen no yoritsuke bozu). A White Opening Marubozu Candlestick, as shown in Figure 4.12, has no shadow line on the closing end of the real body. This happens when the opening price and low price are the same, in other words, when there is no lower shadow but there is a long white real body. This is a sign for the bullish market condition.

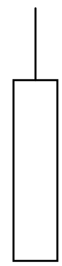

Figure 4.12. White Opening Marubozu Candlestick (*Dai yo sen no yoritsuke bozu*)

4.3.6. Spinning Top Candlesticks (Sho yo sen no gokusen koma/Sho inn sen no gokusen koma). Spinning Top Candlesticks, as shown in Figure 4.13, have a small real body with a long upper shadow line and a long lower shadow line. The real body can be white or black, which is a sign of indecision between a bullish and bearish market. Usually, this kind of candlestick appears when there is not much movement in the price, and the price stays in a certain range for a while. In Japanese, *gokusen* translates to “small line,” and *koma* translates to “spinning tops.”

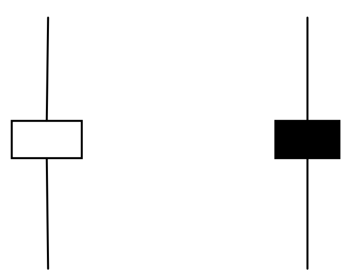

Figure 4.13. Spinning Top Candlesticks (*Koma*) (White - *Sho yo sen no gokusen koma* and Black - *Sho inn sen no gokusen koma*)

4.3.7. Dragonfly Doji Candlesticks (Tombo doji). Dragonfly Doji Candlesticks, as shown in Figure 4.14, have no real body, but there is a long lower shadow line. This happens when the opening price and high price are the same or almost the same. This candlestick pattern indicates a market reversal. In Japanese, *tombo* translates to "dragonfly."

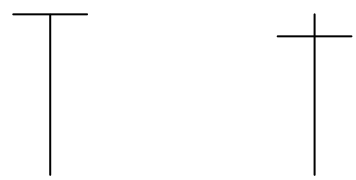

Figure 4.14. Dragonfly Doji Candlesticks (*Tombo doji*)

4.3.8. Gravestone Doji Candlestick (Tohba doji). A Gravestone Doji Candlestick, as shown in Figure 4.15, has no real body, but there is a long upper shadow line. This happens when the opening price and low price are the same. This candlestick pattern is a sign of reversal or the holding of the price at one level. In Japanese, *tohba* translates to "gravestone."

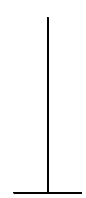

Figure 4.15. Gravestone Doji Candlestick (*Tohba doji*)

4.3.9. Long-Legged Doji Candlestick (Juji). A Long-Legged Doji Candlestick, as shown in Figure 4.16, has no real body, but there is a long upper shadow line and a long lower shadow line. This happens when the opening price and closing price are the same, but when the high price and low price are far from the opening price. This candlestick appears when the market is resisting a movement upward or downward. In Japanese, *juji* translates to "cross."

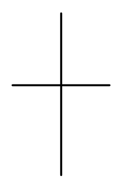

Figure 4.16. Long-Legged Doji Candlestick (*Juji*)

4.3.10. Paper Umbrella Candlesticks (Shimo kage yo sen karakasa/Shimo kage inn sen karakasa). Paper Umbrella Candlesticks, as shown in Figure 4.17, have a small real body and a long lower shadow line but no upper shadow line. This happens when the opening price drops to the low price, but the price comes back to near the opening price when the market closes. This candlestick is a strong reversal sign of the market. When the market is in a downward trend, a Paper Umbrella Candlestick tells the end of the bearish market. However, when the market is in an upward trend, this candlestick tells the end of the bullish market and a price drop is waiting. In Japanese, *karakasa* translates to "paper umbrella."

Figure 4.17. Paper Umbrella Candlesticks (White - *Shimo kage yo sen karakasa* and Black - *Shimo kage inn sen karakasa*)

4.3.11. Hanging Man Candlestick (Kubitsuri). A Hanging Man Candlestick, as shown in Figure 4.18, is a special kind of Paper Umbrella Candlestick that appears in the bullish market, and the real body can be black or white. A Hanging Man Candlestick can become a sign of the end of a bullish market. In Japanese, *Kubitsuri* translates to "hanging" or "decapitation." The Hanging Man Candlestick is a reversal sign of the market.

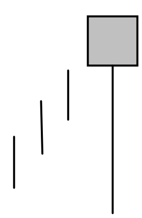

Figure 4.18. Hanging Man Candlestick (*Kubitsuri*)

4.3.12. Hammer Candlesticks (Tonkachi). A Hammer Candlestick, as shown in Figure 4.19, has a small real body and a long upper shadow. This is another special kind of Paper Umbrella Candlestick, and the real body can be black or white. When a Hammer Candlestick appears during the bearish market, this can become a sign for the end of the downward trend. When a Hammer Candlestick appears during the bullish market, this can become a sign for the end of the uptrend. In Japanese, *Tonkachi* translates to "hammer." A Hammer Candlestick is a reversal sign of the market.

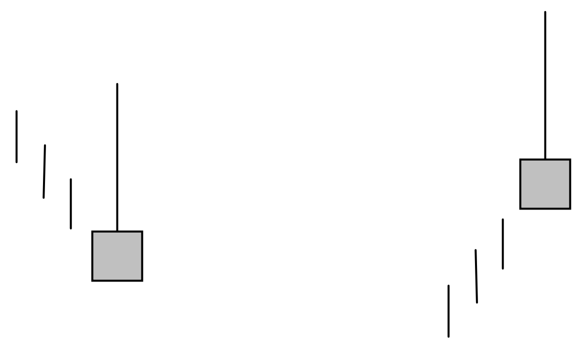

Figure 4.19. Hammer Candlesticks (*Tonkachi*)

4.4. MULTIPLE LINE CANDLESTICK PATTERNS

Multiple Line Candlesticks: Multiple line candlesticks consist of at least two candlesticks to make a pattern. Within each multiple line candlestick pattern, each candlestick represents a separate day for the daily charts or a separate week for the weekly charts. When a pattern requires two candlestick lines for the daily time frame, the first candlestick, the left-hand one, becomes the first day, and the second candlestick, the right-hand one, becomes the second day candlestick. The pattern created with these two candlesticks gives a hint to the future market condition.

4.4.1. The Market Trend and Multiple Line Candlestick Patterns. In general, many traders are interested in determining when the market is going to top out or bottom out. Multiple line candlestick patterns provide signs for each situation. Multiple line candlesticks signal reversal signs of the market, and they usually appear around the top or bottom of a market trend. When one of these signs appears during an upward trend or downward trend, these candlesticks can become a sign of a market trend reversal.

4.4.2. Engulfing Pattern (Tsutsumi). Of the multiple-line candlestick patterns, the Engulfing-Tsutsumi pattern, as shown in Figure 4.20, has a candlestick that completely engulfs the previous candlestick. The first candlestick can be any type of candlestick, but the second candlestick's real body must be bigger than the entire previous candlestick. In other words, the high and low prices of the first candlestick must fit inside the second candlestick's real body.

For a downward trend, as shown in the left-hand side of Figure 4.20, the first candlestick's real body must be black and the second candlestick's real body must be white. For an upward trend, as shown in the right-hand side of Figure 4.20, the first candlestick's real body must be white and the second candlestick's real body must be black.

When an engulfing candlestick pattern appears after a long, continuous upward trend or downward trend, it becomes the important reversal point of the market. In Japanese, *tsutsumi* translates to "covering up, overlaying, and engulfing."

4.4.3. Harami Pattern (Harami). The Harami pattern, as shown in Figure 4.21, first has a candlestick with a long body, followed by a candlestick that is smaller than the first candlestick's real body. When the market is in a downward trend, as shown in the left-hand side of Figure 4.21, a black candlestick appears first and a white candlestick appears next. When the market is in an upward trend, as shown in the right-hand side of the Figure 4.21, a white candlestick appears first and a black candlestick appears next. This pattern is not a strong reversal sign, but it sometimes appears as a change of the market trend. The smaller second candlestick may become a Doji candlestick. In this case, it is called a Harami Cross. In Japanese, *harami* translates to "woman's pregnancy." The first large candlestick represents a mother, and the second small candlestick represents a baby in her stomach.

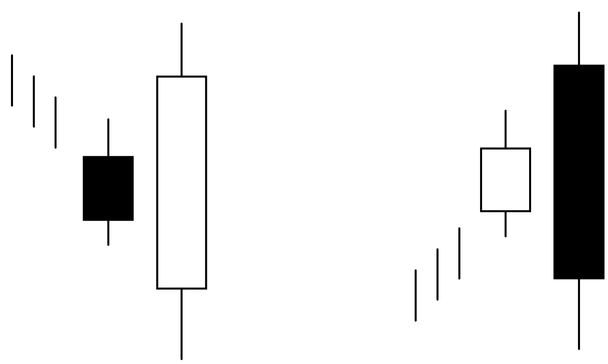

Figure 4.20. Engulfing Pattern (*Tsutsumi*)

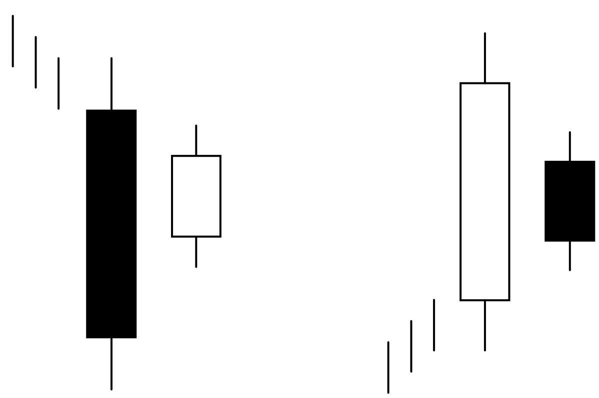

Figure 4.21. Harami Pattern (Harami)

4.4.4. Star Pattern (Hoshi). The Star pattern, as shown in Figure 4.22, is a special kind of Spinning Top Candlestick that appears right after a long candlestick, and the color of the real body can be black or white. Depending on the source, this special kind of Spinning Top Candlestick is also called a Star Candlestick. When this pattern appears in an upward trend, the high price of the long candlestick must be lower than the Star Candlestick's low price. When this pattern appears in a downward trend, the low price of the long candlestick must be higher than the Star Candlestick's high price. In other words, there must be a space between the first candlestick and the second candlestick. This space is called a *mado*, *ana*, or *ku* in Japanese, which is defined as a "window," "hole," or "sky" in English. In Japanese, *hoshi* translates to a "star."

The Spinning Top Candlestick, or Star Candlestick, appears away from the price region of the previous candlestick. When both the Long Candlestick and the Star Candlestick are white in an upward trend, the Star Candlestick becomes a strong bullish sign. When a Black Star Candlestick appears after a Long White Candlestick in an upward trend, this indicates the occurrence of some selling, but a strong bullish sign often remains. When a White Star Candlestick appears after a Long Black Candlestick in a downward trend, that implies the occurrence of some buying, but a bearish sign often remains. When both the Long Candlestick and the Star Candlestick are black in a downward trend, this becomes a sign of further selling.

As shown in Figure 4.23, when there is no real body, in other words, when the candlestick becomes a Doji candlestick, the Star pattern becomes the Cross Star pattern or *Yori Bike Doji* in Japanese. As shown in Figure 4.24, when the upper shadow line or lower shadow line becomes longer, it is called the Shooting Star pattern or *Nagare Boshi* in Japanese. The long shadow line is looked at as a shooting star's tail. The Cross Star pattern and the Shooting Star pattern are similar to the interpretation of the Star Candlestick pattern.

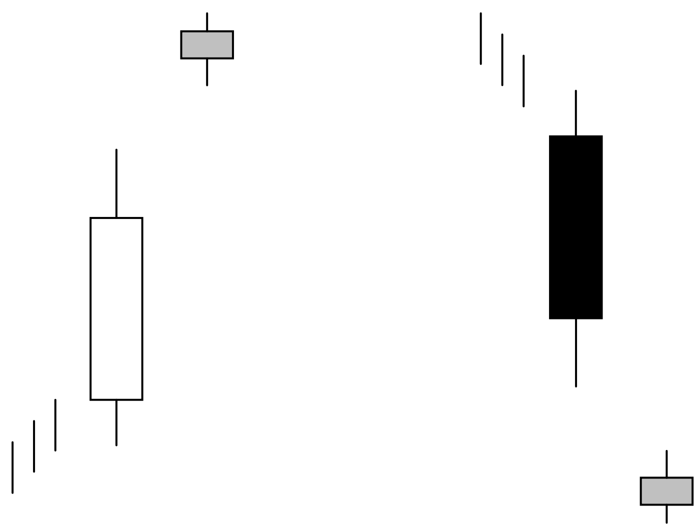

Figure 4.22. Star Pattern (*Hoshi*)

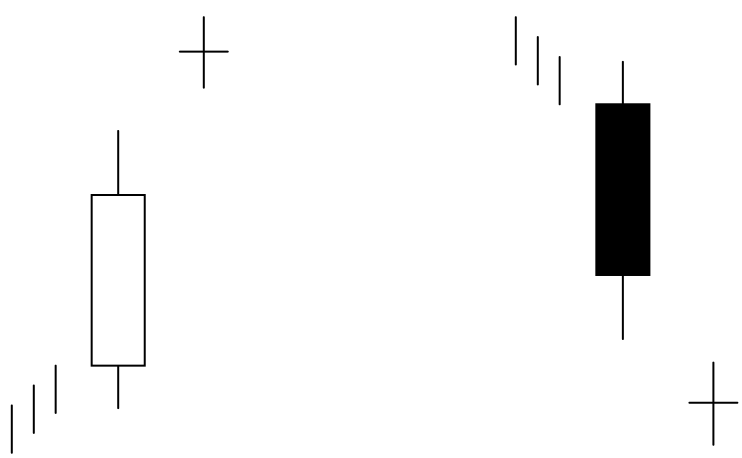

Figure 4.23. Cross Star Pattern (*Yori bike doji*)

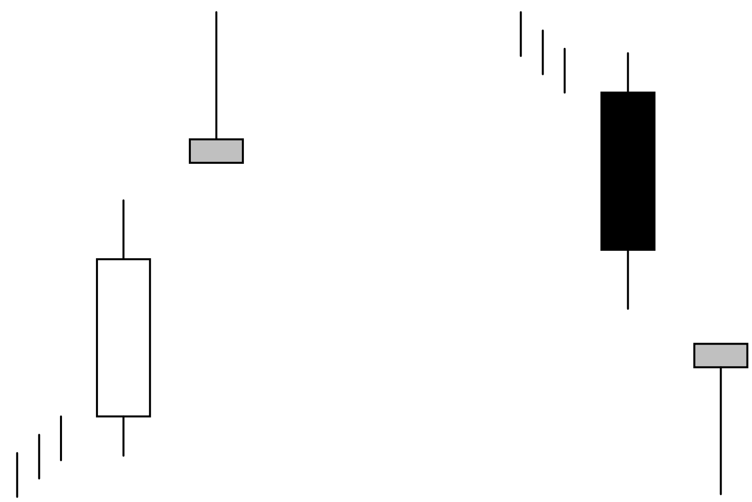

Figure 4.24. Shooting Star Pattern (*Nagare boshi*)

4.4.5. Piercing Line Pattern (Kirikomi). The Piercing Line pattern, as shown in Figure 4.25, appears when the market is in a downward trend. The first candlestick has a long black real body, and the second candlestick has a long white real body. Normally, the second white candlestick does not have an upper shadow line, and the closing price is higher than the center of the previous black candlestick's real body. This pattern shows quite a strong reversal sign. In Japanese, *Kirikomi* translates to "cutting into" or "piercing into."

