DESIGN AND DEVELOPMENT OF NEW FINANCIAL DECISION SUPPORT SYSTEMS

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CERTIFICATE

This is to certify that the work entitled "**Design and Development of New Financial Decision Support Systems**" is a piece of research work done by **Dinesh Kumar Sharma** under my guidance and supervision for the degree of **Doctor of Philosophy in Management** of Devi Ahilya University, Indore, (MP). That the candidate has put in an attendance of more than 200 days with me:

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4. is up to standard both in respect of content and language for being referred to the examiner.

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I, undersigned Ph.D. scholar in Management (Design and Development of New Financial Decision Support Systems) declare that I have not joined any other course or study or appeared at any other examination conducted by the University during the tenure of my registration for the Ph.D. Degree Course.

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ABSTRACT

For many years, intelligent techniques such as artificial neural networks, fuzzy logic, genetic algorithms, rule-based systems, and support vector machines have been used in finance and economics, especially in areas of stock market prediction, investment, and technical analysis. However, each technique used specifically for stock market prediction, investment, and technical analysis has its own strength and weakness. Therefore, there is a need to develop new financial decision support systems that utilize merits of both techniques to enhance future stock predictions and active portfolio management.

The objective of this study is twofold: (1) to design and develop sophisticated decision support systems (hybrid systems) for prediction of stock price movements and construction of an efficient portfolio management, (2) to demonstrate the robustness of systems using real world data. In this study, three novel hybrid systems have been proposed. The first system is designed for forecasting of stock price movements based on signal processing and artificial neural networks. The second system is also designed for forecasting stock price movements combining genetic algorithms and artificial neural networks. The third and final system is designed as a web based fuzzy portfolio management system (FPMS) using two techniques based on multi-criteria decision-making and fuzzy set theory.

The robustness of the signal processing based artificial neural network system (SPANNS) and genetically tuned artificial neural network system (GANNS) was evaluated and implemented for tracking of stock price movements. To demonstrate the robustness of the forecasting systems, DOW30 and NASDAQ100 data was tested. The study found that the predictions of stock market movements by SPANNS and GANNS were more precise than that of any single artificial neural network technique. The robustness of the FPMS for active portfolio management lies in the fact that the system provides the decision-maker an easy to guide user-interface to construct an efficient portfolio of securities. The system can be used as a decision-making tool by both individual investors and financial advisors. The effectiveness and applicability of the system was demonstrated via a case example of DOW30 data set.

The study envisioned the future direction of the research that new studies of SPANNS may utilize the advanced signal processing techniques such as fast Fourier transform and discrete wavelet transform to investigate the effectiveness of these techniques in the stock market predictions. Also, future research work related to GANNS can be carried out with some new hybrid techniques integrating wavelet transform and the adaptive neuro-fuzzy inference technique into GANNS. Furthermore, various tuning parameters such as learning rates, momentum can also be incorporated with GANNS to improve the accuracy of the results. The study further suggested that portfolio management system can be enhanced with global search techniques such as genetic algorithms.

Key words: Financial Decision Support Systems, Stock Forecasting, Portfolio Management, Signal Processing, Artificial Neural Networks, Genetic Algorithms.

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

In the modern era of globalization, organizations are facing complex financial management challenges, despite the advanced computational power driven by technological innovations. Researchers and professionals are innovating to provide feasible solutions for complex financial decisions in extremely volatile financial markets. Although innovations are empowering individual investors and portfolio managers with the best possible systems to fulfill their obligations, recent financial debacles reveal that financial systems failed to predict the impact of economic downturn in a timely manner. The lessons learned by financial professionals are increasing demand for integrated tools and techniques that support real time financial decisions. There are areas in need of improvement, which includes forecasting stock price movement for managing investment risk, active portfolio management, and predicting bankruptcy of financial institutions. The necessity for investment management systems has been increased to cope up with the volatility in financial markets. Therefore, researchers are developing decision support systems (DSS) that are integrating decision theory and artificial intelligence (AI) techniques for forecasting and effectively managing investment portfolios.

A DSS is a computer-based system designed for assisting decision-makers in dealing with semi-structured or ill-structured problems using models that are composed of business intelligence (BI) and analytic techniques, data management systems, and user interfaces. BI is a data-driven DSS that facilitates business decision processes that combine data gathering, data storage, and knowledge management (Burstein & Holsapple, 2008). In data-driven DSS, data mining is defined as extracting knowledge from large amounts of data (Han & Kamber, 2006). Artificial Neural Network is an Artificial Intelligence (AI) technique where data mining applications are useful in making complex predictions in many disciplines (Tjung et al., 2012).

The basic paradigm of traditional DSS consists of four major components: (1) the user interface, (2) the database, (3) the model and analysis tools, and (4) the DSS architecture and networks. However, the major components of DSS depend on the emphasis on supporting decision-making tasks and the use of related technologies. DSS are typically used by upper-level management for strategic and tactical decisions. These decisions tend to have a relatively low frequency of occurrence, and are accompanied with greater potential consequences. The time taken for thinking through and modeling these problems pays off generously in the long run. According to Power (2002; 2004), Shim et al. (2002) and Wang et al. (2002), DSS are categorized into five types : (a) A data-driven DSS collects and provides real time access to a large operational database necessary for making decisions in structured, semi-structured, and unstructured scenarios, (b) A model-driven DSS comprises of a number of models used for planning and scheduling, (c) A knowledge-based DSS includes a small rule-based dispatching system, (d) A communication-based DSS provides warnings triggered by pre-specified rules or conditions to generate messages for operators prior to processing a particular task that requires exceptions, and (e) A document-driven DSS contains a module that assist in retrieving and managing unstructured documents.

The integration of AI techniques into DSS have created a new improved DSS known as Active DSS (Shim et al., 2002). Active DSS can be classified into Expert Systems, Knowledge-based Systems, Adaptive DSS and Intelligent Decision Support Systems (IDSS). Active DSS focus on automating expertise and reusing organizational experience by integrating intelligent systems techniques such as neural networks, fuzzy systems, and genetic algorithms. These techniques are being integrated into DSS for financial decision-making.

The study of intelligent decision support systems' (or intelligent systems) applications in financial management reveals that the financial industry is using fuzzy systems, and genetic algorithms (GA), artificial neural networks (ANN), and case-based reasoning (Turban & Aronson, 2001). An ANN learns from patterns in data and information, and then model complex relationships. Case-based reasoning helps to uncover the hidden expertise and knowledge gained from solved problems, with partial domain knowledge, and uses it to solve new, similar problems. These systems differ in the manner that they store, apply, maintain, adapt to deal with uncertainty, and missing information (Goonatilake & Khebbal, 1995; Medsker, 1995). A Fuzzy system can handle ambiguous and uncertain situations similar to human decision making, while a GA system deals with evolutionary principles and are suitable for applications that involve optimization to find the best possible solutions. Due to the inherent strengths and weaknesses of these systems, using a single technique is inadequate for thorough problem solving. Therefore, there is a need for hybrid intelligent systems to manage active portfolio and enhance future predictions. The conducted research proposes three hybrid financial DSS. The first two systems are developed to predict security trading signals, and the third system is created for active portfolio construction and management. These systems are: (1) Signal Processing based Artificial Neural Network System (SPANNS), (2) Genetic Algorithm based Artificial Neural Network System (GANNS), and (3) Web-based Fuzzy Portfolio Management System (FPMS).

1.2 DECISION SUPPORT SYSTEMS

Decision support systems (DSS) are model-based or knowledge-based systems that support managerial decision making in semi-structured or unstructured situations (Turban & Aronson, 2001). A DSS supports a decision maker by extending decision making capabilities using historical data and providing a user interface that allows decision makers to incorporate their own perspectives (Pol & Ahuja, 2007). The capabilities of a DSS are summarized as follows:

- A DSS design provides graphical capabilities and a user friendly interface;
- A DSS integrates analytical and decision-making abilities that enhances the performance of a decision maker;
- A DSS, in fact, improves the effectiveness of decision making rather than its efficiency;
- A DSS combines data and information with human judgment in semi-structured decision making situations, where standard quantitative techniques or computerized systems alone cannot conveniently solve a problem;

- A DSS provides support for various managerial decisions at all levels of management;
- A DSS design can be either stand-alone/computer based or web-based.

1.2.1 Structure and Components of a DSS

The typical structure of a DSS varies depending on decision-making tasks and the use of related technologies. Generally, a DSS comprises of database, model base, graphical user interface (GUI), and end users (Figure 1.1). A few advanced DSS also contain a knowledge-based component. A detailed discussion on each component's functions is as follows:

(a) Database

A database is a collection of relevant data and information that is organized to be accessed, managed, and updated periodically. It facilitates structuring the decision problem for desired analysis. In computing, databases are often classified according to their organizational approach. The prevailing approaches include relational database, distributive database, and objective-oriented programming database. The most common approach is a relational database, in which data is organized in a tabular format, and can be accessed to provide meaningful information in various ways. Second, form is a distributed database, which facilitates dispersing or replicating the data among different points in a network. Another form of the database is object oriented programming database, which is congruent with the data defined for object categories and sub categories.