4.4.6. Dark Cloud Cover Pattern (Kabuse). The Dark Cloud Cover pattern, as shown in Figure 4.26, appears when the market is in an upward trend. The first candlestick is a white candlestick with a long real body, and the second candlestick has a black real body. The second black candlestick's opening price is higher than the high price of the previous white candlestick, but the closing price drops inside the previous candlestick's white real body. This is a bearish sign. In Japanese, *kabuse* translates to "covering up."

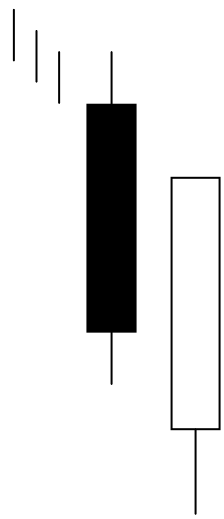

Figure 4.25. Piercing Line Pattern (*Kirikomi*)

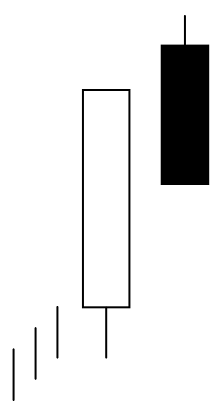

Figure 4.26. Dark Cloud Cover Pattern (*Kabuse*)

4.4.7. Morning Star Pattern (San kawa ake no myojo). The Morning Star pattern, as shown in Figure 4.27, must have three candlesticks. The first candlestick has a black candlestick with a long real body, the second candlestick is a Star Candlestick, and the third candlestick is a white candlestick with a long real body. When this pattern appears at the bottom of a trend, it is said to be a reversal sign. In Japanese, *san kawa* is defined as "three lines," and *ake* in Japanese translates to the "morning." *Myojo* is "Venus shining in the early morning sky," as if the first Long Black Candlestick represents the darkness of the night, and at dawn, Venus is shining to perceive the next day's sunshine. The Star Candlestick can be the Doji Candlestick with short shadow lines.

4.4.8. Evening Star Pattern (San kawa yoi no myojo). The Evening Star pattern, as shown in Figure 4.28, also must have three candlesticks. The first candlestick is a white candlestick with a long real body, the second candlestick is a Star Candlestick, and the third candlestick is a black candlestick with a long real body. When this pattern appears at the top of a trend, it is said to be a bearish sign and the end of an upward trend. In Japanese, *yoi* translates to the "evening." The interpretation of this pattern is the opposite of the Morning Star pattern. The first white candlestick represents as a nice sunny day. However, when Venus appears in the evening sky, that star notifies the coming of the night. A Star Candlestick can be a Doji Candlestick with short shadow lines.

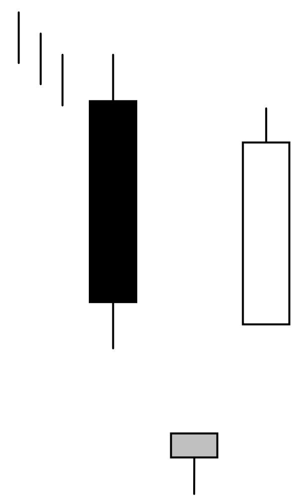

Figure 4.27. Morning Star Pattern (*San kawa ake no myojo*)

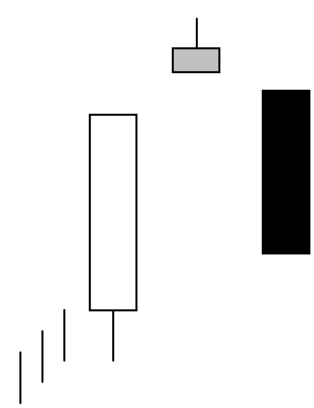

Figure 28. Evening Star Pattern (*San kawa yoi no myojo*)

4.4.9. Three White Soldiers, Advanced Block, and Deliberation Patterns (Aka sanpei, Saki zumari, and Shian boshi). The Three White Soldiers pattern, as shown in Figure 4.29, has three white candlesticks that appear consecutively in an upward trend. The closing price of the white candlestick must be higher than the previous candlestick's closing price. The opening price of the white candlestick also must be higher than the previous candlestick's opening price. This pattern indicates a very strong bullish sign. The third white candlestick holds the key to the strength of the market. When the lower shadow line of the third candlestick is long as shown in Figure 4.29, it still possesses a strong bullish trend. This pattern is called *Aka Sanpei* or *Shiro Sanpei* in Japanese, translates to "Red Soldiers" or "White Solders" in English. As shown in Figure 4.30, when the third candlestick has an upper shadow line, the strength of pulling up the price becomes weak. This is called *saki zumari* in Japanese, or "Advanced Block" in English. As shown in Figure 4.31, when the third candlestick is a Star Candlestick, the buying power of the market becomes weak and it needs a caution for the change of the trend. Basically, this is still a sign of a bullish market. This candlestick pattern is called *shian boshi* in Japanese, or "Deliberation" in English.

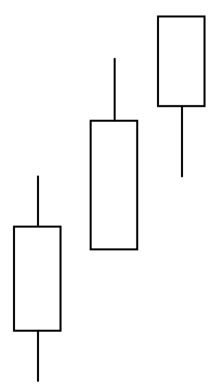

Figure 4.29. Three White Soldiers Pattern (*Aka sanpei or Shiro sanpei*)

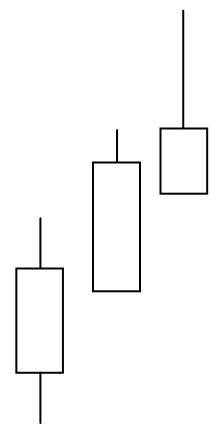

Figure 4.30. Three White Soldiers – Advanced Block Pattern (*Saki zumari*)

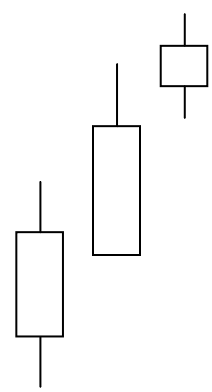

Figure 4.31. Three White Soldiers – Deliberation Pattern (*Shian boshi*)

4.4.10. Three Black Crows, Identical Three Crows, and Three Black Bozu Patterns (Sanba garasu, Doji sanba garasu, and Bozu sanba). Three Black Crows, as shown in Figure 4.32, is a candlestick pattern that has three black candlesticks in a downward trend. In this pattern, all three candlesticks decline consecutively; in other words, the next day's opening price is lower than the previous day's opening price, and the next day's closing price is lower than the previous day's closing price. In Japanese, *Sanba* translates to “three birds,” and *garasu* translates to the “black crows.” The Identical Three Crows pattern, as shown in Figure 4.33, is a special Three Black Crow pattern in which the opening price of the second day’s candlestick has the same or almost the same price as the previous day’s closing price. Then, the opening price of the third candlestick has the same or almost the same price as the previous day’s closing price. In Japan, the crows are usually a bad sign of the future. The Three Black Crows pattern figuratively signals a bad bearish sign of the future market. When there is no lower shadow line on each of the three black candlesticks, as shown in Figure 4.34, it is called Three Black Bozu.   In Japanese, the *Bozu* translates to “Buddhism monk.” When a monk wears his surplice, a funeral is usually held. Figuratively, when three such monks appear, the market is guided to a funeral. In other words, this is a very weak sign for the market, and the trend may still continue downward.

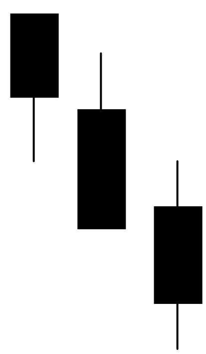

Figure 4.32. Three Black Crows Pattern (*Sanba garasu*)

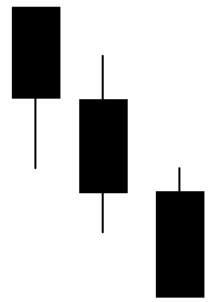

Figure 4.33. Identical Three Crows Pattern (*Doji sanba garasu*)

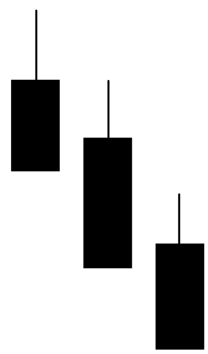

Figure 4.34. Three Black Bozu Pattern (*Bozu sanba*)

4.4.11. White Candlestick Harami Pattern (Yo no yo harami). The White Candlestick Harami pattern, as shown in Figure 4.35, appears when the opening price is higher than the previous day's opening price, but the closing price is lower than the previous day's closing price. When this pattern appears during an upward trend, this may be a sign of the end of an upper trend.

4.4.12. Black Candlestick Harami Pattern (Inn no inn harami). In the Black Candlestick Harami pattern, as shown in Figure 4.36, the first black candlestick has a large real body, and the second black candlestick's real body stays inside the first candlestick's real body. In other words, the opening price of the second day is lower than that of the first day, but the closing price of the second candlestick is higher than that of the first day. Likewise, the third black candlestick's real body stays inside the second candlestick. Also, as in the first two candlesticks, the opening price of the third candlestick is lower than that of the second candlestick, and the closing price of the third candlestick is higher than that of the second candlestick. The third black candlestick signals the end of a downward trend in the market.

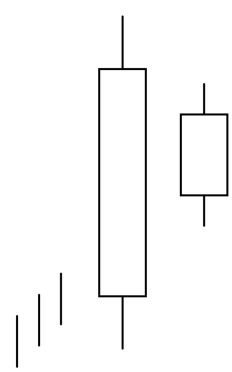

Figure 4.35. White Candlestick Harami Pattern (*Yo no yo harami*)

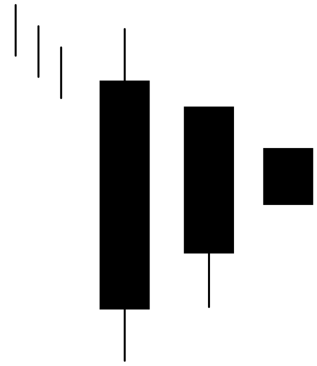

Figure 4.36. Black Candlestick Harami Pattern (*Inn no inn harami*)

5. EARLY SOLUTION APPROACHES

5.1. INTRODUCTION

This section explains the study of existing techniques implemented in the candlestick-based stock market forecasting models. Originally, these techniques were considered to be part of the forecasting model because of the uniqueness and efficiency they presented. However, after the implementation of these techniques, some were found to be useful while others were not promising. This section discusses and summarizes the implementation of the existing techniques applied for an experimental model.

5.2. GENERALIZED REGRESSION NEURAL NETWORKS

5.2.1. Strength of Generalized Regression Neural Networks. Disorntetiwat's (2000) study of forecasting the financial market showed that it is best to let one Generalized Regression Neural Network (GRNN) handle only one category or one data set. In this way, the spread of the data region can be minimized. This works best for a popular non-linear activation function of the radial basis layer in GRNNs.

5.2.2. Weakness of Generalized Regression Neural Networks. The architecture of a GRNN is similar to the Radial Basis Function (RBF). In a GRNN, the first layer is a Gaussian radial basis activation function. This radial basis layer's activation function is $radbas(n) = e^{-n2}$, which produces a bell-shaped curve plot (Demuth, 2001). When the radial basis function is very steep, the input vectors that are close to the target vectors give a much larger output than the other neurons. When the radial basis function becomes smoother, several neurons react to an input vector, and the response may become like a weighted average between all the target vectors (Demuth, 2001).

Therefore, if the regions of the data set are spread too widely, then the data points located near the edge of the bell-shaped curve or outside the curve cannot act as important factors. This is a significant downside of GRNN, and it was for this reason that Disorntetiwat's models did not perform well when the market became volatile.

5.3. EXPERTS AND GATING NETWORKS

5.3.1. A Gating Network for Controlling Experts. A gating network acts as a mediator for all the experts in a committee machine. The gating network investigates the output from each expert and then negotiates them. A gating network screens out or modifies the best output generated by each expert for the final output. In this way, the final output is refined, which generates improved final results.

5.3.2. Weaknesses of Experts and the Gating Network Relationship. The selection of experts for the model becomes important for making rules in a gating network. As the number of experts increases, so does the significance of selecting the experts. In other words, the rules in the gating network should give a certain level of assignment to each expert. If the gating network never assigns rules to certain experts, then the existence of those experts in the network becomes meaningless. Therefore, an investigation of the relationship between each expert and the gating network is recommended. A hierarchical mixture of experts with layers of gating networks can be used to overcome this kind of problem.

5.4. HAVNET-BASED PATTERN RECOGNITION

5.4.1. HAVNET. HAVNET is an abbreviated name for the Hausdorff-Voronoi Network. HAVNET was developed to process complex images, such as 3-D object recognition. Chafin and Dagli's (1999) HAVNET-based model rotates the images, extracts the edge features, and then tests the scales during the image feature extracting process. The feature information extracted from the images by Chafin and Dagli's model is organized in a form that is convenient for isolating the individual objects that comprise the image. The isolated and consolidated features are then combined into sets that become candidate objects for recognition. When the feature set gives the highest degree of similarity, image recognition occurs (Chafin and Dagli, 1999).

5.4.2. Strength of HAVNET-Based Pattern Recognition. This HAVNET-based model is useful for processing complex images and their pattern recognitions. When using Chafin's model, a complex image is decomposed into several features. The object is recognized based on the feature extracted. Chafin's HAVNET-based program was used and tested for image recognition of people's faces (Chafin and Dagli, 1999; Chafin, Dagli, and Mitchell, 1999).

5.4.3. HAVENET for Candlestick Pattern Recognition. Under Chafin's supervision, five candlestick patterns were generated and pictured in bitmap format for the image recognition experiment. During the image feature extracting process, the program rotated the candlestick pattern images, extracted the edge features, and tested the scales. The results were interesting because all of the candlestick patterns were 2-D black and white images drawn with straight lines and rectangles. Therefore, they contained few complexities or unique features, so Chafin's model tended to categorize most of the images into similar objects. For example, a Morning Star candlestick pattern and an Evening Star candlestick pattern fell into very similar candidate objects, but in reality they are very different. A Morning Star candlestick pattern indicates a bullish reversal, or a bottom reversal pattern, while an Evening Star candlestick pattern indicates a bearish reversal, or a top reversal pattern.

In the image recognition experiment, the number of candlesticks in one image was increased to increase the complexity of the images. However, doing so produced insignificant results. In the worst case, the images of the market's upward trend and downward trend fell into a similar object category.

Chafin's HAVNET-based image recognition is useful for complex 3-D images. However, very simple 2-D images, such as images of candlestick patterns, do not contain enough distinct features and therefore cause errors in experiments instead of producing better results. Therefore, Chafin's model could not differentiate the candlestick pattern images to a high enough level to be useful (Chafin and Dagli, 1999; Chafin, Dagli, and Mitchell, 1999).

6. PROPOSED MODELS

6.1. DATA DESCRIPTION AND DATA SOURCES

All of the proposed forecasting models use historical stock data obtained from the Yahoo finance website. The daily stock data used to train and test the models consist of opening price, high price, low price, and closing price. Five trading days is considered one week, and the testing data is grouped on a weekly basis.