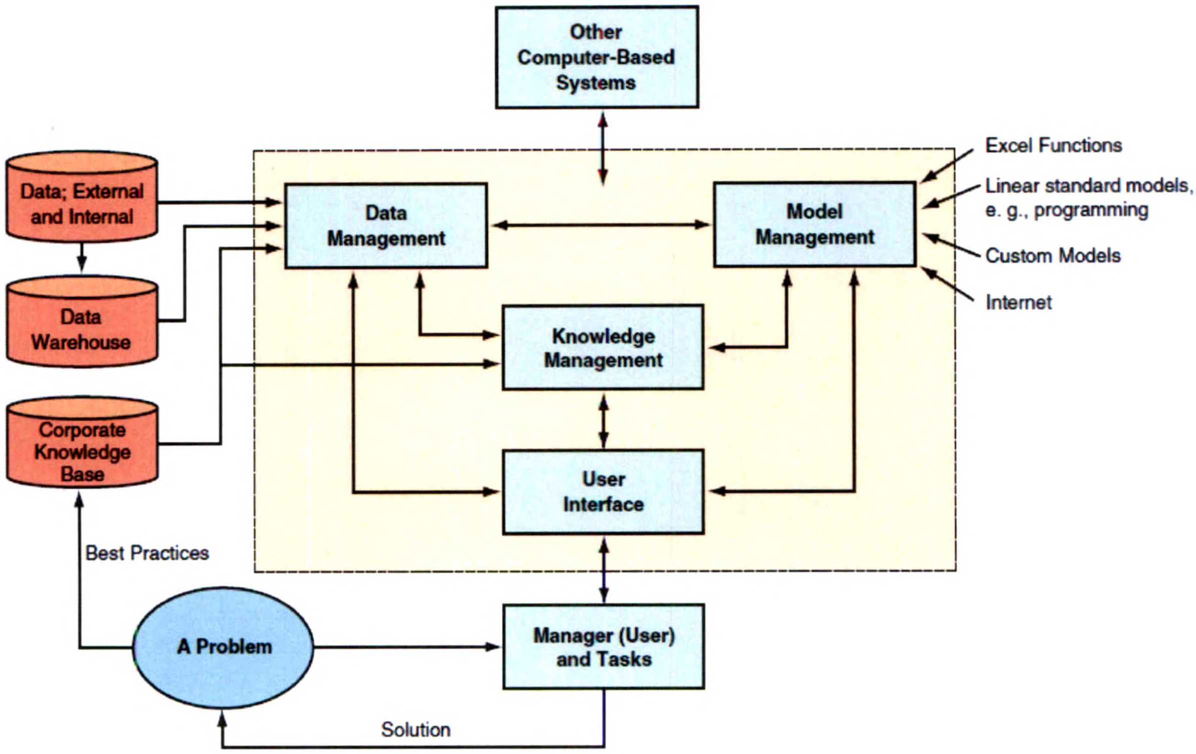


Figure 1.1: DSS and Its Computing Environment (Turban & Aronson, 2001).

(b) Model Base

A model base contains models that are applied to the raw data to support the decision-making process. A model base holds computational models consist of statistical, optimization, financial or simulation models that provide the analysis capabilities in a DSS. These models include linear programming, integer programming, goal programming, and nonlinear programming, and allow the user to invoke, run, and change any model or combine multiple models to interact with database component.

(c) Knowledge Base

The knowledge base component of a DSS is closed or open information repository and can be categorized, machine readable knowledge bases, human readable knowledge bases, and knowledge base analysis and design. Machine-readable knowledge base stores knowledge in a computer readable form for the purpose of automated deductive reasoning that applies to them. The design of a human-readable knowledge base component allows users to retrieve and use the knowledge it contains. A knowledge base analysis and design is an approach that allows users to perform analysis and design such that results in a knowledge base are used later on to make informative decisions (Dam, 2009).

(d) Graphical User Interface

A graphical user interface (GUI) encompasses all aspects of communication between a user and DSS application. The GUI functions as a bridge between DSS and user, and also links the database, model base, and knowledge base. Thus, the GUI allows the user to enter new data or update data, run the chosen model, view results of the model, or even rerun the application with a different combination of data and/or model. This is also an important component, which enhances ease of use, power, and flexibility of a DSS.

(e) User

A user is the person that interacts with the systems such as managers, system specialists, engineers, and decision makers. A DSS designing requires to fully comprehend the needs of user in order to design a user friendly DSS. For example, a manager expects a DSS, which is more user-friendly than a system specialist.

1.2.2 Categories of DSS

According to Power (2002; 2004), Shim et al. (2002) and Wang et al. (2002), DSS fall into five categories:

(a) Data-driven DSS

A data-driven DSS collects and provides real time access to a large operational database necessary for making structured, semi-structured, and unstructured decisions, which help managers organize, retrieve, and analyze large volumes of relevant data using database queries.

(b) Model-driven DSS

A model-driven DSS includes computerized systems that use accounting and financial models, representational models, and/or optimization models to assist in decision-making. Model-driven DSS also contain a number of models used for planning and scheduling.

(c) Communication-based DSS

A communication-based DSS derives its functionality from communications and information technologies that are used in the system to support shared decision-making. The system provides warnings triggered by pre-specified conditions that are manually or automatically generated data and information sent to users during the processing.

(d) Document-driven DSS

A document-driven DSS contains a module for engineering specifications, which integrate a variety of storage and processing technologies to provide managers document retrieval and analysis.

(e) Intelligent(Knowledge-based) DSS

An intelligent (knowledge-based) DSS utilizes knowledge, which is stored using Artificial Intelligence or statistical tools like Bayesian rules or case-based reasoning, rules, frames and Bayesian for making suggestions or recommendations. The component provides the primary functionality for the decision support system or subsystem.

1.3 INTELLIGENT DECISION SUPPORT SYSTEMS

Intelligent decision support systems (IDSS) employ techniques from the field of artificial intelligence (AI) to generate DSS behaviors that would be deemed as "intelligent" as observed in humans. The knowledge component of an IDSS facilitates storing and managing of emerging AI tools such as artificial neural networks, fuzzy logic, genetic algorithms, etc. These tools support repetitive and complex real-time decision making, which is created from the knowledge acquired from the previous case examples and decisions. Artificial neural networks and genetic algorithms are the most notable approaches for designing and developing IDSS (Power, 2002). However, IDSS have been designed using (1) Expert Systems, (2) Artificial Neural Networks, (3) Fuzzy Logic, and (4) Genetic Algorithms.

1.3.1 Expert Systems

Expert Systems (ES) contain a knowledge base, inference engine, and explanation system, and are most useful in situations involving reasoning and deduction (Slater et al., 1993). A knowledge-based expert system uses human experiences in a specific application domain to make decisions based on a given repository of data (Felson, 1990; Glazier, 1990; Stein, 1991; Zirilli, 1997). The human experiences are normally of individuals thought to be experts in their related field. ES are generally cost-effective only for frequently recurring problems of a very narrow scope that can be solved by a knowledge base that is essentially static (Hawley et al., 1990).

1.3.2 Artificial Neural Networks

An Artificial Neural Network is a type of artificial intelligence (AI) technology that attempts to mimic the human brain's powerful ability to recognize patterns (Kaastra & Boyd, 1995). The human brain is composed of billions of non-reproducing cells called neurons. Neurons function in groups called networks. Each group contains thousands of highly interconnected neurons (Trippi & Turban, 1993). Unlike the conventional "expert systems", the artificial neural network model has the capability to simulate the biological process of logical reasoning, mimicking the human brain's ability to recognize patterns. An Artificial Neural Network model creates new knowledge through its unique ability to deal with incomplete, and imprecise or partially incorrect data (Sharma & Alade, 1999).

1.3.3 Fuzzy Logic

The concept of fuzzy logic was originally introduced by Zadeh (1965) as a mathematical method to represent vagueness in everyday life, and its use spread in business applications (Nguyen & Walker, 1999). Fuzzy logic allows dealing with uncertainties by simulating the process of human reasoning. The logic behind this approach is that decision making is not usually precise, but intends to achieve target goals and objectives as closely as possible. In fact, a real world decision-making process often depends on the variables that are fuzzy, which means that the variables are unstructured, rambling or contentious, or rambling, and, therefore, the process can be improved using fuzzy logic (Nguyen & Walker, 1999).

1.3.4 Genetic Algorithms

A Genetic Algorithm technique is a stochastic heuristic optimization search technique specifically designed by following the natural selection process in biological evolution to arrive at optimal or near-optimal solutions in complex decision making problems (Holland, 1975). An initial population of individuals representing possible solutions is created when this technique is applied to a problem. Each of these individuals differs in characteristics, which make them somewhat difficult to fit as members of the population. The fittest members will have a higher probability of mating than lesser fit members, to produce an offspring that may have a significant probability of retaining the desirable attributes of their parents (Sharma & Jana, 2009).

1.4 WEB-BASED DECISION SUPPORT SYSTEMS

A web-based decision support system requires access through the World Wide Web. A typical web-based DSS requires data, a database management system (DBMS), a programming language, and a web-enabling device (Pol & Ahuja, 2007). A DBMS stores, manages, and processes the data and a graphical user interfaces (GUI) designed using a programming language that facilitates complex data processing and presentation, and connects external optimization engines. These systems involve databases and are prevalent with a focus on web-enabled capabilities, which are critical to the efficient functioning of any organization. Traditionally, DSS have supported relatively simple data processing and presentation tasks. However, the DSS have become more pervasive with the growth of organizations to process enormous and more complex amounts of data. A well-developed web-enabled intelligent DSS is needed to assimilate the data and information to derive meaningful decisions of managerial and economic significance.

1.5 FINANCIAL DECISION SUPPORT SYSTEMS

A financial DSS is a computer information system that provides information in the specific problem domain of finance using analytical decision models and intelligent techniques. A financial DSS is similar to any other DSS because of similar components that includes: (a) the database, (b) the model base, and (c) the user interface (Weber, 2008). The system simplifies access to databases in order to support effective financial decision making to solve complex and ill structured problems. A financial DSS directly supports modeling decision problems and identifying the best alternatives (Palma-dos-Reis & Zahedi 1999). The system helps decision makers based on financial planning, control, analysis and projections in solving financial management problems, (Zhang et al., 2009). Thus, the system formalizes domain knowledge about financial management and portfolio selection problems so that it is amenable to modeling and analytic reasoning (Weber, 2008).