The companies are selected randomly from several fields of industries. The model forecasts the next day's stock price for those companies' quotes. Those forecasted prices are compared with the actual historical data of those companies' stock prices.

6.2. CANDLESTICK TECHNIQUE IMPLEMENTATION

To develop the candlestick charts for the randomly selected companies, the same daily stock data consisting of opening price, high price, low price, and closing price are used. The previous day's candlestick patterns are used for forecasting. In other words, the candlestick patterns used for daily forecasting are different each day.

For Model 1, basic, single candlesticks are used. Either the white candlestick or the black candlestick is generated on a daily basis. The previous day's candlestick pattern is used for forecasting. Model 2 follows the same pattern of generating a white or black candlestick on a daily basis for forecasting purposes. In addition, the relative sizes of candlesticks are compared weekly to represent the strengths and weaknesses of the market influences. Candlestick pattern recognition was performed using type-1 fuzzy logic systems. For Model 3, the single-line and multiple-line candlestick patterns described in Section 4 are implemented for forecasting the next day's stock prices. Type-2 fuzzy logic systems are utilized for identifying those candlestick patterns.

6.3. MODEL 1 – EXPERIMENTING WITH CANDLESTICK TECHNIQUES

6.3.1. Model 1 Description. The purpose of developing Model 1 is to test the computational feasibility of candlestick techniques for financial forecasting. As mentioned in a previous section, candlestick pattern image recognition presents challenges, and the actual data consisting of the stocks' opening price, high price, low price, and closing price are used to create the candlestick patterns.

The simple architecture of a committee machine, a hierarchical mixture of experts, is used for building the models. The structure of Model 1 is illustrated in Figure 6.1. The historical data are the inputs for each expert. Each expert is generalized regression neural network (GRNN)-based and handles one dataset. For example, a dataset containing the opening price goes to Expert 1 to generate the output y_1. Outputs from each GRNN-based expert are investigated by the gating network. This architecture is illustrated below.

In the gating network, the candlestick patterns are identified. Based on their classification, the rules and weight ratios are generated for each expert's outputs. After the experts' outputs are adjusted with this gating network, they are combined to produce the overall output, which is the next day's forecasted closing price. The structure of the inside gating network is illustrated in Figure 6.2. For this experimental model, three elements of candlestick patterns are implemented.

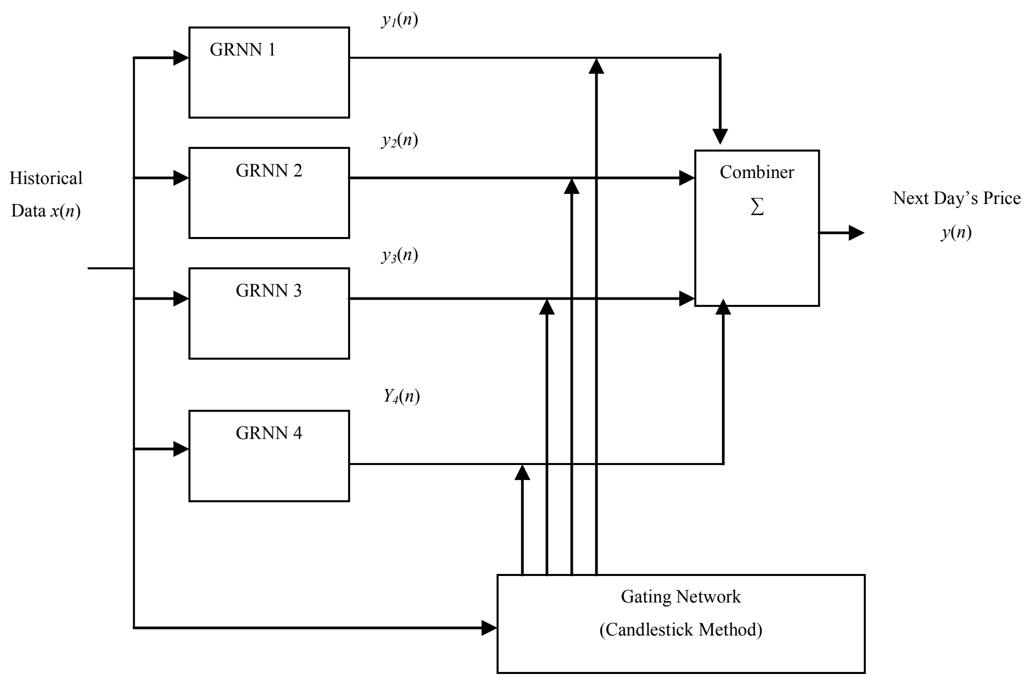

Figure 6.1. Model 1 with Candlestick Method

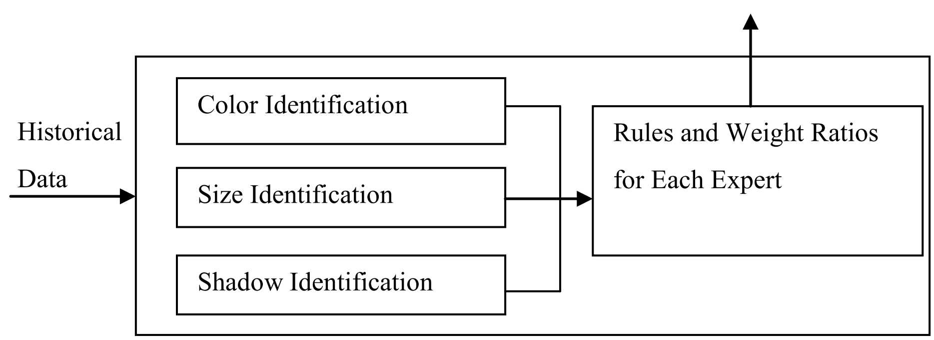

Figure 6.2. Inside Gating Network for Model 1

Here is an example of the basic rules of the candlestick method implemented for this model. This process is handled in the gating network. The following example is based on the color of a single candlestick:

- *if* the real body of a candlestick is white,

  then the market is bullish.

- *if* the real body of a candlestick is black,

  then the market is bearish.

- *if* the real body of a candlestick is doji (not white, not black),

  then the market is neutral.

The decision made by the gating network is applied to each expert to produce the overall output. The performance of Model 1 is compared with a simple GRNN-based forecasting model. The difference between the two models is the existence of the gating network. Model 1 implements candlestick techniques, while the GRNN-based model does not.

6.3.2. Model 1 Experiment Setup. Both models forecast the next day's stock price for the following companies' quotes: Exxon Mobil (XOM), General Electric (GE), General Motors (GM), Google (GOOG), Microsoft (MSFT), and Wells Fargo (WFC). The period of historical data used for the experiment is April 15, 2002, through March 31, 2006. This period contains 1000 trading days. To forecast Google's stock prices, because its IPO date was August 19, 2004, the data between August 19, 2004, and March 31, 2006, were used.

For training the neural networks, the previous five days are used. The testing data are grouped on a weekly basis. The candlestick patterns are generated on a daily basis using the daily stock quotes of each company. Because single candlestick patterns are used for Model 1, the previous day's candlestick pattern is used for forecasting. Three kinds of candlestick patterns are implemented in Model 1 due to the experimental purposes. The outputs of both models are compared with the actual data, and the performance of the model is evaluated based on the mean squared error (Kamo and Dagli, 2006).

6.4. MODEL 2 - EXPERIMENTING WITH FUZZY LOGIC

6.4.1. Model 2 Description. Model 2 is built to test fuzzy logic and the Japanese candlestick techniques. In reality, the Japanese candlestick method is a perception-based technique, and precision is not essential. The implementation of candlestick methods in Model 1 actually improves financial forecasting. However, the way in which the Japanese candlestick technique is implemented in Model 1 is with crisp, not fuzzy, data sets. Model 2 implements the Japanese candlestick method with fuzzy logic. Fuzzy logic provides a wide variety of concepts and techniques to represent knowledge that is uncertain or imprecise (Zadeh, 1992).

The architecture of Model 2 is based on a hierarchical mixture of expert committee machines that is similar to Model 1. However, Model 2 uses an IF-THEN fuzzy logic rule-based fuzzy logic system for candlestick pattern recognition. Figure 6.3 shows the illustration of the architecture of Model 2. The elements of candlestick patterns identified inside a fuzzy logic-based system are shown in Figure 6.4.

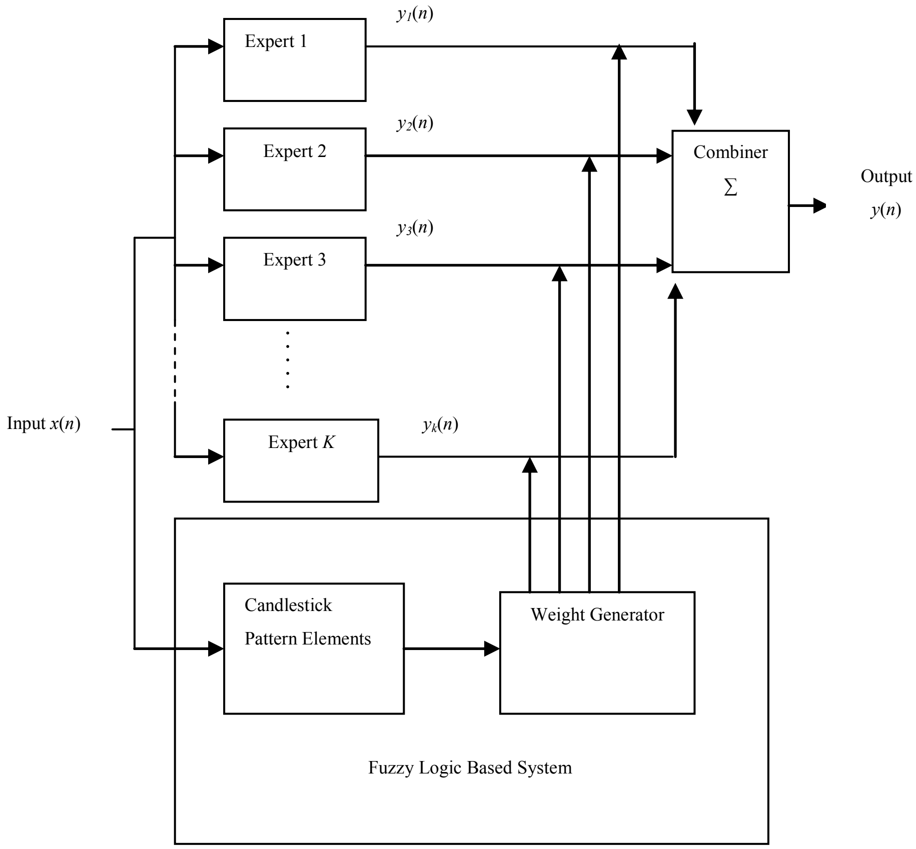

Figure 6.3. Structure of Model 2

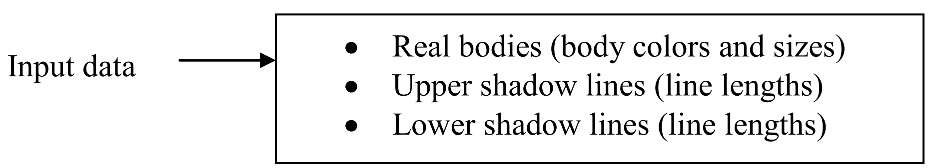

Figure 6.4. Candlestick Pattern Elements

Each element is identified with a fuzzy expression; for example, real body A is big and white, real body B is small and white, upper shadow A is very short, and so on. Each element is now assigned to the membership function with a specific range; IF-THEN rules evaluate those elements. The results generated by the rules are combined and produce a crisp number, which indicates the strength of the market and is assigned to each expert as a weight.

The overall fuzzy logic system is shown in Figure 6.5. Fuzzy expressions generated from the first section are moved to the next section to apply the rules. The results generated from the rules move to the combiner to help produce price strength and weakness as output. This output then is applied to each expert to generate the final result.

The fuzzy logic systems use standard IF-THEN rules to formulate the conditions of the elements. For example, when only one element of a candlestick pattern is applied to one fuzzy rule,

- *If* the real body size is very large,

  then the stock strength is very strong.

When more than one element is considered for a candlestick pattern, more than one rule is applied:

- *If* the real body size is very small and the upper and lower shadow lines are long,

  then the stock strength is neutral.

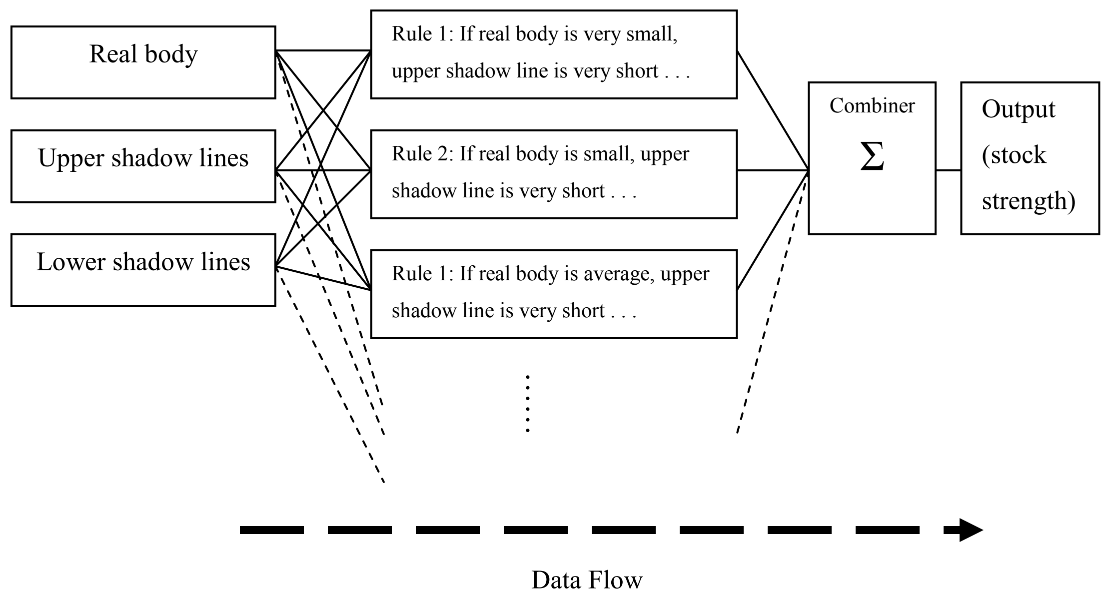

Figure 6.5. Fuzzy Logic Systems for Model 2

6.4.2. Model 2 Experiment Setup. Model 2 uses the following five companies' daily stock quotes to forecast the next day's closing stock prices: Hewlett-Packard (HPQ), Bank of America (BAC), Ford (F), DuPont (DD), and Yahoo (YHOO). The period of historical data used for the experiment is October 1, 2001, through September 18, 2007. This period contains a total of 1500 trading days.

The previous five days are used to train networks for generalized regression neural networks (GRNN) in each expert. Each expert handles only one category of the data set.

Candlestick patterns are generated on a daily basis. Because single candlestick patterns are used for the models, the previous day's candlestick becomes a priority for forecasting the next day's stock quote.