The portfolio management process requires the analysis of several variables including vast amount of data and information (Elton & Gruber 1995; Zopounidis et al., 1995). The evaluation process of information related to every available security for inclusion into real-time portfolio management decisions is a cognitive and technical challenge. Therefore, the process requires significant support of a specifically designed computer system to facilitate the data management process, as well as implementing appropriate financial models. The role of a financial DSS is similar to that of a normative system that leads to a clear solution where recommendations are based on established theoretical principles. The system can also be a decision analytic DSS that supports the process of decision making but retains subjective elements and does not necessarily lead to a clear ranking and a unique best alternative (Weber, 2008).

Recent research in financial management has been leaning towards combining of the advanced analytical tools available in the DSS framework with the latest modeling techniques available for soft computing including neural networks, genetic algorithm and fuzzy sets. This study focuses on design and development of financial management systems for forecasting of stock price movement and active portfolio management, discussed in the following chapters.

1.6 MOTIVATION OF THE STUDY

The motivation for this study is based on the review of literature related to financial decision support systems (FDSS). However, there are still some deficiencies in existing systems used for portfolio management including forecasting applications. Constructing an optimal investment portfolio of securities that maximizes the returns with the lowest possible risk is a quadratic problem. While the statistical methods in use are limited in predictions as they provide solutions for the problem of a linear combination (Refenes et al., 1994). There have been several issues in existing systems where non-linearity functions have been addressed adequately in the forecasting of stock prices fluctuations and lack of ability to mimic human brain's power of pattern recognition. Therefore, the motivation for the study is to find solutions for some of problems related to forecasting and portfolio management. This research demonstrates how to integrate the signal processing techniques with artificial neural networks (ANN) to propose a predictive model for financial forecasting, especially for equity portfolios. The integration of Genetic Algorithms (GA) with ANN provides improved intelligent system that will meet demands of investors and portfolio professionals for stock index predictions in a global financial stock market. Additionally, the goal programming (GP) and fuzzy set theory provide flexibility and accommodate impreciseness associated with real world situations of the portfolio selection and management process.

The key motivations for the study are summarized as follows:

- To overcome deficiencies in existing systems used for forecasting stock prices and estimating portfolio returns for investors;
- To integrate signal processing with ANN and GA with ANN for enhancing features of DSS for stock market forecasting decisions;
- To integrate multi-criteria decision-making and the fuzzy set theory to incorporate impreciseness in the portfolio management model; and finally
- To empower investment professionals with a superior system that yields the highest possible returns and facilitates active portfolio management.

The aforesaid issues have been discussed in the past in several studies. However, the integration of signal processing with ANN, GA with ANN, and multi-criteria decision-making (MCDM), and the fuzzy set theory in a single coordinated research effort, will resolve some of these issues and make this research study both novel and worthwhile.

1.7 PROBLEM STATEMENT

For several decades, the financial industry is extensively using computing methods and technologies collectively known as decision support systems (DSS) to aid investors. The gradual paradigm shift in DSS is triggered by several factors such as analysis of a large volume of data and information in an uncertain and complex economic environment. Decision making in finance and investment is often a very complicated and ill-structured task involving the exploitation and evaluation of various information, data, and alternative solutions or actions for forecasting trends. Managers and individual financial decision-makers (portfolio management professionals and investors) face such problems on a daily basis and the existence of a tool to assist them in making the appropriate decisions is considered to be of vital importance.

The existing systems in the financial industry are applying intelligent techniques such as artificial neural networks (ANN), genetic algorithms (GA), fuzzy logic, rule-based systems, and support vector machines. Each technique, which is in use specifically for stock market prediction, investment, and technical analysis, has its own strength and weakness. For example, ANN are good for learning ability and forecasting, but lack the explanatory capability, while GA do not rely on training data sets yet deciding a suitable fitness function in GA is a tedious task. However, the hybrid intelligent system that utilizes merits of both techniques can enhance future stock predictions and active portfolio management.

This study proposed design and development of three novel hybrid systems combining two techniques to maximize the capabilities of the systems. The first system designed for forecasting of stock price movements based on Signal Processing/Gaussian Zero-phase (GZ) filter and Artificial Neural Networks/Multi-Layered Perceptron (ANN-MLP). The second system combines GA and ANN to develop a hybrid forecasting system. The final system intends to provide an active portfolio management system using a multi-criteria decision-making and the fuzzy set theory to incorporate impreciseness in the model.

1.8 OBJECTIVES OF THE STUDY

This research examines, analyzes and proposes effective integration of two techniques as a forecasting and portfolio management tool in the financial domain. The main focus of this study is to design and develop three hybrid systems: (1) Signal processing based artificial neural network system (SPANNS), (2) Genetically tuned artificial neural network system (GANNS), and (3) Web-based fuzzy portfolio management system (FPMS). The study can be summarized as follows:

- To review the literature on existing tools and techniques for stock market forecasting and portfolio management decisions;
- To design and develop SPANNS & GANNS for stock market forecasting;
- To evaluate the performance of SPANNS & GANNS by using root mean square error and mean absolute percentage error;
- To compare the trends between ANN & SPANNS and ANN & GANNS.
- To design and develop FPMS to incorporate impreciseness in the portfolio management;
- To suggest directions for implementation and future development of hybrid systems.

1.9 SCOPE OF THE STUDY

This study proposes effective integration of artificial intelligence (AI) techniques for designing and developing forecasting systems and integration of multi-criteria decision-making (MCDM) and the fuzzy set theory to incorporate impreciseness in the portfolio management. It will encompass the areas related to trading securities and active portfolio management of stocks, bonds and mutual funds. Though, the systems designed in the study have been tested using Dow Jones Industrial Average (DJIA) and National Association of Security Dealers Automated Quotations (NASDAQ) stock market data in the USA, it can also be applied in decision making in any security market throughout the world.

The signal processing based artificial neural network system (SPANNS) was designed and implemented in the forecasting of stock price movements. Back Propagation Neural Network (BPNN) was applied and results from both systems were compared for DJIA and NASDAQ stock data prediction. Genetic algorithm based artificial neural network system (GAANS) was implemented in predicting the stock prices and BPNN was applied and results from both were compared for DJIA and NASDAQ stock data prediction. The predicted output obtained using SPANNS and GANNS were compared with the actual output and the performance was compared using root mean square error (RMSE) and mean absolute percentage error (MAPE). Performance benchmark on prediction was compared with BPNN.

1.10 SIGNIFICANCE OF THE STUDY

The significance of study lies in the robustness of the systems predicted power enhanced by signal processing based artificial neural network system (SPANNS) and genetically tuned artificial neural network system (GANNS) for making more precise and reliable stock price predictions. The study shows that the predicted stock prices using SPANNS and GANNS were close to actual market prices. The study can be utilized in predicting prices of other security instruments such as currency rates, bonds, and even can be extended to derivative products. Also, the study will provide a basis for researchers who are interested in applying SPANNS and GANNS for technical analysis. Additionally, this study will encourage further development of advanced systems using ANN in term of different architecture selections for security price prediction and security selection for active portfolio management. Also, FPMS can be used as a decision-making tool by both individual investors and financial advisors.

1.11 RESEARCH METHODOLOGY

The proposed research methodology is implemented after exploring previous research work related to the topic and the latest quantitative research techniques for forecasting trends for the financial industry, specifically security markets. Artificial intelligence techniques such as neural network and genetic algorithm based systems are being developed for stock market prediction. The design of the systems is accomplished through the detailed design analysis and planning. Efforts have been made to employ the latest computational methodologies such as neural network, genetic algorithms and fuzzy goal programming. The proposed systems' performances were tested by various data sets to achieve optimal solutions. The research methodology is summarized in Figure 1.2, which illustrate the research structure.