The author consults a table lookup for the fuzzification of the input; that is, the membership functions for fuzzy sets are developed by the experts' experiences and knowledge. Each candlestick element falls into a single membership or multiple memberships. The membership function type used for this experiment is a Gaussian-based membership function, which is not complex and is suitable for this experiment. The membership functions are developed using the Fuzzy Logic Toolbox of MATLAB. As an example, plots of the membership function are shown in Figure 6.6.

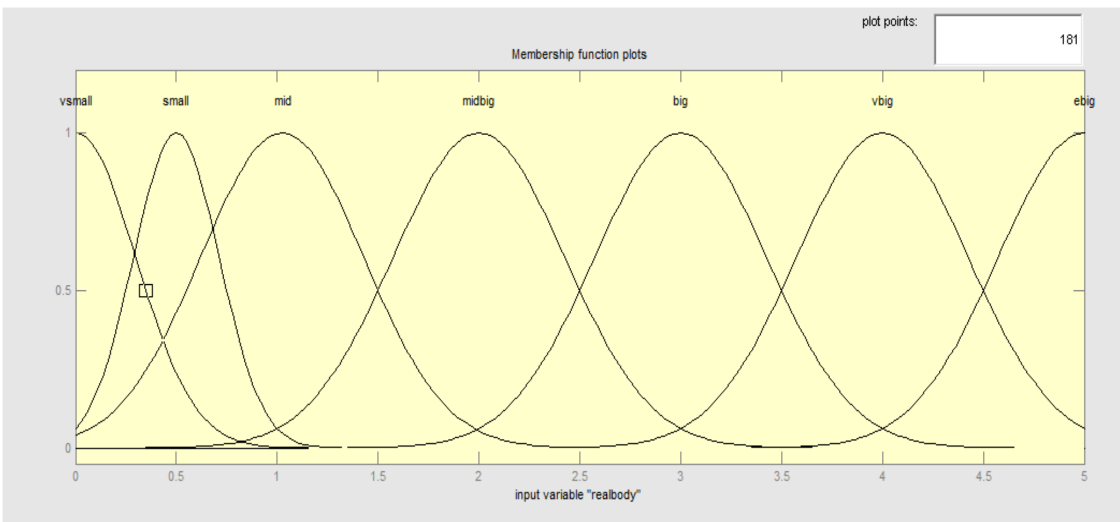

Figure 6.6. Membership Function Plots

For the fuzzy membership function, the inputs range between 0 and the universe of discourse. In Figure 6.6, the input range is between 0 and 5. The linguistic values big, small, long, short, and so on are based on the previous five days' candlestick pattern observations. The results from the fuzzy logic process in a hybrid gating network, the weight, is calculated and assigned to the experts.

The performance of Model 2 is compared with that of Model 1. The outputs of both models are compared to the actual stock quotes, and the performance of the models is evaluated based on the mean squared error (Kamo & Dagli, 2008).

6.5. MODEL 3 - EXPERIMENTING WITH TYPE-2 FUZZY LOGIC

6.5.1. Model 3 Description. Model 3 extends Japanese candlestick pattern recognition through the use of type-2 fuzzy logic systems. Model 2 proved that the fuzzy logic system is good at handling ambiguous Japanese candlestick pattern definitions. However, Model 2 uses a type-1 fuzzy logic system, which has crisp membership functions that may not be able to utilize the candlestick pattern definitions because all experts and traders have their own perceptions and comprehensions. That is, the crisp membership functions of type-1 fuzzy logic systems are not suitable for representing differences in knowledge among a group of experts and traders. For this reason, type-2 fuzzy membership functions are implemented for Japanese candlestick pattern recognition for Model 3.

The architecture of Model 3 is an advanced version of Model 2. Figure 6.7 shows the diagram of the architecture of Model 3. Model 3 has a committee machine task system that divides the stock price monitoring tasks. In this system, actual opening, high, low, and closing prices are monitored each day of forecasting. Also, based on the monitoring process, the system generates a proposed set of price elements for forecasting for final processing.

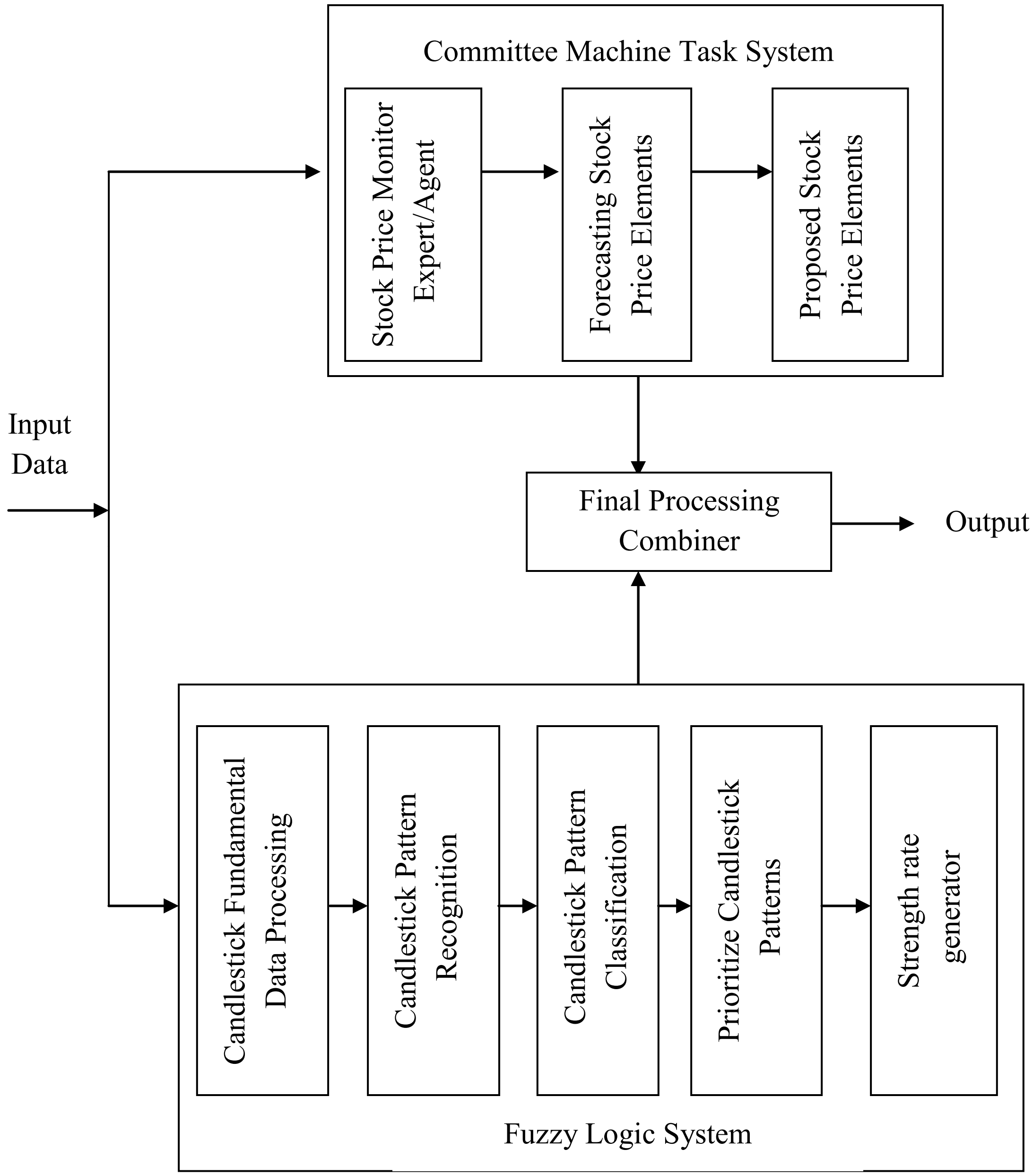

Figure 6.7. Structure of Model 3

Model 3 also contains a fuzzy logic system, which is used to conduct candlestick patterns. As mentioned above, a type-2 fuzzy logic system is implemented in Model 3. In the fuzzy logic system, a preparation of candlestick pattern recognition with type-2 fuzzy logic is performed after the fundamental data for processing candlestick patterns are categorized and processed based on user needs. Once candlestick patterns are recognized, they then are classified and prioritized to generate stock price strength for final processing. In the final processing combiner, results from both systems are combined to produce a final output set. The final output set consists of daily forecasted stock prices.

For this experiment, more candlestick patterns are added in Model 3 for investigating the performance of fuzzy membership functions and overall forecasting results. Table 6.1 shows the complex candlestick patterns that Model 3 can handle.

Table 6.1. Additional Candlestick Patterns for Model 3

Marubozu	Black Closing Marubozu	White Closing Marubozu
Black Opening Marubozu	White Opening Marubozu	Spinning Top
Dragonfly Doji	Gravestone Doji	Long-Legged Doji
Paper Umbrella	Hanging Man	Hammer Man
Engulfing	Harami	Star
Piercing Line	Dark Cloud Cover	Morning Star
Evening Star	Three White Soldiers	Three Black Crows

6.5.2 Model 3 Experiment Setup. The five companies' daily stock quotes are used for forecasting the next day's closing stock price in Model 3. The five companies include Bank of America (BAC), General Electric (GE), Google (GOOG), Monsanto (MON), and Toyota (TM). The period of historical data used for this experiment is between March 3, 2008, and February 28, 2011. There are 756 trading days in this period.

The committee machine task system contains the experts that are based on generalized regression neural networks (GRNN). There are five training days for generalized regression neural networks. Experts monitor their own localized regions to avoid the problem of data spread. These experts monitor the stock price movement and produce the proposed daily forecasting prices.

The candlestick patterns were generated on a daily basis. Because Model 3 can manage multiple, complex candlestick patterns, a few candlestick patterns are stored until just prior to the forecasting day. Candlestick pattern and chart analysis books are consulted for the definitions of candlestick patterns (Nison, 2001, Morris, 1992), which are applied to develop membership functions for type-2 fuzzy logic systems. Interval type-2 fuzzy logic, which has secondary membership functions that are zero or one, is used for Model 3. One type of primary membership function is a primary membership function with an uncertain standard deviation. In other words, the primary membership functions have fixed mean values.

An example of the basic data flow for a candlestick pattern identification process in a pattern composed of two candlesticks is shown in Figure 6.8. If a third candlestick exists in the pattern, a third candlestick pattern identification should be added after the second candlestick pattern identification process, which will occur before processing the candlestick relationships.

Each box in the figure above contains the fuzzy rules to accomplish the task. The number of rules depends upon the type of candlestick pattern identification.

The performance of Model 3 is compared with that of Model 2. The outputs of both models are compared to the actual stock quotes, and the performance of the models is evaluated based on the mean squared error.

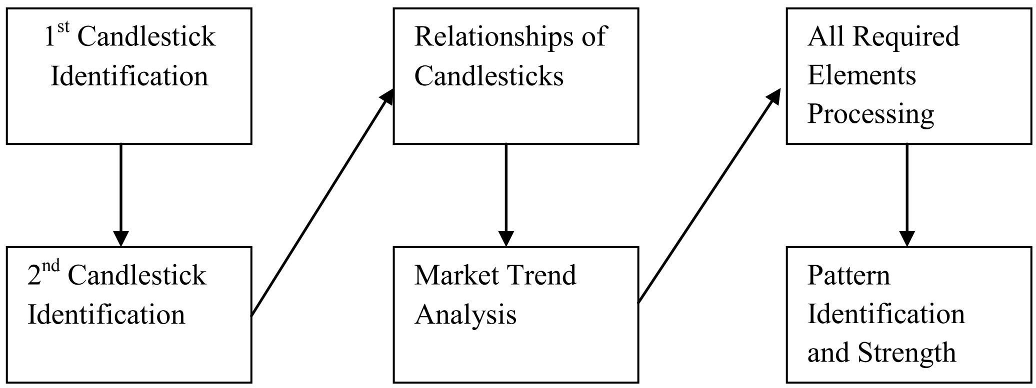

Figure 6.8. Data Flow for Candlestick Pattern Identification

7. EXPERIMENTAL RESULTS

7.1. MODEL 1

7.1.1. Model 1 Results. The results from Model 1 and a simple, generalized regression neural network-based model are shown in Table 7.1 below. The results are in mean squared error.

Table 7.1. Results of Model 1

	Simple GRNN Model	Hybrid Approach with Candlestick Techniques (Model 1)
Exxon Mobil (XOM)	0.2634	0.2134
General Electric (GE)	0.1397	0.1274
General Motors (GM)	0.4102	0.3232
Google (GOOG)	37.48	28.22
Microsoft (MSFT)	0.0962	0.0918
Wells Fargo (WFC)	0.1938	0.1898

7.1.2. Model 1 Review. The results of Model 1 for forecasting Exxon Mobil are used for reviewing the performance of Model 1. The graph presented in Figure 7.1 below shows part of Exxon Mobil's actual price movement and the prices forecasted by both Model 1 and a simple, generalized regression neural network model. The time period displayed in this graph is between January 2004 and April 2004. During this period, especially between March 23 and April 30, the hybrid model demonstrated a faster reaction to the market than the simple, generalized regression neural network model.

Model 1 reacted more quickly because the candlestick information took effect. The same time period for the candlestick chart is shown in Figure 7.2 below. On the candlestick chart, between x = 70 and x = 80, there are two candlesticks without a real body. This is called a doji candlestick pattern, and it means that the market became neutral. After that, a relatively large, black candlestick appeared, indicating that the end of the bull market began around x = 20. The network caught this change and took action to adjust the forecasting decision made by the experts. Then, the overall output was pulled down to lower the forecasted price.

The candlestick chart between x = 55 and x = 70 also contains a large, black candlestick. However, the network considered the market unstable and did not adjust much toward the experts' decisions. In fact, very few differences exist between the forecasting data generated by the simple model and Model 1.

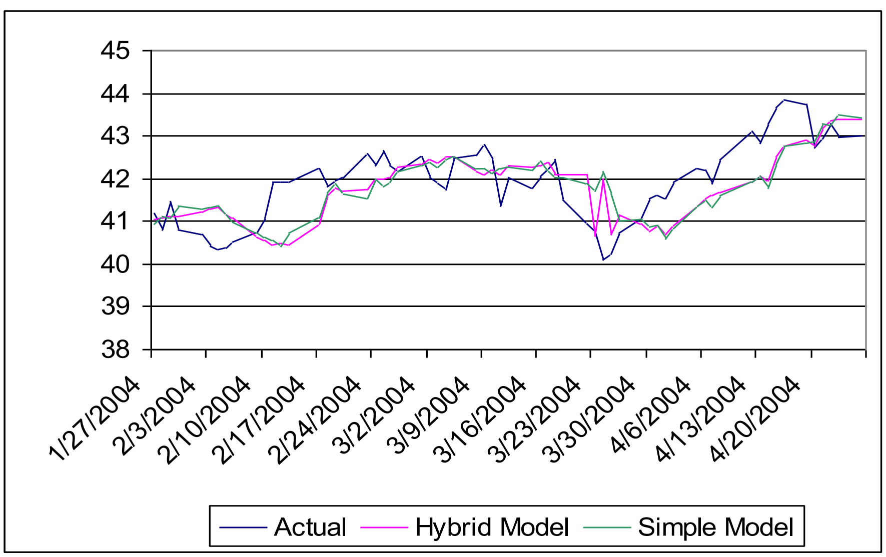

Figure 7.1. Result of Exxon Mobil between March 23, 2004, and April 30, 2004

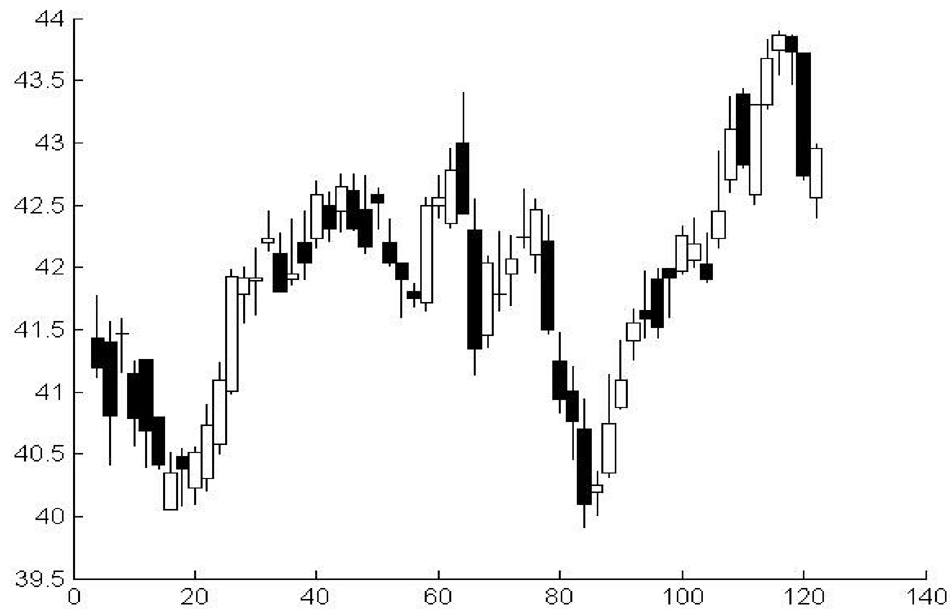

Figure 7.2. Candlestick Chart of Exxon Mobil between March 23, 2004, and April 30, 2004

7.2. MODEL 2

7.2.1 Model 2 Results. The results from Model 2 and Model 1 are shown in Table 7.2 below in mean squared error. Model 2 produced better forecasting results than Model 1. Figure 7.3 shows the forecasting result for Bank of America (BAC) in the line chart. The y-axis represents the price, and the x-axis shows the trading date.

7.2.2 Model 2 Review. Figure 7.4 shows each model's forecasting results for Bank of America between March 1, 2006, and June 28, 2006. The forecasting result generated by Model 2 produced smoother line curves than Model 1 because the hybrid gating network contains fuzzy rules that can see the market conditions in the same way in which traders watch price movements. For example, Model 1 does not have fuzzy membership functions, and it observes candlestick patterns whether the market is bullish or bearish, giving yes or no answers. On the other hand, Model 2, which has a fuzzy logic-based hybrid gating network, can observe the strength or weakness of candlestick patterns like traders do.

Table 7.2. Results of Model 1 and Model 2

	Model 1	Model 2
Bank of America (BAC)	2.886	0.138
DuPont (DD)	2.991	0.283
Ford (F)	0.2550	0.0469
Hewlett-Packard (HPQ)	1.223	0.1527
Yahoo(YHOO)	1.228	0.2432

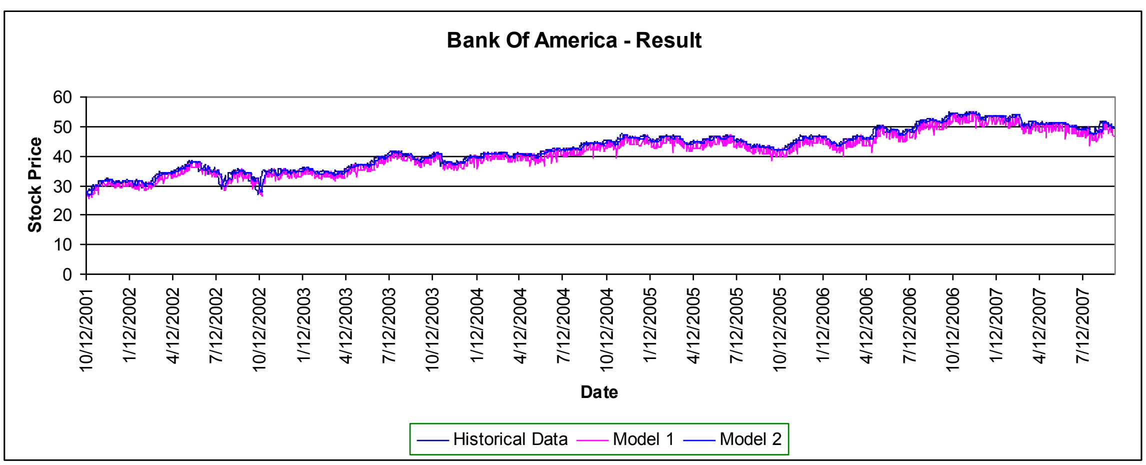

Figure 7.3. Results of Bank of America in a Line Chart

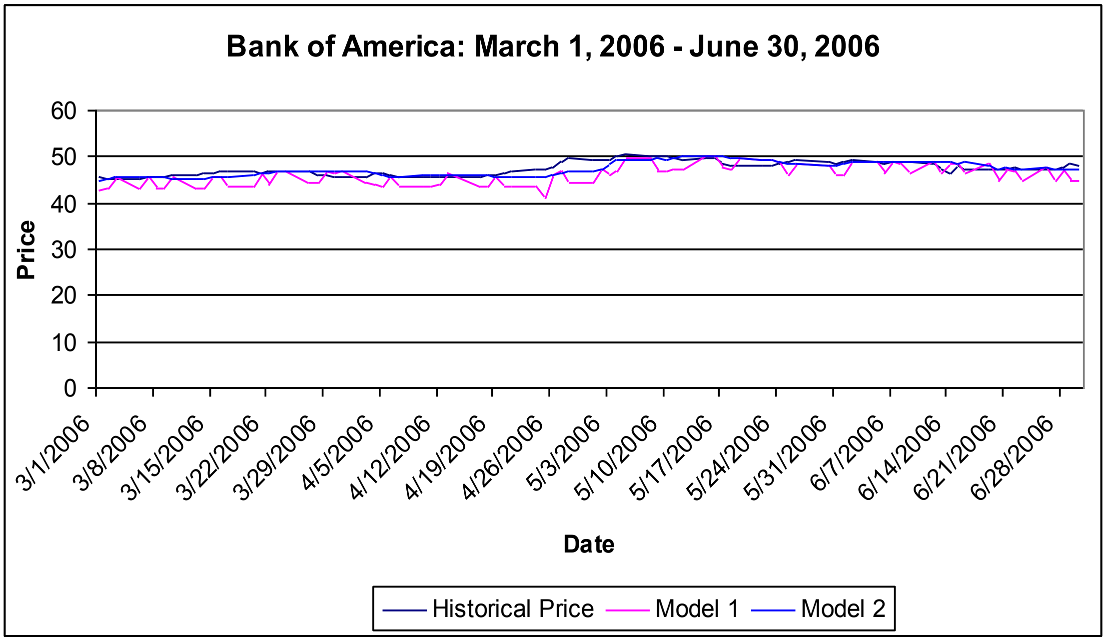

Figure 7.4. Results in a Line Chart between March 1, 2006, and June 28, 2006

When the market does not display much movement, both models produce smoother lines. However, Model 1, the simple, gating network-based model, still produces a slightly rougher line movement. Figure 7.5 shows the results of the two models for Bank of America from April 20, 2006, to May 19, 2006. During this period, there was no significant movement in the market, and both models performed fairly well. However, Model 2 produced a smoother curve line than Model 1. Figure 7.6 shows the candlestick chart for the same period.

Closer observation reveals slight movement of the line in the result of Model 1 around April 28, 2006 (Figure 7.5). When x = 20 in Figure 7.6, a few black candlesticks appeared, and Model 1 considered this to be significant. The black candlestick is a sign of bearish market conditions. Due to this black candlestick pattern, Model 1 determined the stock price to be falling and sent its decision to the experts to generate the final output. However, one large, white candlestick also appeared in the middle of the run of black candlesticks. Model 2 took this white candlestick appearance into account when generating the forecasting prices. The white candlestick is a sign of a bullish market condition. Therefore, the forecasting data of Model 1 is lower than that of Model 2 after April 30, 2006. As shown in Figure 7.5, the forecasting price result from Model 1 did not show an upward trend in movement until a few white candlesticks appeared at the beginning of May, x = 30 in Figure 13.

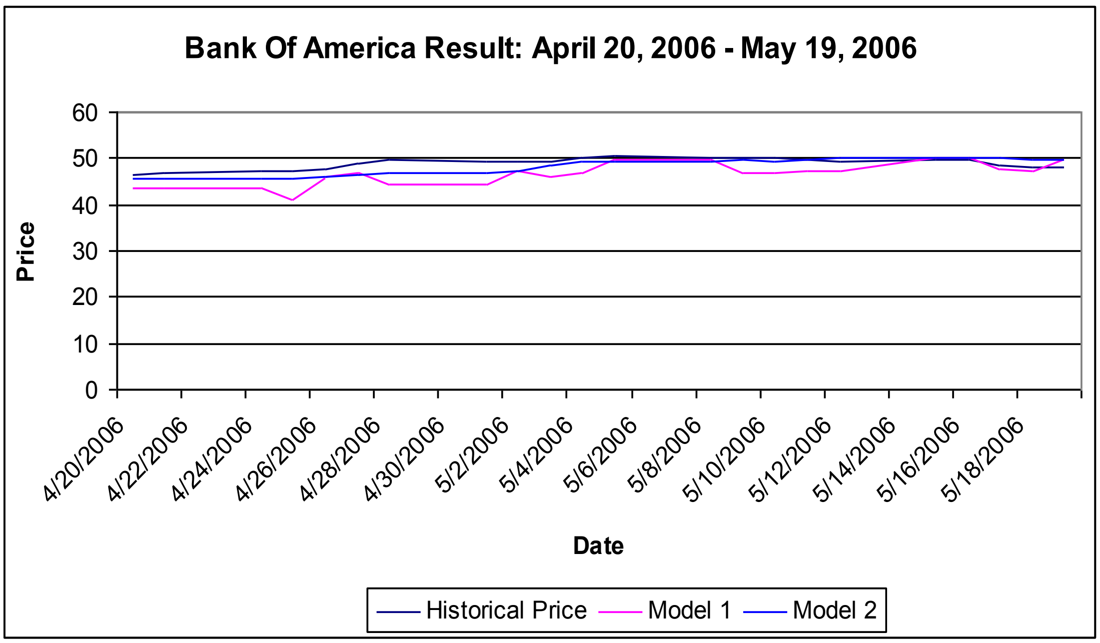

Figure 7.5. Results in a Line Chart between April 20, 2006, and May 19, 2006

As illustrated in Figure 7.7, Model 1 was not stable, and the forecasted price line moved up and down rapidly. On the other hand, Model 2 demonstrated a smooth price movement, and the forecasted price line moved along the actual historical data. Model 1, the simple, gating network-based model, cannot see the relative size of candlesticks well.

Also, the simple gating network makes YES or NO type crisp decisions, so there is less flexibility. Therefore, Model 1's simple gating network cannot send ambiguous weight decisions to the experts, so the overall output is far from the actual historical prices.

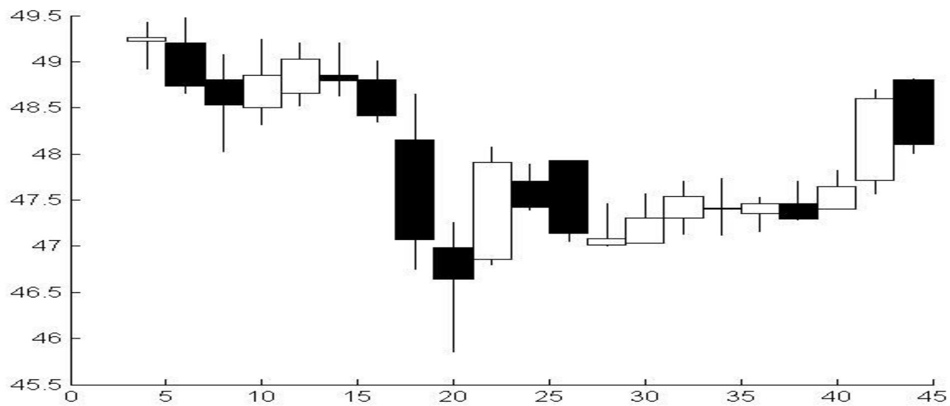

Figure 7.6. Candlestick Chart (Bank of America) between April 20, 2006, and May 19, 2006

Model 2, the hybrid gating network-based model, however, can see the relative sizes of candlesticks and generate flexible decisions due to its use of fuzzy membership functions. The membership functions control the weight decisions from the gating network based on the relative size of the candlestick patterns. For example, the relatively large, white candlestick, which appeared around x = 10 in Figure 7.8, became a bullish sign, and Model 2 decided that the stock price could go up. Several white candlesticks appeared after x=10 in Figure 7.8. However, the black candlestick and the doji candlestick, which appeared between x=10 and x=20 in Figure 15, show the hesitation of the stock prices, and the fuzzy logic-based gating network decided not to raise the stock price any further. The fuzzy membership function considers the black candlestick to be a negative sign in regards to stock price movement. However, the black candlestick is not significantly large. Therefore, the hybrid gating network did not decide that the stock price was falling and did not send “a stock price is going down” decision to the experts. Actually, the hybrid gating network sent the decision “the stock price might have a chance of going down” to the experts.