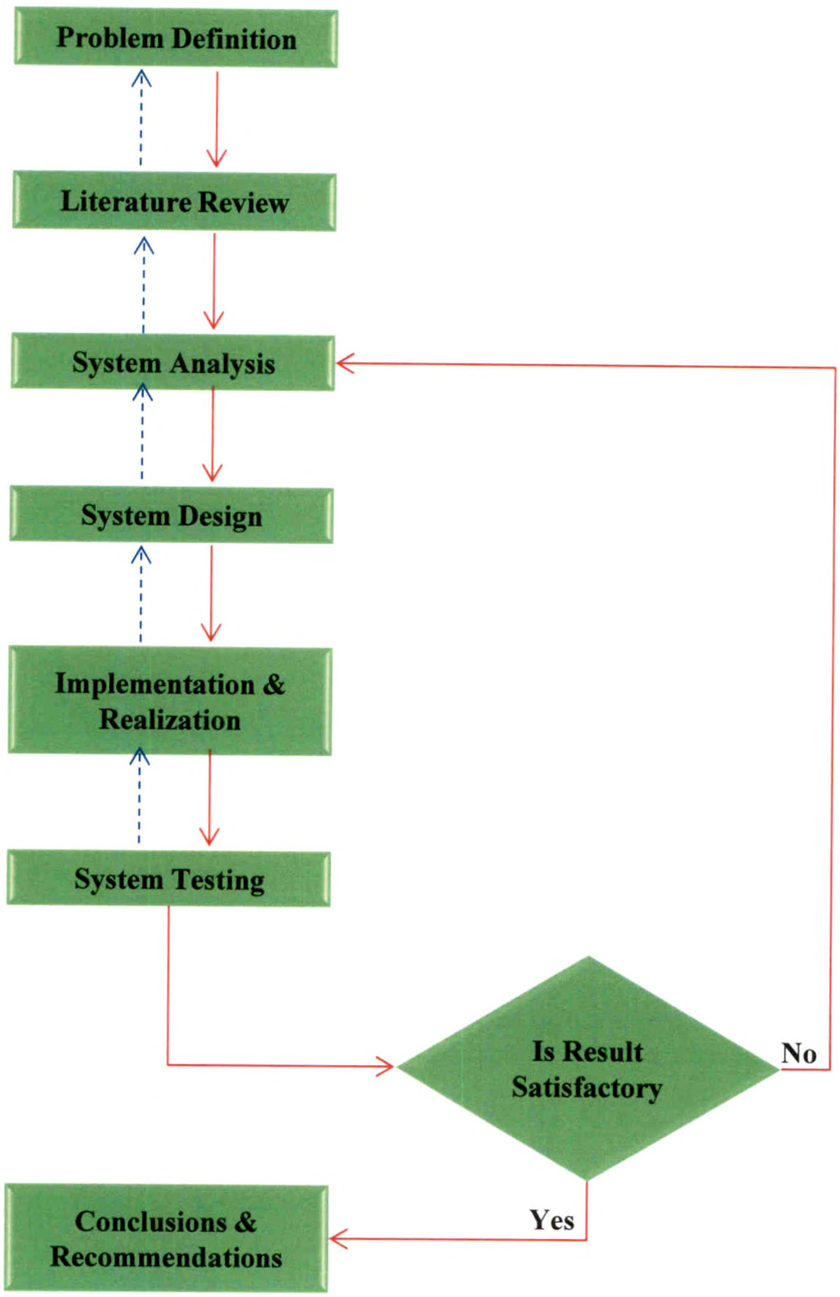


Figure 1.2: Research Methodology.

1.12 ORGANIZATION OF THE THESIS

This thesis is organized into eight chapters. The contents of each chapter are summarized as follows.

Chapter 1 provides an overview of the problem, background, and motivation. Additionally, researcher articulated the problem statement, objectives, scope, significance, and research methodology framework for study in the chapter.

Chapter 2 presents a review of the relevant literature including the research areas of financial decision support systems, traditional, intelligent and hybrid forecasting techniques, and portfolio management optimization techniques. The literature review identifies the accumulated literature on decision support systems related to stock market predictions and portfolio management for further analysis and synthesis.

Chapter 3 entails the research methodology, which consists of problem definition, literature review, system analysis, system design, implementation and realization, system testing, and conclusion and recommendation. This chapter also presents data descriptions including data collection and preprocessing. The system design and development section highlights designing of a SPANNS, GANNS and FPMS; and finally the last section summarizes the overall methodology.

Chapter 4 proposes a hybrid system that combines signal processing and artificial neural network (SPANNS) to develop a predictive system for stock market price movements. The integrated system is tested for different decision making situations. Also, the results and trends of actual and predicted values are compared for ANN and SPANNS techniques. The effect of signal processing on the prediction reliability and the impact of the accuracy measure used to evaluate the system performance is also discussed in the chapter.

Chapter 5 presents a design and development of the genetically tuned artificial neural network system (GAANS) to accommodate the current needs of investors and portfolio professionals. The system has both a genetic and ANN module. A genetic algorithm (GA) technique optimizes the weights of the ANN for stock market forecasting. Also, the results and trends of actual and predicted values are compared for both ANN and GANNS.

Chapter 6 focuses on designing and developing a web-based fuzzy portfolio management system (FPMS). The FPMS includes three tiers: (1) the client, (2) application, and (3) database level for investment decisions. The chapter highlights the software applications used in designing the system. Additionally, the chapter describes the architecture of FPMS, which is enriched by quantitative finance model formulation using goal programming (GP) and fuzzy set theory.

Chapter 7 discusses the results and findings of the study, which include the performance metrics as well as a comparison of systems. Additionally, discussion highlights the findings on the computation of the root mean square error (RMSE), and the mean absolute percentage error (MAPE) between the original data vector and the predicted vector. Furthermore, RMSE and MAPE were compared to assess the precision of the results and performance evaluation of both SPANNS and GANNS. Finally, the chapter discusses the results and analysis of FPMS, which is a web based fuzzy portfolio management system (FPMS) using the goal programming (GP) and fuzzy set theory.

Chapter 8 concludes the research work including valuable research insights and findings, which correspond to the research objectives and proficiencies gained through this research. Finally, contributions, implications and future research directions are envisioned and documented.

Also, a list of references used in this study is added at the end of the thesis.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter provides a comprehensive review of the relevant literature including the research areas of financial decision support systems (FDSS), financial forecasting techniques such as artificial neural networks (ANN), genetic algorithms (GA), hybrid techniques; and financial optimization techniques. The objective of the literature review is to identify the accumulated literature on decision support systems related stock market predictions and portfolio management. The review focuses on published journals and conference proceedings in order to maintain the integrity and size of the literature review manageable. The references used for this review are contained at the end of the thesis. The organization of the chapter is divided into several sections. The next section offers a review of FDSS, followed by an analysis of financial forecasting techniques including artificial neural networks (ANN), genetic algorithms (GA), hybrid techniques; and financial optimization techniques. Finally, the last section closes the chapter with a brief summary.

2.2 REVIEW OF FINANCIAL DECISION SUPPORT SYSTEMS

Financial decision support systems (FDSS) came into being with the introduction of decision support systems (DSS) in late 1960s and are being employed to tackle a variety of practical financial management problems, including financial forecasting and portfolio management. The researchers have designed DSS for various areas of financial management to implement DSS in most of fields including financial planning (Hayen, 1982); portfolio management (Singh & Cook, 1986); banking (Langen, 1989). Several authors developed interactive multi-criteria DSS including the CASH MANAGER system (McBride et al., 1989), the ADELAIS system (Siskos & Despotis, 1989), the BANKADVISER system (Mareschal & Brans, 1991), the BANKS system (Mareschal & Mertens, 1992), the MINORA system (Zopounidis, 1993), the INVEX system (Vranes et al., 1996), the FINEVA system (Zopounidis et al., 1996), the FINCLAS system (Zopounidis & Doumpos, 1998). Multi-criteria DSS were preferably designed for portfolio management. The literature review shows that Interactive Financial Planning System (IFPS) using DSS financial models has been in use for several years (Sharda et al., 1988).

Intelligent Decision Support Systems (IDSS) have been also proposed in several fields of financial management. Examples of IDSS studies include Portfolio Management Intelligent Decision Support System (Lee & Stohr, 1985) for portfolio selection and management; Lending Analysis Support System (Duchessi & Belardo, 1987); Intelligent Stock Portfolio Management System (Lee et al., 1989). However, a paradigm shift occurred in the 1990's, when advanced database technology and client/server capabilities emerged in DSS designing techniques. Financial institutions began upgrading their network infrastructure, object oriented technology and data warehousing for better decision making. The researchers designed and developed DSS for financial analysis (Siskos et al., 1994). The CGX system (Srinivasan & Ruparel, 1990; Ruparel & Srinivasan, 1992), and CREDit EXpert system (Pinson, 1989 & 1992) for credit granting problems; the KABAL system (Hartvigsen, 1990 & 1992) for financial analysis, and the FINancial EVAluation system (Zopounidis et al., 1996).

Zopounidis et al. (1995) developed a methodological framework for the design and development of a multi-criteria DSS for portfolio management. Zopounidis et al. (1997) provided an excellent review on knowledge-based DSSs in financial management. Academic researchers also focused on employing advanced mathematical programming techniques to develop financial decision support systems (Ballestero & Romero, 1996). The majority of DSS applications in the finance area were developed to support credit evaluation and management (Curnow et al, 1997). Additionally, advancements have been made in management of financial audits, projects, fixed income portfolios, credit risk, home mortgage portfolios, and investment portfolios (Palma-dos-Reis & Zahedi, 1999). Thus, DSS applications were evolved, designed, developed and studied for further developments with the technological innovations and the demand from the financial industry. Researchers used multiple frameworks to help build and explain these systems.

Zopounidis and Doumpos (2001) proposed an alternative DSS approach to the classical statistical methodologies that have been extensively used for the study of financial classification problems. Samaras & Matsatsinis (2003) developed the Intelligent INVESTOR, an intelligent multicriteria DSS which aims at offering an overall consideration of the portfolio management problem. Lin & Hsiech (2004) suggested an integrated framework that incorporates fuzzy theory into strategic portfolio selection. Recently, mathematical programming, decision analysis, and simulation techniques are being widely used in building model-driven DSS (Power & Sharda, 2007).