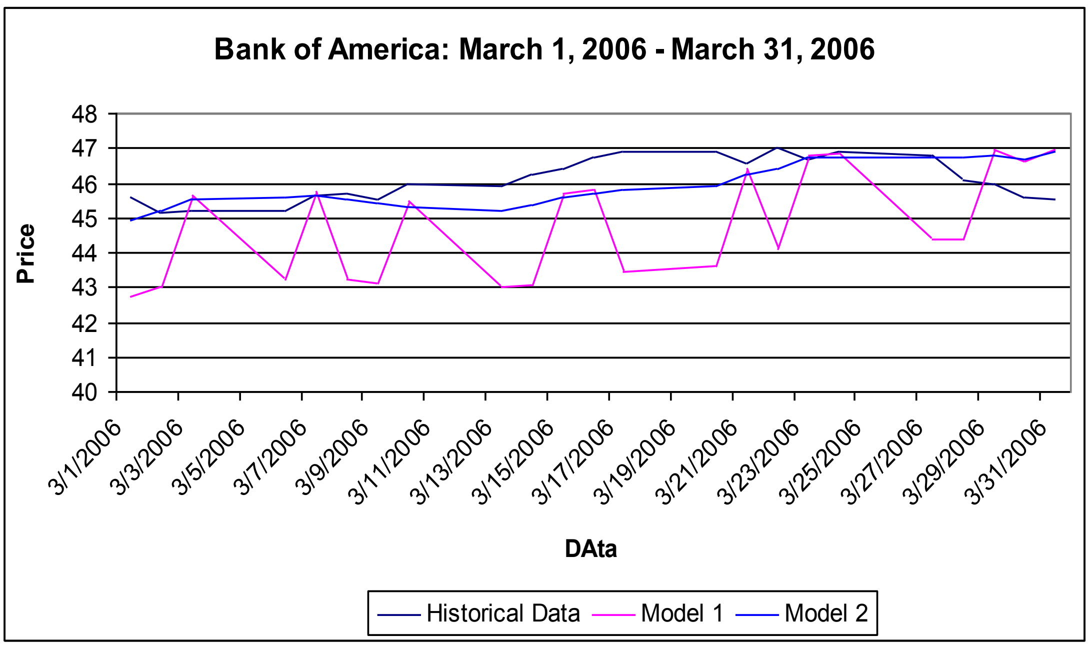

Figure 7.7. Results in a Line Chart between March 1, 2006, and March 31, 2006

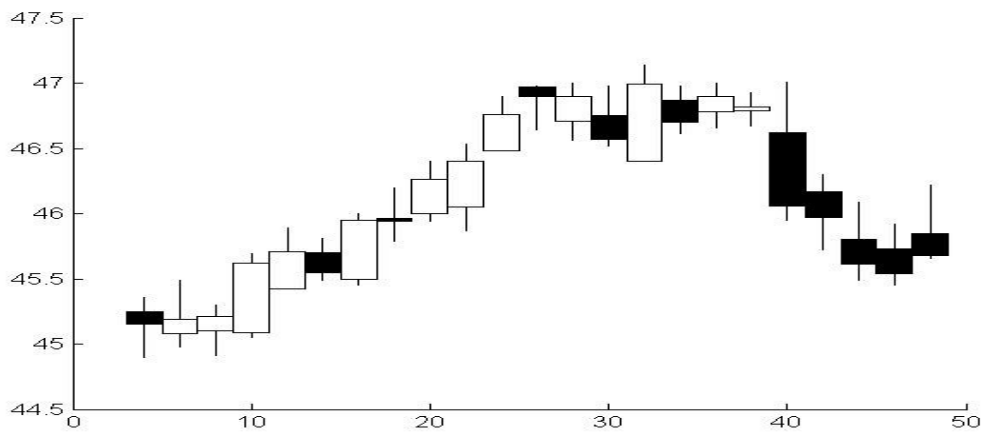

Figure 7.8. Candlestick Chart (Bank of America) between March 1, 2006, and March 31, 2006

7.3. MODEL 3

7.3.1. Model 3 Results. The results from Model 3 and Model 2, in mean squared error, are shown in Table 7.3. Model 3 produced better results than Model 2, and the results fall into satisfactory ranges.

Table 7.3. Results of Model 2 and Model 3

	Model 2	Model 3
Bank of America (BAC)	0.9358	0.8235
General Electric (GE)	0.2144	0.1918
Google (GOOG)	83.85	80.92
Monsanto (MON)	4.963	4.634
Toyota (TM)	2.293	2.215

7.3.2. Model 3 Review. Figure 7.9 shows the candlestick chart of General Electric between August 2, 2010, and September 28, 2010. The y-axis represents the price, and the x-axis represents the trading date. Between x=40 and x=50, a morning star candlestick pattern appears. This represents a market reversal pattern. Figure 7.10 shows the line chart of actual historical quotes and the forecasting prices generated by Models 2 and 3. As indicated in Figure 7.10, Model 3 identified the morning star candlestick pattern and reacted accordingly. Table 7.4 shows the forecasting results of both Models 2 and 3 for General Electric during the same time period, between August 2, 2010, and September 28, 2010. Model 3, an interval type-2 fuzzy logic system-based model, produced better results than Model 2, a type-1 fuzzy logic system-based model.

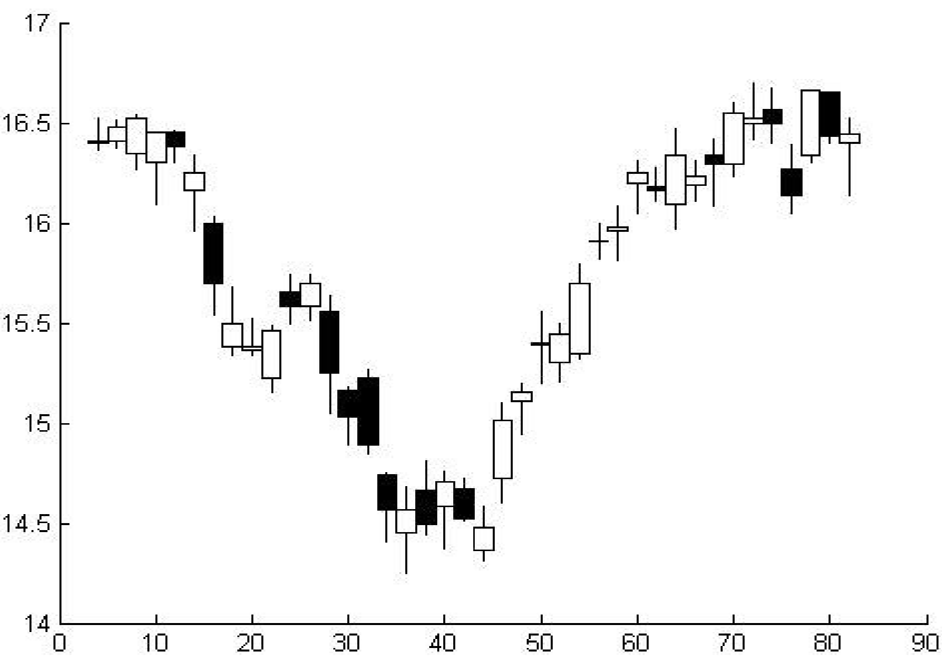

Figure 7.9. Candlestick Chart (General Electric) between August 2, 2010, and September 28, 2010

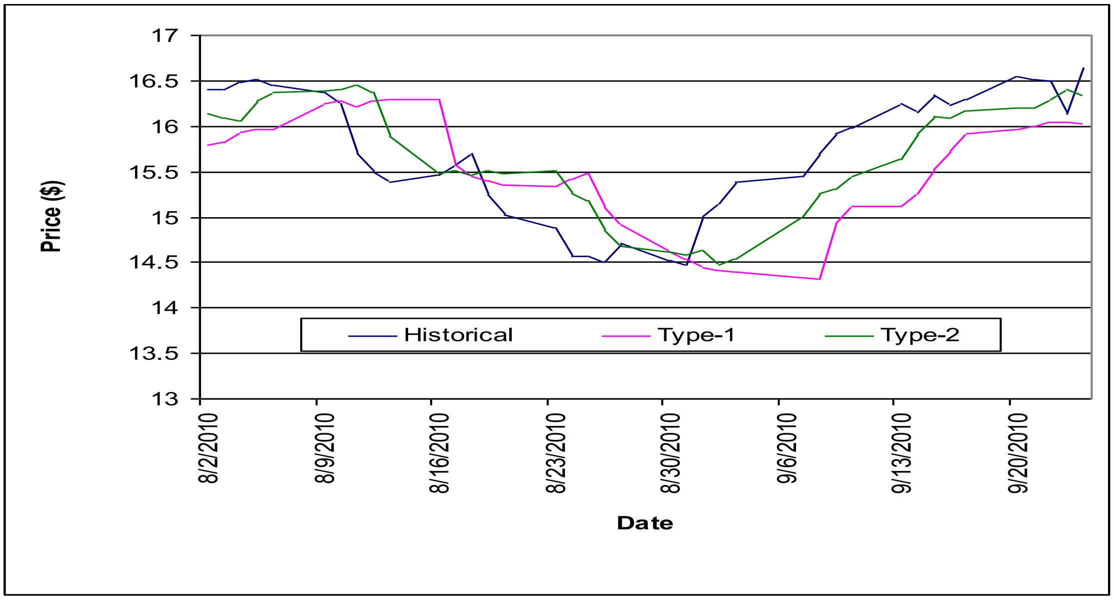

Figure 7.10. Price Movement of General Electric between August 2, 2010, and September 28, 2010

Table 7.4. Results of General Electric between August 2, 2010, and September 28, 2010

	Type-2 Fuzzy Logic System	Type-1 Fuzzy Logic System
General Electric(GE)	0.0158	0.0413

The period between August 2, 2010, and September 28, 2010, was selected for the investigation because of the appearance of a morning star candlestick pattern. Membership functions of type-1 fuzzy logic are crisp. Therefore, Model 2 could not recognize the small, white candlestick pattern that appeared between x=40 and x=50. Model 3 tracked the trend of the market during this time period as a downward trend. When a large, white candlestick pattern appeared just before x=50, it checked the candlestick patterns backward to see if this pattern had any meaning. Model 3 identified a small, white candlestick pattern on a previous day as a star candlestick pattern. Also, just before the appearance of this star candlestick pattern, there was a black candlestick. So, Model 3 checked the overall relationships of these candlestick patterns and market trends to decide that there was a morning star candlestick pattern in this time period, and it adjusted the forecasting price.

8. CONCLUSIONS

This research explores computational financial forecasting using the candlestick pattern technique to represent qualitative forecasting. Fuzzy associative memories manage the ambiguous definitions of candlestick patterns for forecasting. The results indicate that candlestick pattern technique-based forecasting works better than traditional forecasting that has been studied and modeled in practice. This research will serve as a foundation for future studies of computational financial forecasting using the Japanese candlestick technique.

This dissertation filled gaps in the literature pertaining to understanding qualitative representations of financial forecasting that uses the candlestick chart technique and implementing a process of representing the qualitative information of candlestick patterns using fuzzy associative memories. This research contributes to the literature by exploring how fuzzy associative memories represent ambiguous candlestick pattern definitions and influence the model's performance.

Li's research presented in *Financial Prediction and Trading via Reinforcement Learning and Soft Computing* (2005) discussed quantitative statement-based financial forecasting systems that help investors make decisions. Chavaranakul's financial research, *The Development of Hybrid Intelligent Systems for Technical Analysis-Based Equivolume Charting* (2007), used a volume adjusted moving average, neuro-fuzzy-based genetic algorithm to improve trading performance. Both Li and Chavaranakul's studies contain qualitative decision-making procedures, and their findings indicate that quantitative representation can improve financial forecasting decisions. However, their studies do not discuss the candlestick chart technique, which also represents financial forecasting qualitatively. Therefore, this dissertation becomes the first introduction of a candlestick pattern technique-based approach to represent computational financial forecasting qualitatively.

The qualitative approach was accomplished with fuzzy associative memories representing candlestick pattern definitions. The forecasting results given by the fuzzy associative memories can all be expressed qualitatively, such as stock prices rising, falling, and remaining neutral. The qualitative representation basis of this model does not tell the exact price changes of stocks, and these qualitative results are not practical for comparing the performance of different models. Therefore, the qualitative results were defuzzified to produce quantitative results for comparison purposes.

An additional point related to fuzzy associative memories surrounds the types of fuzzy membership functions involved. Based on a finding of the final proposed model consisting of type-2 fuzzy membership functions, higher-order fuzzy membership functions recognized candlestick patterns better than lower-order fuzzy membership functions, such as type-1 fuzzy membership functions, which could not detect complex candlestick patterns well.

This dissertation also makes the following contributions to the literature:

- Discussions of the fundamental issues in traditional time series-based financial forecasting and neural network-based financial forecasting that led to this research.
- Comprehensive descriptions and definitions of candlestick patterns that can be used for real-world financial forecasting situations.

- A new, systematic approach for constructing a fuzzy logic system-based forecasting model with committee machine architecture.
- A study of HAVNET-based pattern recognition software usage for candlestick pattern recognition and comments.
- Establishment of fuzzy associative memories that represent ambiguous candlestick pattern definitions in qualitative representations. Linguistic values represent the visual appearances of candlestick patterns and charts, such as “long real body,” “small real body,” “medium-length upper shadow line,” “short-length lower shadow line,” and so on.

The current investigation was limited by the knowledge and expertise regarding the representation of candlestick pattern definitions from available publications. The authors of those publications are real financial traders. However, there are many other investment traders and experts of candlestick chart techniques. Their individual opinions and views toward the interpretation of and financial strategies benefitting from the candlestick chart technique are not reflected in this research. The proposed model is designed to present the standardized, candlestick pattern definition-based forecasting systems. However, the model is flexible and adaptable to those individual perspectives. In addition, the proposed models are for forecasting the next day’s stock prices. The use of candlestick pattern techniques for other financial products and long-term financial investment is not examined because the models must be examined in a controlled environment for comparison purposes. Therefore, it is recommended that further research be undertaken in these areas as well.

The following recommendations for further research are based on the findings of this study:

- **Research Validation with Models for Real-World Settings.** The models developed in this research are examined and evaluated with the fuzzy associative memories and rules developed from publications related to the use of the candlestick chart technique for investment. Real stock traders and investors may have different views, knowledge, and experiences than those discussed in these publications. Therefore, it is interesting to evaluate those real-world financial investors' and traders' expertise and knowledge through fuzzy associative memory and rules. The models developed in this study are flexible and adaptive so that differences in their strategies and rules can be managed. The broad views and knowledge of type-2 fuzzy membership functions are particularly adaptable.
- **Extension of Type-2 Fuzzy Logic.** The extensive research regarding interpretations of candlestick patterns using general type-2 fuzzy logic is interesting because the proposed model was limited to processes with interval type-2 fuzzy logic-based secondary membership functions. This technique can be extended to higher-order general type-2 fuzzy membership functions. The general type-2 fuzzy membership functions provide broad flexibility in interpreting not only candlestick pattern definitions but also the rules and knowledge that real-world investors and stock traders apply to their own investment strategies.

Type-2 fuzzy membership functions handle ambiguity and uncertainty well because the membership functions have multi-dimensional spaces. More research is required to determine the appropriate parameters for standard deviations and mean values. If the multi-dimensional spaces are too wide, then the results could remain undetermined. If the spaces are too narrow, then there could be no difference between type-1 and type-2 membership functions.

- **Higher-Order Committee Machines.** One feature of committee machines that is useful for managing issues of large data sets is that they can divide a large system into smaller systems to solve a complex problem. Candlestick pattern recognition is controlled by one large system in the current research. Dividing this large system into smaller systems is interesting but challenging work, especially when general type-2 fuzzy membership functions are introduced to represent the ambiguous definitions of candlestick patterns, which requires searching for appropriate algorithms for combining small, partitioned systems.
- **Japanese Candlestick Chart Techniques for Other Financial Products.** Current research reveals that the Japanese candlestick chart technique works well for daily stock price forecasting. However, no study investigates forecasting other financial products with candlestick chart techniques. The potential use of candlestick chart techniques to forecast foreign stock exchange markets, stock option markets, and foreign currency exchange markets should be explored. The change of forecasting

areas would necessitate changing the time frames of candlesticks because other financial products require different investment strategies. For the currency exchange market, day trading is the popular approach, and it prefers minute-based candlestick charts for trading strategies. On the other hand, long-term investment management prefers multi-day, weekly, and monthly candlestick charts for forecasting stock prices.

Computational financial forecasting using the candlestick pattern technique is still new. Much research in relevant areas must still be conducted to study financial forecasting with this Japanese candlestick chart technique.

APPENDIX A.