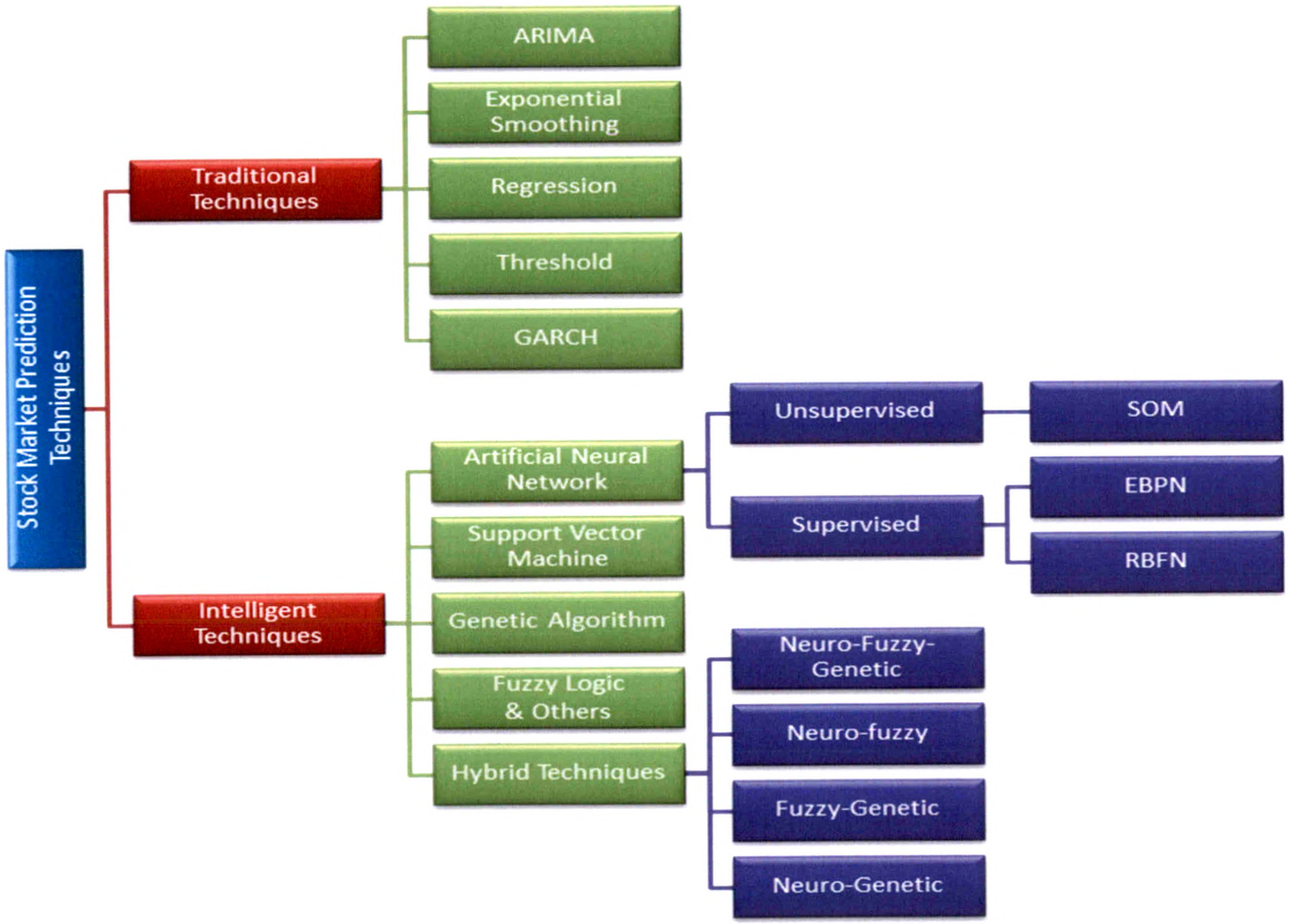


Figure 2.1: Stock Market Forecasting Techniques.

expected irregular and infrequent future events (Lee & Yum, 1998; Lee et al., 1990; Sharma & Alade, 1999).

The review of the literature reveals that several traditional forecasting models have been used by financial researchers. Autoregressive integrated moving average (ARIMA), exponential smoothing, regression, threshold, generalized autoregressive conditionally heteroskedastic (GARCH) are widely used traditional techniques (Wagner et al., 2011).

The ARIMA (Box & Jenkins, 1976), exponential smoothing and regression techniques are linear techniques and have a linear functional form for time series modeling. The threshold (Makridakis et al., 1998) and GARCH (Bollerslev, 1986) techniques can be considered as non-linear techniques. Several authors have utilized time series to study the stock market price movements (Amihud et al., 2010; Guresen et al., 2011; Chang et al., 2012). Many forecasting studies employ a variation from the aforesaid techniques (Wagner et al., 2011) and such studies include Engle and Granger (1987), Shoesmith (1992), Cheung & Lai (1993), Baille & Bollerslev (1994), Clements & Hendry (1995), Dua & Smyth (1995), Sarantis & Stewart (1995), Stock & Watson (2002), Ramos (2003), Chen & Leung (2003), Tourinho & Neelakanta (2010). He et al. (2010), and Hjalmarsson (2010).

The studies, which employed statistical techniques, to handle time series demand with unusual characteristics includes a Bayesian method to forecast demand for products with extremely short demand histories (Dolgui & Pashkevich, 2008), a regression tree analysis for handling forecasting demand for products influenced by promotions (Ozden et al., 2009), and a choice of from statistical measures to help users manually select a forecasting model for a particular demand series (Chern et al., 2010, Wagner et al., 2011).

However, these models have limitations due to noise and nonlinearity in stock price movements. Therefore, the output can deviate from real movements significantly, and preciseness of prediction is somewhat questionable.

The relevant finance areas selected for the literature review include the academic research specific to stock market movements and portfolio management. However, bankruptcy prediction has also been reviewed because similar DSS techniques have been used and the bankruptcies have significant effects on stock prices of other firms in general. Table 2.1 entails the data for the period 2000-2012, and analysis of 233 studies reveals that 48% research work has focused on the stock market forecasting, 12% studies on portfolio management, approximately 40% on bankruptcy prediction. The majority of research studies related to bankruptcy predictions were done in 2008 and 2009, the period of economic downturn in the USA.

Table 2.1
A Sample of Publication by Year and Financial Applications

Year	Stock Market Forecasting	Portfolio Management	Bankruptcy Prediction	Total
2000	3		3	6
2001	2	4	5	11
2002	3	1	2	6
2003	3		3	6
2004	6	3	7	16
2005	8	5	4	17
2006	6	2	5	13
2007	11	2	8	21
2008	4	2	15	21
2009	12	4	36	52
2010	6	1	4	11
2011	37	2	2	41
2012	10	1	1	12
Total	111	27	95	233

Table 2.2 A Sample of AI Techniques in Financial Management							
Year	Artificial Neutral Network	Expert System	Fuzzy Logic	Genetic Algorithm	Hybrid System	Support Vector Machines	Total
2000	5	1					6
2001	8	2			1		11
2002	3				3		6
2003	3	1			2		6
2004	10	1	1	1	3		16
2005	7	3		1	6		17
2006	3	1		2	6	1	13
2007	8	1	1		11		21
2008	6	3	1		11		21
2009	12	4	1		35		52
2010	2		1		7	1	11
2011	19		1	5	12	4	41
2012	5			2	5		12
Total	91	17	6	11	102	6	233

Although the survey of literature provided in this chapter includes only 233 studies, a comprehensive review of literature is presented at the Appendix A.

2.3.2 Artificial Intelligence Techniques

Artificial intelligence (AI) techniques are different from the traditional techniques because precise forecasting is possible even when data is chaotic, filled with noise and provides no definitive conclusion. An AI approach filters fuzzy data into meaningful information and provides a new and more precise approach to solving complex problems. Additionally, AI is knowledge based technique that assists human reasoning process through the use of computers with the goal of processing information and gaining knowledge. The review of the literature reveals that the AI techniques are being used in financial forecasting and portfolio management (Table 2.2) including the following:

- Artificial Neural Networks (ANN)
- Genetic Algorithms (GA)
- Fuzzy Logic (FL)
- Support Vector Machines (SVM)
- Hybrid Techniques (HT)

The aforesaid studies have been summarized into two dimensions (1) intelligent techniques and (2) financial applications (Table 2.3). The analysis reveals that the hybrid systems have been used in 102 studies out of 233. However, it is used only 4 studies in portfolio management during the period of study.

Table 2.3
A Sample of Intelligent Techniques & Applications in Financial Management

Financial Application	Artificial Neural Network	Expert System	Fuzzy Logic	Genetic Algorithm	Hybrid System	Support Vector Machines	Total
Bankruptcy Prediction	29	5		4	55	2	95
Portfolio Management	7	9	2	5	4		27
Stock Market Forecasting	55	3	4	2	43	4	111
Total	91	17	6	11	102	6	233

2.4 ARTIFICIAL NEURAL NETWORKS

In this section, artificial neural networks (ANN) and its applications in the stock market forecasting are briefly reviewed.

2.4.1 Background

An ANN is a type of intelligence technique that attempts to mimic the human brain's powerful ability to recognize patterns (Kaastra & Boyd, 1995). The human brain is composed of billions of non-reproducing cells called neurons. Neurons function in groups called networks. Each group contains thousands of highly interconnected neurons (Trippi & Turban, 1993).

An ANN consists of three layers where an input layer distributes a pattern through the network; a middle layer acts as a collection of feature detectors; and an output layer generates an appropriate response. Additionally, there are three main components in an ANN: a network topology, a spreading activity, and a training mechanism (Hsieh, 1993). In a generic neural network, each neuron of an ANN receives and processes input(s) and delivers a single output. The input can be raw data or the output of another neuron. Though ANN are mainly collection of neurons grouped into layers and directly linked to each other, they are inter-connected in a vast array of topologies (Figure 2.2).

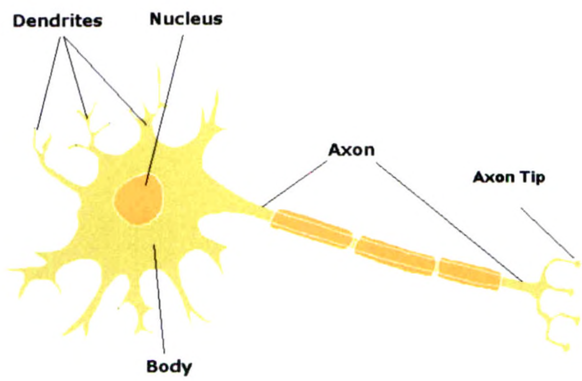


Figure 2.2: Structure of Neuron.

Figure 2.2 shows a portion of a biological network where the cell's center is the nucleus engraved by dendrites to provide input to it. The signals (outputs) are sent via the axon terminals to Neuron #2, which can be transmitted unchanged or over synapses. A synapse increases or decreases the strength of the connection, exciting or inhibiting the subsequent neuron. The artificial neuron is analogous to the biological neuron. Thus, an ANN emulates the neural activity of the human brain and can actually ream (Sharma & Alade, 1999).

An ANN has several advantages such as less time is required to recognize patterns and are suited for intuitive decisions (Slater, et al., 1993). An ANN is able to deduce probabilities through their iterative training process while it is difficult for rule based expert systems to develop rules from historical data when inputs are highly correlated (Trippi & Turban, 1993). Therefore, an ANN is fundamentally dynamic, rather than static; they continue to adapt and improve when exposed to new data or information.

Researchers have identified weaknesses of ANN that they are only useful in narrowly defined problem domains, and often identify irrelevant factors. If an ANN is designed to over-fit their training set of data such that it may fail the test on real data. In other words, an ANN cannot tell the user how it processes the information and reaches its conclusion (Hawley et al., 1990). Furthermore, complexity and costs of developing ANN models make their use prohibitive in the business world.

ANN have been most effectively applied to three types of pattern recognition tasks: classification, associative memory, and clustering (Hawley et al., 1990). Classification involves assigning input vectors to predefined groups. An example is a computer recognizing certain persons' voices for audio security access. Associative memory is useful when only part of a pattern is available. An example is the digital reconstruction of a smudged fingerprint. Clustering involves grouping inputs with other similar inputs and filtering the data. An example is clustering corporate bonds into different risk classes. This differs from classification, because the categories are not predefined. ANN have a variety of applications to different industries. Of interest here, is the application to areas of finance specifically forecasting of stock price movements.

2.4.2 ANN Applications in Stock Market Forecasting

The forecasting of stock price performance involves the interaction of many variables, making forecast extremely difficult and complex. Various techniques like the traditional statistical methods and expert systems have been used to predict stock price movements. However, because these models require some basic assumptions or continued review and refinement as economic condition change, they have not proved to be extremely reliable (Trippi & Turban, 1996).

Studies have shown that artificial neural networks (ANN) provide a promising alternative approach to time series forecasting (Trippi & Turban, 1993; Sharda & Patil, 1990). An ANN method has demonstrated its capability of addressing problems with a great deal of complexity. A neural network specifically designed to take a pattern of stock price data and generalize from it, enhances an investor's forecasting ability. The ANN ability to forecast in a fuzzy sense is more appropriate than the other forecasting methods. ANN can be trained to approximate the underlying mapping of the series. However, the accuracy of approximation depends on a number of factors such as ANN structure, learning method, and training procedure (Alade et al., 1997).

Over the past two decades, several financial researchers have applied ANN to stock price predictions. White (1988) investigated an ANN to conduct time series analysis on the IBM common stock daily returns. Kimoto et al. (1990) demonstrated a prediction system for the Tokyo Stock Exchange Prices Index by using a modular neural network. Kamijo & Tanikawa (1990) applied the recurrent neural network for analyzing candlestick charts to understand stock price patterns. Trippi and DeSieno (1992) applied technical analysis to investigate the effectiveness of a specific neural network trading system for S&P 500 index futures contracts. Lin & Lin (1993) used ANNs to forecast Dow Jones Industrial average. Kryzanowski et al. (1993) adopted the Boltzmann machine for neural network training to classify stock return as negative, neutral, or positive. Refenes et al. (1993) applied a feed forward network with 4 layers (two hidden ones). Refenes et al. (1994) compared regression models with a back-propagation network for stock forecasting. Refenes et al. (1994) compared regression models with a back-propagation network for stock forecasting. Choi et al. (1995) used ANN to predict the daily change in the S&P 500 index. Dropsy (1996) applied neural networks as a nonlinear forecasting tool to predict international equity risk premia. Wang and Leu (1996) presented ARIMA based neural networks for predicting mid-term trends in Taiwan stock market. Motiwalla and Wahab (2000) used a back propagation neural network.

Wang (2003) presented a fuzzy stochastic method to predict stock prices. Lee (2004) developed an intelligent agent based stock prediction system using hybrid radial basis function (RBF) recurrent network. Lam (2004) presented the ability of ANNs, specifically, the back propagation algorithm, to integrate fundamental and technical analysis for financial performance predictions. Qing et al. (2005) applied ANN to predict stock price movements for firms traded on the Shanghai stock exchange. Constantinou et al. (2006) used a MLP Network with 2 inputs. Roh (2007) integrated an ANN with time series model for capturing the volatility of the stock market index. Zhu et al. (2008) used

ANN in forecasting with the data of stock returns and volumes from NASDAQ, DJIA and STI indices. Atsalakis and Valavanis (2009) presented an intensive literature review on the stock market forecasting.

A more recent study of Manjula et al. (2011) applied neural network models to predict the daily returns of the Bombay Stock Exchange Sensex. Multilayer perceptron network was used to build the daily return's model and the network was trained using Multiple linear regression (MLR) provides a better alternative for weight initialization. Qing et al. (2011) evaluated the predictive power of several forecasting models including a single-factor CAPM-based model and the three-factor model of Fama and French and compared the forecasting ability of each of these models with ANN.

2.5 GENETIC ALGORITHMS

In this section, genetic algorithms and its applications in the stock market forecasting are briefly reviewed.

2.5.1 Background

Genetic algorithms (GA) are search algorithms, which are inspired by the Darwinian Theory, which suggests the survival of the fittest. Holland (1975) originated the idea of GA in the early 70's. Since then GA have become extremely powerful tools in finance, economics, accounting, operations research, and other fields. This is mainly because heuristic algorithms might lead to a local optimum, while GA are more likely to avoid local optima by evaluating multiple solutions simultaneously and adjusting their search bias toward more promising areas. Further, GA have been known to have superior performance to other search algorithms for data sets with high dimensionality. There have been a significant amount of work using GA in the field of computer science and engineering but a little work is found in the finance related areas. The GA applications demonstrate that they can handle irregularities such as non-differentiability and discontinuity in a convenient and efficient way and have an advantage over techniques such as gradient search, hill-climbing or other similar algorithms (Dorsey & Mayer, 1995; Michalewicz 1996; Wagner et al., 2011). The components of forecasting of procedure includes data selection, data analysis, and construction of an appropriate model for training the model, and finally implement for future predictions (Makridakis et al., 1998). Michalewicz (1992) and Mitchell (1996) gave detailed descriptions of GA applications. Several researchers including Chambers (1995), Chiraphadhanakul et al. (1997), Kim and Kim (1997), Ju et al. (1997), Goto et al. (1999), and Venkatesan and Kumar (2002) developed GA applications for forecasting.

2.5.2 GA Applications in Stock Market Forecasting

GA techniques have been used in a variety of hybrid approaches to financial time series predictions. The trends of S&P500 stock market index were studied by Noever and Baskaran (1994) using GA techniques. Bauer and Liepins (1992) explored linkage of genetic algorithms to investments. Bauer (1994) offered practical solutions using GA for stock trading strategies based on fundamental analysis. Mahfoud and Mani (1996) presented a new GA based system for predicting the future performances of individual stocks. Chambers (1995) applied GA for financial forecasting application. Mahfoud and Mani (1996) predicted future performances of individual stocks. Additionally, they made a comparison of GA and ANN applications to financial forecasting. Kai and Wenhua (1997) developed an application where GA were used to train ANNs for predicting a stock price index. Chiraphadhanakul et al. (1997), Ju et al. (1997) and Kim and Kim

(1997) also used GA for stock market forecasting applications. Allen and Karjalainen (1999) used GA to discover technical trading rules.

Kim and Han (2000) used a GA approach in order to feature discretization and the determination of connection weights for ANN to predict the stock price index. Xia et al. (2000) proposed a new model using GA for portfolio selection. Fernández-Rodríguez et al. (2001) combined GA with a simple trading rule and applied to Madrid Stock Exchange to provide evidence for successful use of GA. Oh et al. (2005) used GA for portfolio optimization for index fund management. Huarng and Yu (2006) applied an ANN to establish fuzzy relationships in fuzzy time series for forecasting stock prices. Papadamoua and Stephanides (2007) employed GA for improving the efficiency and performance of computerized trading systems. Yet in spite of enormous technical advances over these years in storage, speed, functionality of tools and even interface design, the improvement to be seen in the effectiveness and extent of DSS and IDSS usage has been relatively modest.

2.6 HYBRID SYSTEMS

In this section, hybrid systems and its applications in the stock market forecasting are briefly reviewed.

2.6.1 Background

The literature reveals that hybrid systems are widely being used to improve forecasting. ANN are commonly used in these hybrid models (Wagner et al., 2011). Many authors have used ANN, GA, or a combination of both to stock market prediction, which were mostly designed to optimize the networks weights or to find a suitable topology (Branke, 1995; Yao, 1999; Kwon & Moon, 2007; Mandziuk & Jaruszewicz, 2011).