MATLAB SCRIPTS FOR MAIN DATA FLOW TRANSACTION PROGRAM

```
clear all;


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%% Selecting an Excel File and Channel the file with MATLAB          %%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

File = 'appl1.xls';

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

channel = ddeinit('excel',File);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%% Each Columns of EXCEL                                    %%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% col 1 = Date
% col 2 = Open price
% col 3 = High price
% col 4 = Low price
% col 5 = Close price
% col 6 = trading volume

% row 1 & 2 = Label
% row 3 = data starts

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%% Numbers of DATA (Not Input)                              %%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
num_start = 2;
num_end = 50;   %original 504
num_row = num_end - num_start;
num_input = 5;
   % Last row = End of the data = 600
   % the number of row = 600-2 = 598

avg_can = 3; % this number must be less than num_input
   % numbers of candles used for averaging

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%  Retreive the DATA
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Data = ddereq(channel,'r2c2:r1000c6');  %%  always check the size
```

```
Open = Data(1:num_row,1);
High = Data(1:num_row,2);
Low = Data(1:num_row,3);
Close = Data(1:num_row,4);
Vol = Data(1:num_row,5);

%  All Combined Matrix
A = [Open High Low Close Vol];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%  For Finding Candlestick Elements
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[Body_Size, Color, Doji, C_of_RB]= Candle_Basic(Open,Close,num_row);

Body_Size;
Body_Size = abs(Body_Size);
Color;
Doji;
C_of_RB;

%# of data checking: = # of data should be the same as # of "num_row"
%num_Body_Size = size(Body_Size);  % checking the size of array

%%%%% previous setting

% Candle_Size;
% Candle_Size = abs(Candle_Size);
% Color;
% Doji;
%   Table_Candle_Basic = [Body_Size Color C_of_RB];

[Up_Shadow_L, Low_Shadow_L, C_of_Up_Shadow, C_of_Low_Shadow] ...
              = Shadow_Basic(Open,High,Low,Close,Body_Size,num_row);

Up_Shadow_L;
Low_Shadow_L;
C_of_Up_Shadow;
C_of_Low_Shadow;

%# of data checking: = # of data should be the same as # of "num_row"
%num_Up_Shadow_L = size(Up_Shadow_L);

%   Table_Shadow_Basic ...
%         = [Up_Shadow_L Low_Shadow_L C_of_Up_Shadow C_of_Low_Shadow];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%%%% Market Trend Line
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
%   This market trend line is calculated from the day before forecasting
%   day.  In other words, if the forecasting day is A, then trend line is
%   from day (A-1).  Trend_5 is calculated based on days of (A-1, A-2,
%   A-3, A-4, and A-5), Trend_3 is w/ days of (A-1, A-2, and A-3).
%   Trend line is good at checking the average movement of the price.
%   Not the same as Moving Average (MA)

[C_Trend_2, C_Trend_3, C_Trend_4, C_Trend_5, ...
  O_Trend_2, O_Trend_3, O_Trend_4, O_Trend_5, ...
  C_of_RB_Trend_2, C_of_RB_Trend_3, C_of_RB_Trend_4, C_of_RB_Trend_5] ...
   = Trend_Basic(Open, Close, C_of_RB, num_row);

C_Trend_2;
C_Trend_3;
C_Trend_4;
C_Trend_5;

O_Trend_2;
O_Trend_3;
O_Trend_4;
O_Trend_5;

C_of_RB_Trend_2;
C_of_RB_Trend_3;
C_of_RB_Trend_4;
C_of_RB_Trend_5;

%# of data checking: = # of data should be the same as # of "num_row"
% num_C_Trend_2 = size(C_Trend_2);
% num_C_Trend_3 = size(C_Trend_3);
% num_C_Trend_4 = size(C_Trend_4);
% num_C_Trend_5 = size(C_Trend_5);

% Table_C_Trend_Basic = [C_Trend_2 C_Trend_3 C_Trend_4 C_Trend_5];
% Table_O_Trend_Basic = [O_Trend_2 O_Trend_3 O_Trend_4 O_Trend_5];
% Table_C_of_RB_Trend_Basic = ...
%     [C_of_RB_Trend_2 C_of_RB_Trend_3 C_of_RB_Trend_4 C_of_RB_Trend_5];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%% Market Trend Line ID (Positive or Negative)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% [C_Trend_ID, C_of_RB_ID] = Trend_ID(num_row, Close, C_of_RB);
```

```
%
% C_Trend_ID;
% C_of_RB_ID;


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%  Checking Up Trend based on closing price (positive trend - upward)

[Up_Close_Trend_3, Up_Close_Trend_4, Up_Close_Trend_5, ...
   Up_Close_Trend_6, Up_Close_Trend_7] ...
   = Trend_Close_Up(num_row, Close);

Up_Close_Trend_3;
Up_Close_Trend_4;
Up_Close_Trend_5;
Up_Close_Trend_6;
Up_Close_Trend_7;

%size(Up_Close_Trend_3)
%size(Up_Close_Trend_4)
%size(Up_Close_Trend_5)
%size(Up_Close_Trend_6)
%size(Up_Close_Trend_7)
%%% Test
%Table_Close_Trend = [Up_Close_Trend_3 Up_Close_Trend_4]


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%  Checking Up Trend based on closing price (Negative trend - downward)

[Down_Close_Trend_3, Down_Close_Trend_4, Down_Close_Trend_5, ...
   Down_Close_Trend_6, Down_Close_Trend_7] ...
   = Trend_Close_Down(num_row, Close);

Down_Close_Trend_3;
Down_Close_Trend_4;
Down_Close_Trend_5;
Down_Close_Trend_6;
Down_Close_Trend_7;

%size(Down_Close_Trend_3)
%size(Down_Close_Trend_4)
%size(Down_Close_Trend_5)
%size(Down_Close_Trend_6)
%size(Down_Close_Trend_7)
%%% Test
```

```
%Table_Close_Trend = [Up_Close_Trend_3 Up_Close_Trend_4]

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%  Checking Up Trend based on center of real body (CRB)
%%%%  Positive trend (upward trend)

[Up_C_RB_Trend_3, Up_C_RB_Trend_4, Up_C_RB_Trend_5, ...
   Up_C_RB_Trend_6, Up_C_RB_Trend_7] = Trend_C_RB_Up(num_row, C_of_RB);

Up_C_RB_Trend_3;
Up_C_RB_Trend_4;
Up_C_RB_Trend_5;
Up_C_RB_Trend_6;
Up_C_RB_Trend_7;

% size(Up_C_RB_Trend_3)
% size(Up_C_RB_Trend_4)
% size(Up_C_RB_Trend_5)
% size(Up_C_RB_Trend_6)
% size(Up_C_RB_Trend_7)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%  Checking Up Trend based on center of real body (CRB)
%%%%  Negative trend (downward trend)

[Down_C_RB_Trend_3, Down_C_RB_Trend_4, Down_C_RB_Trend_5, ...
   Down_C_RB_Trend_6, Down_C_RB_Trend_7] ...
   = Trend_C_RB_Down(num_row, C_of_RB);

Down_C_RB_Trend_3;
Down_C_RB_Trend_4;
Down_C_RB_Trend_5;
Down_C_RB_Trend_6;
Down_C_RB_Trend_7;

% size(Down_C_RB_Trend_3)
% size(Down_C_RB_Trend_4)
% size(Down_C_RB_Trend_5)
% size(Down_C_RB_Trend_6)
% size(Down_C_RB_Trend_7)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%% Moving Average for Closing Price per body size

[Avg_Body_Size_3, Avg_Body_Size_4, Avg_Body_Size_5, ...
   Avg_Body_Size_6, Avg_Body_Size_7, MA_Close_3, MA_Close_4, ...
```

```
    MA_Close_5, MA_Close_6, MA_Close_7, MA_Close_3_Dir, ...
    MA_Close_4_Dir, MA_Close_5_Dir, MA_Close_6_Dir, MA_Close_7_Dir] ...
    = MA_Close(num_row, Close, Body_Size);

Avg_Body_Size_3;
Avg_Body_Size_4;
Avg_Body_Size_5;
Avg_Body_Size_6;
Avg_Body_Size_7;

MA_Close_3;
MA_Close_4;
MA_Close_5;
MA_Close_6;
MA_Close_7;

MA_Close_3_Dir;
MA_Close_4_Dir;
MA_Close_5_Dir;
MA_Close_6_Dir;
MA_Close_7_Dir;

% size(Avg_Body_Size_4);
% size(MA_Close_4);
% size(MA_Close_7_Dir);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%% Moving Average for Center of real body Price per body size

[MA_C_RB_3, MA_C_RB_4, MA_C_RB_5, MA_C_RB_6, MA_C_RB_7,
MA_C_RB_3_Dir, ...
    MA_C_RB_4_Dir, MA_C_RB_5_Dir, MA_C_RB_6_Dir, MA_C_RB_7_Dir] ...
    = MA_C_RB(num_row, C_of_RB, Body_Size);

MA_C_RB_3;
MA_C_RB_4;
MA_C_RB_5;
MA_C_RB_6;
MA_C_RB_7;

MA_C_RB_3_Dir;
MA_C_RB_4_Dir;
MA_C_RB_5_Dir;
MA_C_RB_6_Dir;
MA_C_RB_7_Dir;
```

```
% size(MA_C_RB_7)
% size(MA_C_RB_7_Dir)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%% Candlestick Pattern Identification Section
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%    Basic Candlestick Identification
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%  Body_Ratio is for checking if the candlestick is long or short

%% 4 day average body size (devided by 4 days data)

[Avg_Body_Size, Body_Ratio, Body_Ratio_12, Avg_Body_Size10, ...
   Body_Ratio10]= Body_Ratio(num_row, Body_Size);

Avg_Body_Size;
Body_Ratio;
Body_Ratio_12;
Avg_Body_Size10;
Body_Ratio10;

% size(Body_Ratio10);

%# of data checking: = # of data should be the same as # of "num_row"
% num_Body_Ratio = size(Body_Ratio)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%  Shadow_Ratio is for checking if the candlestick has long shadows or
%%  short shadows.

%%  4 days Average (divided by 4 days data)

[Avg_Up_Shadow_L, Avg_Low_Shadow_L, Up_Shadow_Ratio, ...
   Low_Shadow_Ratio, Up_Low_Shadow_Ratio, Low_Up_Shadow_Ratio]= ...
   Shadow_Ratio(num_row, Up_Shadow_L, Low_Shadow_L);

 Avg_Up_Shadow_L;
 Up_Shadow_Ratio;
 Avg_Low_Shadow_L;
 Low_Shadow_Ratio;
 Up_Low_Shadow_Ratio;
 Low_Up_Shadow_Ratio;

% b = size(Up_Low_Shadow_Ratio)
```

```
%# of data checking: = # of data should be the same as # of "num_row"
% num_Up_Shadow_Ratio = size(Up_Shadow_Ratio)

% table format for testing
% a = [Up_Low_Shadow_Ratio Low_Up_Shadow_Ratio];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%  Body_Shadow_Ratio is for checking the balance of candlestick upper
%%  shadow and lower shadow and real body

[U_Shadow_Body_Ratio, L_Shadow_Body_Ratio, ...
    U_Shadow_Avg_Body_Ratio, L_Shadow_Avg_Body_Ratio] = ...
    Shadow_Body_Ratio(num_row, Up_Shadow_L, Low_Shadow_L, Body_Size, ...
    Color, Avg_Body_Size);

 U_Shadow_Body_Ratio;
 L_Shadow_Body_Ratio;
 U_Shadow_Avg_Body_Ratio;
 L_Shadow_Avg_Body_Ratio;

% table format for testing
% a = [Up_Shadow_L Body_Size U_Shadow_Body_Ratio
U_Shadow_Avg_Body_Ratio];

%# of data checking: = # of data should be the same as # of "num_row"
%num_U_Shadow_Body_Ratio = size(U_Shadow_Body_Ratio)
                                    % checking the size of array

%  Table_Shadow_Body_Ratio = ...
%  [U_Shadow_Body_Ratio L_Shadow_Body_Ratio ...
%                  U_Shadow_Avg_Body_Ratio L_Shadow_Avg_Body_Ratio];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%    Single Candlestick Identification
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%      MaruBozu Candlestick Pattern - Identification - Fuzzy

[Marubozu_rate] = Marubozu_Fuzz(num_row, U_Shadow_Avg_Body_Ratio, ...
    L_Shadow_Avg_Body_Ratio, Body_Ratio);

Marubozu_rate;

% size(Marubozu_rate)
```

```
% for testing
% body_table = [Body_Ratio Up_Shadow_L Low_Shadow_L Marubozu_rate];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%  Closing Marubozu

[C_Marubozu_rate] = C_Marubozu_Fuzz(num_row, U_Shadow_Avg_Body_Ratio, ...
    L_Shadow_Avg_Body_Ratio, Color, Body_Ratio);

C_Marubozu_rate;

% body_table = [Color Body_Ratio Up_Shadow_L Low_Shadow_L C_Marubozu_rate];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%  Opening Marubozu

[O_Marubozu_rate] = O_Marubozu_Fuzz(num_row, U_Shadow_Avg_Body_Ratio, ...
    L_Shadow_Avg_Body_Ratio, Color, Body_Ratio);

O_Marubozu_rate;

% body_table = [Color Body_Ratio Up_Shadow_L Low_Shadow_L O_Marubozu_rate];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%  Spinning  Top (Koma)
%
[Spin_Tops_rate] = Spin_Tops_Fuzz(num_row, Up_Shadow_L, ...
    Low_Shadow_L, Body_Ratio, Body_Size);

Spin_Tops_rate;

% body_table = [Color Up_Shadow_L Low_Shadow_L Body_Size Body_Ratio ...
% Spin_Tops_rate];

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%  Doji - All types of Doji Patterns including
%%         Long Legged Doji, Gravestone Doji, and Dragonfly Doji

[Long_Leg_Doji_rate, Gravestone_Doji_rate, Dragonfly_Doji_rate] = ...
    Doji_fuzz(num_row, Body_Ratio, Up_Shadow_Ratio, Low_Shadow_Ratio);

Long_Leg_Doji_rate;
Gravestone_Doji_rate;
Dragonfly_Doji_rate;
%ignore the first 4 numbers(outputs)
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%  Paper Umbrella

[Paper_Umbrella_rate] = Paper_Umbrella_fuzz(num_row, Body_Ratio, ...
   L_Shadow_Body_Ratio);

Paper_Umbrella_rate;

% Avg_Up_Shadow_L;
% Up_Shadow_Ratio;
% Avg_Low_Shadow_L;
% Low_Shadow_Ratio;
% Up_Low_Shadow_Ratio;
% Low_Up_Shadow_Ratio;
%
% Up_Shadow_L;
% Low_Shadow_L;
% Up_Low_Shadow_Ratio;
% Low_Up_Shadow_Ratio;

%%%%  for testing purpose, all below commented

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%  MULTIPLE-COMBO CANDLESTICK PATTERNS
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%  Engulfing Patterns

[Engluf_Down_fuzz_rate] = Engulf_Down_fuzz(num_row, Color, Body_Size, ...
   Open, Close, Body_Ratio_12, ...
   Down_C_RB_Trend_6, Down_C_RB_Trend_7, MA_C_RB_6_Dir,
MA_C_RB_7_Dir);

Engluf_Down_fuzz_rate;

% %size(Engluf_Down_fuzz_rate)

[Engluf_Up_fuzz_rate] = Engulf_Up_fuzz(num_row, Color, Body_Size, ...
   Open, Close, Body_Ratio_12, ...
   Up_C_RB_Trend_6, Up_C_RB_Trend_7, MA_C_RB_6_Dir, MA_C_RB_7_Dir);

Engluf_Up_fuzz_rate;

%size(Engluf_Up_fuzz_rate);
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Piercing Patterns

[Piercing_fuzz_rate] = Piercing_fuzz(num_row, Color, Body_Size, ...
   Open, Close, Low, C_of_RB, Body_Ratio, Body_Ratio10, ...
   Down_C_RB_Trend_6, Down_C_RB_Trend_7, MA_C_RB_6_Dir,
MA_C_RB_7_Dir);

Piercing_fuzz_rate;

size(Piercing_fuzz_rate);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Dark Cloud Cover Patterns

[Dark_Cloud_fuzz_rate] = Dark_Cloud_fuzz(num_row, Color, Body_Size, ...
   Open, Close, High, C_of_RB, Body_Ratio, Body_Ratio10, ...
   Up_C_RB_Trend_6, Up_C_RB_Trend_7, MA_C_RB_6_Dir, MA_C_RB_7_Dir);

Dark_Cloud_fuzz_rate;

% size(Dark_Cloud_fuzz_rate);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Morning_Star Patterns

[Morning_Star_fuzz_rate] = Morning_Star_fuzz(num_row, Color, ...
   Body_Size, Open, Close, Low, C_of_RB, Body_Ratio_12, ...
   Body_Ratio, Body_Ratio10, ...
   Down_C_RB_Trend_6, Down_C_RB_Trend_7, MA_C_RB_6_Dir,
MA_C_RB_7_Dir);

Morning_Star_fuzz_rate;

%size(Morning_Star_fuzz_rate);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Evening Star Patterns

[Evening_Star_fuzz_rate] = Evening_Star_fuzz(num_row, Color, ...
   Body_Size, Open, Close, Low, C_of_RB, Body_Ratio_12, ...
   Body_Ratio, Body_Ratio10, ...
   Up_C_RB_Trend_6, Up_C_RB_Trend_7, MA_C_RB_6_Dir, MA_C_RB_7_Dir);

Evening_Star_fuzz_rate;
```

```
% size(Evening_Star_fuzz_rate);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% White Solders Patterns

[White_Soldiers_fuzz_rate] = White_Soldiers_fuzz(num_row, Color, ...
   Body_Size, Open, Close, Low, High, C_of_RB, ...
   Body_Ratio, Body_Ratio10, Up_Shadow_L, ...
   Down_C_RB_Trend_6, Down_C_RB_Trend_7, MA_C_RB_6_Dir,
MA_C_RB_7_Dir);

White_Soldiers_fuzz_rate;

% % size(White_Soldiers_fuzz_rate)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% Black Crows Patterns

[Black_Crows_fuzz_rate] = Black_Crows_fuzz(num_row, Color, ...
   Body_Size, Open, Close, Low, High, C_of_RB, ...
   Body_Ratio, Body_Ratio10, Low_Shadow_L, ...
   Up_C_RB_Trend_6, Up_C_RB_Trend_7, MA_C_RB_6_Dir, MA_C_RB_7_Dir);

Black_Crows_fuzz_rate;

% size(Black_Crows_fuzz_rate)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%  Prep for combination/weights generation

%%%% when it's up trend (reversal sign from bull to bear)

[wt_B_Marubozu_rate wt_C_B_Marubozu_rate wt_O_B_Marubozu_rate ...
   wt_Long_Leg_Doji_rate wt_Gravestone_Doji_rate ...
   wt_Dragonfly_Doji_rate wt_Paper_Umbrella_rate ...
   wt_Engluf_Up_fuzz_rate wt_Dark_Cloud_fuzz_rate ...
   wt_Evening_Star_fuzz_rate wt_Black_Crows_fuzz_rate ...
   ct_B_Marubozu_rate ct_C_B_Marubozu_rate ct_O_B_Marubozu_rate ...
   ct_Long_Leg_Doji_rate ct_Gravestone_Doji_rate ...
   ct_Dragonfly_Doji_rate ct_Paper_Umbrella_rate ...
   ct_Engluf_Up_fuzz_rate ct_Dark_Cloud_fuzz_rate ...
   ct_Evening_Star_fuzz_rate ct_Black_Crows_fuzz_rate] ...
   = wt_bear(num_row, Color, Marubozu_rate, C_Marubozu_rate, ...
   O_Marubozu_rate, Long_Leg_Doji_rate, Gravestone_Doji_rate, ...
   Dragonfly_Doji_rate, Paper_Umbrella_rate, Engluf_Up_fuzz_rate, ...
   Dark_Cloud_fuzz_rate, Evening_Star_fuzz_rate, Black_Crows_fuzz_rate);
```

```
wt_B_Marubozu_rate;
wt_C_B_Marubozu_rate;
wt_O_B_Marubozu_rate;
wt_Long_Leg_Doji_rate;
wt_Gravestone_Doji_rate;
wt_Dragonfly_Doji_rate;
wt_Paper_Umbrella_rate;
wt_Engluf_Up_fuzz_rate;
wt_Dark_Cloud_fuzz_rate;
wt_Black_Crows_fuzz_rate;

ct_B_Marubozu_rate;
ct_C_B_Marubozu_rate;
ct_O_B_Marubozu_rate;
ct_Long_Leg_Doji_rate;
ct_Gravestone_Doji_rate;
ct_Dragonfly_Doji_rate;
ct_Paper_Umbrella_rate;
ct_Engluf_Up_fuzz_rate;
ct_Dark_Cloud_fuzz_rate;
ct_Black_Crows_fuzz_rate;


% size(wt_Gravestone_Doji_rate);
% size(Dark_Cloud_fuzz_rate);
% size(wt_O_Marubozu_rate);
% size(ct_Gravestone_Doji_rate);
% size(ct_Dark_Cloud_fuzz_rate);
% size(ct_Black_Crows_fuzz_rate);

%%%% when it's down trend (reversal sign from bear to bull)

[wt_W_Marubozu_rate wt_C_W_Marubozu_rate ...
   wt_O_W_Marubozu_rate wt_Spin_Tops_rate wt_Engluf_Down_fuzz_rate ...
   wt_Piercing_fuzz_rate wt_Morning_Star_fuzz_rate ...
   wt_White_Soldiers_fuzz_rate ...
   ct_W_Marubozu_rate ct_C_W_Marubozu_rate ct_O_W_Marubozu_rate ...
   ct_Spin_Tops_rate ct_Engluf_Down_fuzz_rate ct_Piercing_fuzz_rate ...
   ct_Morning_Star_fuzz_rate ct_White_Soldiers_fuzz_rate] ...
   = wt_bull(num_row, Color, Marubozu_rate, C_Marubozu_rate, ...
   O_Marubozu_rate, Spin_Tops_rate, Engluf_Down_fuzz_rate, ...
   Piercing_fuzz_rate, Morning_Star_fuzz_rate, White_Soldiers_fuzz_rate);

wt_W_Marubozu_rate;
wt_C_W_Marubozu_rate;
```

```
wt_O_W_Marubozu_rate;
wt_Spin_Tops_rate;
wt_Engluf_Down_fuzz_rate;
wt_Piercing_fuzz_rate;
wt_Morning_Star_fuzz_rate;
wt_White_Soldiers_fuzz_rate;

ct_W_Marubozu_rate;
ct_C_W_Marubozu_rate;
ct_O_W_Marubozu_rate;
ct_Spin_Tops_rate;
ct_Engluf_Down_fuzz_rate;
ct_Piercing_fuzz_rate;
ct_Morning_Star_fuzz_rate;
ct_White_Soldiers_fuzz_rate;

% size(wt_O_W_Marubozu_rate);
% size(wt_Engluf_Down_fuzz_rate);
% size(wt_Piercing_fuzz_rate);
% size(wt_Morning_Star_fuzz_rate);
% size(wt_White_Soldiers_fuzz_rate);
% size(ct_C_W_Marubozu_rate);
% size(ct_Morning_Star_fuzz_rate);
% size(ct_White_Soldiers_fuzz_rate);
% size(ct_Spin_Tops_rate);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%  forecasting control system

[wt_down wt_up wt_side] = wt_gen(num_row, wt_B_Marubozu_rate, ...
   wt_C_B_Marubozu_rate, wt_O_B_Marubozu_rate, ...
   wt_Long_Leg_Doji_rate, wt_Gravestone_Doji_rate, ...
   wt_Dragonfly_Doji_rate, wt_Paper_Umbrella_rate, ...
   wt_Engluf_Up_fuzz_rate, wt_Dark_Cloud_fuzz_rate, ...
   wt_Evening_Star_fuzz_rate, wt_Black_Crows_fuzz_rate, ...
   ct_B_Marubozu_rate, ct_C_B_Marubozu_rate, ct_O_B_Marubozu_rate, ...
   ct_Long_Leg_Doji_rate, ct_Gravestone_Doji_rate, ...
   ct_Dragonfly_Doji_rate, ct_Paper_Umbrella_rate, ...
   ct_Engluf_Up_fuzz_rate, ct_Dark_Cloud_fuzz_rate, ...
   ct_Evening_Star_fuzz_rate, ct_Black_Crows_fuzz_rate, ...
   wt_W_Marubozu_rate, wt_C_W_Marubozu_rate, wt_O_W_Marubozu_rate, ...
   wt_Spin_Tops_rate, wt_Engluf_Down_fuzz_rate, wt_Piercing_fuzz_rate, ...
   wt_Morning_Star_fuzz_rate, wt_White_Soldiers_fuzz_rate, ...
   ct_W_Marubozu_rate, ct_C_W_Marubozu_rate, ct_O_W_Marubozu_rate, ...
   ct_Spin_Tops_rate, ct_Engluf_Down_fuzz_rate, ct_Piercing_fuzz_rate, ...
   ct_Morning_Star_fuzz_rate, ct_White_Soldiers_fuzz_rate, ...
```

```
   Up_C_RB_Trend_6, Up_C_RB_Trend_7, ...
   Down_C_RB_Trend_6, Down_C_RB_Trend_7, MA_C_RB_6_Dir,
MA_C_RB_7_Dir);

wt_down;
wt_up;
wt_side;

% size(wt_down)
% size(wt_up)
% size(wt_side)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%% Neural Networks
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% For Recurrent Networks

% [RNN_S, RNN_C] = Recurrent(Open, High, Low, Close, Candle_Size, ...
%     Color, Doji, num_row, num_input);
%

% For Generalized Regression Neural Networks

[S_GRNN_Result] = S_GRNN(Open, High, Low, Close, Vol, num_row, num_input);
S_GRNN_Result;

% wk1write('GRNN_Result1.wk1',S_GRNN_Result); % Record the GRNN Result


% [GRNN_S, GRNN_C] = S_GRNN(Open, High, Low, Close, Candle_Size, ...
%    Color, Doji, num_row, num_input);

% Adaptive Neural Networks

% [Result_Adapt] = Adapt(Open, High, Low, Close, Vol, Candle_Size, Color,...
%     Doji);
%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%  Joining Neural Networks and Candles
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[Forecast_GRNN Forecast_Data] = ForecastGRNN(num_input, avg_can, ...
             S_GRNN_Result, Candle_Size, Color, Doji);
```

```
Forecast_GRNN;
Forecast_Data;

wk1write('Forecast_GRNN.wk1',Forecast_GRNN);% Record Forecasted GRNN Result
wk1write('Forecast_Data.wk1',Forecast_Data);% Record Forecasted Data

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%  Fuzzy Logic 1
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[Forecast_Fuzz_comp] = Forecast_Fuzzy_Comp(num_row, S_GRNN_Result, ...
   wt_down, wt_up, wt_side);

Forecast_Fuzz_comp;

size(Forecast_Fuzz_comp);

wk1write('Forecast_Fuzz_comp.wk1',Forecast_Fuzz_comp);
                              % Record Forecasted Data

[Forecast_Data_Fuzz Fuzz_Center_List] ...
   = Forecast_Fuzzy_Basic(num_input, avg_can, S_GRNN_Result, ...
   Candle_Size, Color, Doji);

Forecast_Data_Fuzz;
Fuzz_Center_List;
wk1write('Forecast_Data_Fuzz.wk1',Forecast_Data_Fuzz);
                              % Record Forecasted Data

wk1write('Fuzz_Center_List.wk1',Fuzz_Center_List);
                              % record data

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%  Mean Squared Error Report for GRNN
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[MSE_Forecast_Data MSE_Forecast_GRNN Data_Counter] = Result_Ck(Close, ...
                        avg_can, Forecast_Data, Forecast_GRNN);

MSE_Forecast_Data;
MSE_Forecast_GRNN;
Data_Counter

wk1write('MSE_Forecast_Data.wk1',MSE_Forecast_Data);
                                 % Record Forecasted GRNN Result
wk1write('MSE_Forecast_GRNN.wk1',MSE_Forecast_GRNN);
                                 % Record Forecasted Data
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%  Mean Squared Error Report for Fuzzy logic
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[MSE_Forecast_Fuzz] = Result_Ck_F(Close, avg_can, Forecast_Data_Fuzz);

MSE_Forecast_Fuzz;

wk1write('MSE_Forecast_Fuzz.wk1',MSE_Forecast_Fuzz);
                                % Record Forecasted Fuzz Result

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%  Mean Squared Error Report for Fuzzy logic
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[MSE_Forecast_Fuzz_Comp] = Result_Ck_F_Comp(Close, avg_can, ...
                                     Forecast_Fuzz_comp);

MSE_Forecast_Fuzz_Comp
size(MSE_Forecast_Fuzz_Comp)

wk1write('MSE_Forecast_Fuzz_Comp.wk1',MSE_Forecast_Fuzz_Comp);
                                     % record data
```