2.6.2 Hybrid Systems Applications in Stock Market Forecasting

Trippi and DeSieno (1992) combined ANN with rule-based expert system to outperform passive investment in the stock index. Nikolopoulos and Fellrath (1994) proposed a hybrid expert system for investment advising and used genetic algorithms to train and configure the architecture of investor's neural network component. Hiemstra (1995) developed fuzzy expert systems to predict stock market returns and suggested that ANN and fuzzy logic could capture the complexities of functional mapping. Muhammad and King (1997) devised evolutionary fuzzy networks to forecast the foreign exchange market. Kohara et al. (1997) incorporated non-numerical factors such as political and international events as prior knowledge to demonstrating an improvement in the stock market predictions. Also, Tsaih et al. (1998) combined a rule-based technique with ANN to predict the direction of change of the S&P 500 stock index futures on a daily basis. Lee and Jo (1999) developed an expert system, which uses knowledge in a candlestick chart analysis.

Pan et al. (2005) presented an application of mutation only genetic algorithm for the extraction of investment strategy in financial time series. Pai and Lin (2005) developed a hybrid system by combining ARIMA models and support vector machines for stock prices forecasting. Kim (2006) proposed a new hybrid model of ANN and GA for instance selection and applied to stock market analysis. Kwon and Moon (2007) offered a hybrid neuro-genetic system for stock trading, where the goal was to predict the company's stock price. Huang (2008) suggested a new definition of risk for portfolio selection in fuzzy environment and designed a hybrid intelligent algorithm to illustrate the optimization idea and the effectiveness of the designed algorithm. Valenzuela et al. (2008) also recommended a hybrid system with intelligent techniques and ARIMA models for time series prediction. Aladag et al. (2009) combined Elman's recurrent ANN and ARIMA models for time series forecasting. Chang et al. (2009) applied ANN, dynamic time windows, and Case Based Reasoning (CBR) to predict stock trading and concluded that percentage prediction accuracy for stock buying or selling decisions was promising. Chang et al. (2009) also developed a model combining neural networks and intelligent piecewise linear representation to track the stock turning points. The results showed that the hybrid system can assist in making a significant and constant amount of profit compared to other approaches.

Mostafa (2010) developed a multi-layer perception (MLP) and generalized regression ANN to forecast the closing price movements of Kuwait stock exchange. Cheng et al. (2010) presented a hybrid system using GA and rough set theory for stock price predictions. Merh and et al. (2010) applied hybrid of ANN and ARIMA with different versions on five different stock indices and the result obtained are compared with individual technique: ARIMA and ANN in terms of various error measures RMSE, MAPE and MAE. Wagner et al. (2011) offered a hybrid system that applies statistical and GA techniques for time series modeling, analysis, and prediction. Mandziuk & Jaruszewicz (2011) presented an introduction and experimental evaluation of neuro-genetic system for short-term stock index prediction. Gupta et al. (2011) suggested a hybrid approach to facilitate the investors in investment decision making. Recently, Bermúdez et al. (2012) presented an efficient portfolio model construction integrating fuzzy ranking strategy into GA.

2.7 REVIEW OF FINANCIAL OPTIMIZATION TECHNIQUES

This section provides a review of financial optimization techniques for portfolio management.

2.7.1 Background

Modern portfolio theory (MPT) is a theory which was devised by A Nobel Prize winning economist, Henry Markowitz in the 1952. The theory attempts to describe how to maximize expected portfolio returns for various levels of portfolio risk. Other contributors to expand MPT have been Miller and Modigliani for the Arbitrage Pricing Theory (APT); Sharpe, Lintner, and Black for the Capital Asset Pricing Model (CAPM); and Black, Sholes, and Merton for the Option-Pricing Model; and Fama for the Efficient Market Hypothesis (EMH). The EMH, developed by Eugene Fama in the early 1960s, explained that the knowledge about a stock has already been incorporated into the price of that stock, and no investor is in a position to make in excess of average returns consistently on a risk adjusted basis by forecasting future prices based on historical prices (Fama, 1965). The EMH concepts are divided into three versions: (1) weak, (2) semi-strong, and (3) strong. The weak-form of EMH assumes that prices of traded securities already reflect all publicly available information. The semi-strong-form EMH assumes that prices reflect all publicly available information, and new public information is reflected in prices at any given point of time. The strong-form EMH claims that the hidden or "insider" information is also reflected instantly in the current market prices.

The proponents of the hypothesis advocate that the market efficiency is a simplification of the real world situations which is not expected to be true always, and that the market is practically efficient for investment purposes for most individuals.

The study of EMH further suggests that the proponents of weak EMH claim that current market prices only take into account past stock price data and the underlying assumption is that no predictions can be made based only on stock price data as they follow a random walk in which successive changes have zero correlation. However, a large number of researchers have been developing systems to forecast stock prices based on historical data and claim that stock prices can be precisely forecasted using fundamental analysis, technical analysis, and traditional time series models.

2.7.2 Applications of Optimization in Portfolio Management

Applications of optimization techniques have been developed using the MPT theory pioneered by Markowitz (1952, 1959) and Sharpe (1963). Markowitz developed the foundation of a framework for mean-variance portfolio optimization and suggested that the portfolio selection is a parametric quadratic programming problem. Since then several portfolio selection models have been proposed based on mean-variance formulation while the complexity of models requires advanced knowledge of quadratic programming formulation. Sharpe (1963) simplified the model and summarized the process of portfolio selection using the assumptions of: (1) making probabilistic estimates of the future performance of securities, (2) analyzing those estimates to determine an efficient set of portfolios, and (3) selecting from that set a portfolio that is best suited to the investor's performance (Lee & Lerro, 1973).

The review of historical development of portfolio construction and optimization theory and applications will provide a basis for this research. Initially, linear programming (LP) approach was used to solving portfolio selection problems and demonstrating that LP models can provide acceptable results by simplifying the assumptions of mean-variance mode (Sharpe, 1967; Stone 1973). Since portfolio selection problems involve conflicting objectives such as the maximizing returns as well as minimizing risk, the conventional LP model becomes less adequate to handle portfolio selection problems as LP model can only handle a single objective function. This complexity of the problem that results from multiple and conflicting objectives was attempted to solve with goal programming (GP). The GP technique was developed to handle multi-criteria situations within the general framework of LP. The essence of this technique is the achievement of the "best possible" solution, which comes closest to meet the stated goals given the constraints of the problem (Romero, 1991).

Starting with Lee's (1972) classic goal programming (GP) work, a number of GP studies in the 1970's surfaced and demonstrated the usefulness of the multiple GP as a technique for optimal allocation of financial assets (i.e., stocks and bonds) into portfolios (Lee & Lerro, 1973; Hsu, 1976; Lee & Chesser, 1980). Lee and Lerro (1973) developed a GP portfolio selection model for mutual funds. Kumar et al. (1978) developed a conceptual GP model for portfolio selection of dual-purpose funds. Lee and Chesser (1980) demonstrated how linear beta coefficients are used to reflect risk in alternative investments and proposed a GP model to construct an efficient portfolio. Levary and Avery (1984) introduced a GP model representing the investor's priorities and also compared the use of linear programming to GP for the selection of the best possible portfolio. Schniederjans et al. (1993) illustrated the use of

GP as an aid to planning investment portfolios for individuals using arbitrage pricing theory (APT) instead of Capital Asset Pricing Model (CAPM). Sharma et al. (1995) presented GP as an aid for investors or financial planners planning investment portfolios for individuals and/or companies by using beta coefficients and other vital parameters. Additionally, Pendaraki et al. (2004) has applied GP on a sample of Greek mutual funds. Sharma and Sharma (2005) offered a GP model to select an optimum mutual fund portfolio that satisfies investor's multiples objectives. Sharma et al. (2007) proposed a goal interval programming for Credit Union Portfolio Management. Recently, Ballestero et al. (2012) proposed a portfolio selection based on a new financial-ethical bi-criteria model with absolute risk aversion coefficients and targets depending on the investor's ethical profile.

The study of literature review concludes GP is an efficient and flexible technique that provides the best compromising solutions to the Multi-Criteria Decision-Making (MCDM) problems depending on precise definitions of the goals and constraints. The GP approach has served to arrive at a better solution for a given set of goals and objectives than LP. However, there could be better solutions if goals and constraints can be somewhat relaxed that have been accommodated in fuzzy goal programming (FGP). A FGP technique provides better tools to solve a problem which is comprised of fuzzy goals and objectives. A system integrated with FGP is accommodates constraints or coefficients which are always imprecise or fuzzy in a real world situation.

Östermark (1996) implement fuzzy models for dynamic portfolio management. Tanaka and Guo (1999) developed a quadratic programming model for solving portfolio selection problems. Inuiguchi and Ramík (2000) also presented a review of fuzzy mathematical programming and compared with stochastic programming in portfolio selection problem. Tanaka et al. (2000) offered two portfolio selection models based on fuzzy probabilities and possibility distributions.