APPENDIX B.

HISTORICAL STOCK PRICE DATA SOURCES

Model 1 Experiment Data References

Exxon Mobil (XOM): April 15, 2002 through March 31, 2006.

http://finance.yahoo.com/q/hp?s=XOM+Historical+Prices

General Electric (GE): April 15, 2002 through March 31, 2006.

http://finance.yahoo.com/q/hp?s=GE+Historical+Prices

Google (GOOG): August 19, 2004 through March 31, 2006.

http://finance.yahoo.com/q/hp?s=GOOG+Historical+Prices

Microsoft (MSFT): April 15, 2002 through March 31, 2006.

http://finance.yahoo.com/q/hp?s=MSFT+Historical+Prices

Wells Fargo (WFC): April 15, 2002 through March 31, 2006.

http://finance.yahoo.com/q/hp?s=WFC+Historical+Prices

Model 2 Experiment Data References

Hewlett-Packard (HPQ): October 1, 2001 through September 18, 2007.

http://finance.yahoo.com/q/hp?s=HPQ+Historical+Prices

Bank of America (BAC): October 1, 2001 through September 18, 2007.

http://finance.yahoo.com/q/hp?s=BAC+Historical+Prices

Ford (F): October 1, 2001 through September 18, 2007.

http://finance.yahoo.com/q/hp?s=F+Historical+Prices

DuPont (DD): October 1, 2001 through September 18, 2007.

http://finance.yahoo.com/q/hp?s=DD+Historical+Prices

Yahoo (YHOO): October 1, 2001 through September 18, 2007.

http://finance.yahoo.com/q/hp?s=YHOO+Historical+Prices

Model 3 Experiment Data References

Bank of America (BAC): March 3, 2008 and February 28, 2011.

http://finance.yahoo.com/q/hp?s=BAC+Historical+Prices

General Electric (GE): March 3, 2008 and February 28, 2011.

http://finance.yahoo.com/q/hp?s=GE+Historical+Prices

Google (GOOG): March 3, 2008 and February 28, 2011.

http://finance.yahoo.com/q/hp?s=GOOG+Historical+Prices

Monsanto (MON): March 3, 2008 and February 28, 2011.

http://finance.yahoo.com/q/hp?s=MON+Historical+Prices

Toyota (TM): March 3, 2008 and February 28, 2011.

http://finance.yahoo.com/q/hp?s=TM+Historical+Prices

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