Para et al. (2001) employed fuzzy set theory to construct optimal investment portfolios and extended Markowitz's mean-variance idea. These models applied the same idea that investment return was based on the expected value of the securities and risk on the variance from the expected value. León et al. (2002) suggested a portfolio construction framework using fuzzy optimization for risk–return trade-off. Ong et al. (2005) proposed a grey and possibilistic regression models to formulate a novel portfolio selection model while Tiryaki and Ahlatcioglu (2005) offered a new ranking and weighting method and applied to stocks portfolio selection problem. Lacagnina and Pecorella (2006) designed a multistage stochastic fuzzy model to solve portfolio management problems. Huang et al. (2006) suggested revisions to conventional mean–variance method to solve a portfolio selection problem. Bilbao-Terol et al. (2006) used fuzzy compromise programming for portfolio selection. Zhang et al. (2007) developed two different portfolio selection models using lower and upper possibilistic means and possibilistic variance. Huang (2007) solved a portfolio selection problem accommodating randomness and fuzziness of security returns. Topaloglou et al. (2008) proposed a dynamic stochastic programming model for international portfolio management. Gupta et al. (2008) adapted mean–variance optimization portfolio model into semi-absolute deviation model and applied multi criteria decision making using fuzzy programming for developing a comprehensive model for portfolio optimization. Hasuike et al. (2009) considered several portfolio selection problems including probabilistic future returns with ambiguous expected returns assumed as random fuzzy variables and random fuzzy portfolio selection problems were formulated as nonlinear programming problems based on both stochastic and fuzzy programming approaches. Tiryaki and Ahlatcioglu (2009) proposed fuzzy analytic hierarchy process to solve fuzzy portfolio selection problem and discussed the relevant merits and demerits by comparison to existing models. Sharma et al. (2009) applied an additive FGP approach to Credit Union Portfolio Management. Also, Sharma et al. (2010) presented a FGP model using varying domain optimization technique to construct a portfolio from different types of mutual funds based on the desired priority structure by the decision maker. The effectiveness and applicability of the model was demonstrated via a case example from broad categories of mutual funds.

Recently, Bhattacharyya et al. (2011) utilized interval numbers in fuzzy set theory and extended the classical mean–variance portfolio selection model into a mean–variance–skewness model while Liu (2011) discussed a fuzzy portfolio optimization problem where the asset returns were represented by fuzzy data. A mean-absolute deviation risk function model and Zadeh's extension principle were utilized for the solution method of portfolio optimization problem with fuzzy returns.

2.8 SUMMARY

The literature review suggests that Artificial Neural Networks (ANN) and Hybrid Systems for financial predictions and portfolio management models are being effectively used. Additionally, Genetic Algorithms (GA) and Fuzzy Logic are also showing promising results. Furthermore, the review of the literature reveals that during the past twelve years, the application of intelligent DSS for forecasting, portfolio optimization, and bankruptcy prediction, has been increasing in the financial Services industry. Also, Portfolio selection theory with fuzzy returns has been well developed and widely applied.

Although the intelligent DSS are going through the maturity life cycle, yet there is potential to improve intelligent DSS using hybrid techniques that can make systems adaptive, flexible and robust for the dynamic financial market.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 INTRODUCTION

The research methodology plays a crucial role in conducting a research study. This research methodology has been chosen carefully from the recent research methodologies found in profound literature review. The details of the methodology are divided into several sections: research methodology description, data description, system design and development methodologies, and summary of the chapter. The research methodology description consists of problem definition, literature review, system analysis, system design, implementation and realization, system testing, and conclusion and recommendation. Data description section contains data collection and data preprocessing. The system design and development section highlights designing of a signal processing based artificial neural network system (SPANNS), genetically tuned artificial neural network system (GANNS) and web based fuzzy portfolio management system (FPMS); and finally the last section summarizes the overall methodology.

3.2 RESEARCH METHODOLOGY DESCRIPTION

The research methodology involved several stages to ensure the achievement of the research objectives as discussed in chapter 1. These stages are: (1) Problem definition, (2) Literature Review, (3) System analysis, (4) System design, (5) System implementation, (6) System testing and (7) Conclusion and Recommendation. Figure 3.1 illustrates the flow of research methodology of this study. The different stages/phases of this process are briefly discussed as follows:

3.2.1 Problem Definition

Defining a problem is a hierarchical process, which means that the problem should be identified from a generalized to the specialized method based on a comprehensive review of the existing literature. A good problem forms a strong foundation for developing a model or system designing process. Thus, defining a problem precisely and clearly provides a strong base for the next phases of system development. In this phase, we identified that the existing systems in the financial industry have some drawbacks. As discussed in previous chapters, the forecasting techniques using ANN are good for learning abilities, but lack the explanatory capabilities. On the other hand, GA techniques do not rely on training data sets yet deciding a suitable fitness function is a tedious task because it requires human intervention. Therefore, the hybrid intelligent system that utilizes merits of both techniques can enhance future stock predictions and active portfolio management. Therefore, this study attempts to solve some of the problems in existing systems by designing and developing three hybrid intelligent systems. These systems utilize merits of Artificial Neural Networks (ANN), Genetic Algorithms (GA) and Fuzzy Goal Programming (FGP) techniques for enhancing stock price predictions and active portfolio management.

3.2.2 Literature Review

A comprehensive literature review was conducted to identify the aforesaid problems of existing systems in the areas of stock forecasting and portfolio management. The study analyzed the existing literature review conducted in the study from various perspectives including understanding the research methodologies used, generating ideas for research directions, challenges, strengths' and weakness of the previous research studies to articulate the problem statement for this study. The various sources that were used for the review of literature included the internet, academic journals and books relevant to the research topic. Specifically, we reviewed the research work on signal processing, artificial neural networks, genetic algorithms, and fuzzy goal programming to utilize in the proposed approach.

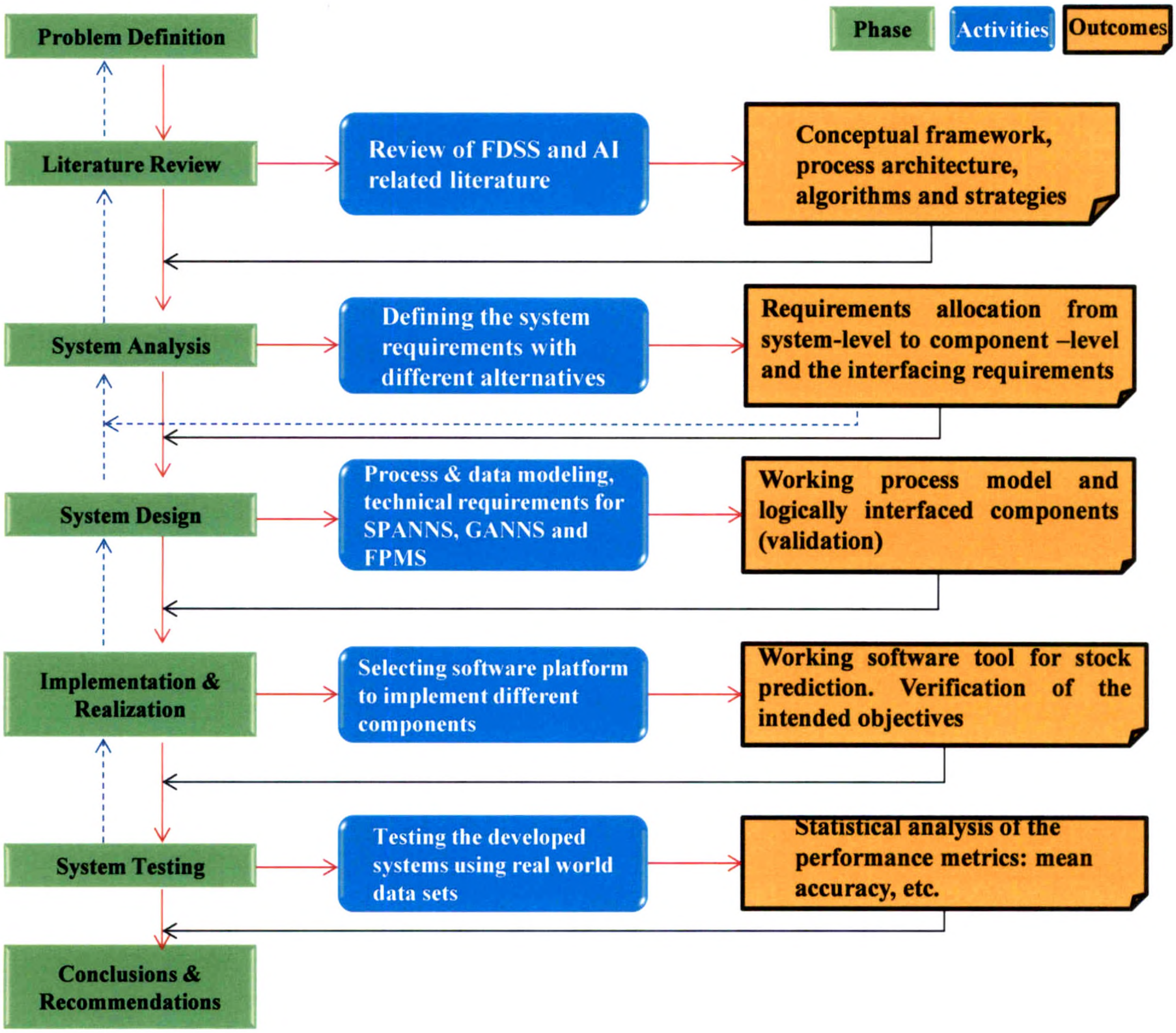


Figure 3.1: Research Methodology.

3.2.3 System Analysis

The study analyzed the previous researches related to DSS on time series predictions from the system-level architecture perspectives. Based on analysis of systems designs in previous studies, the study defined the system-level architectures as a blue print for the system realization. Additionally, domain problems were also investigated for the techniques including ANN, GA and FGP used in smoothing of time series modeling and active portfolio management system to generate the idea for a better choice of system design from system level to component level and interfacing requirements.

3.2.4 System Design

The design phase is deals with describing of task which are to be performed by system of meeting the proposed system requirements. According to the defined architecture in the previous phase, the study defined component-level requirements and interfaces, which were essential for all components to function internally and together as a system.

3.2.5 Implementation and Realization

System implementation elaborated the constructed systems to be applied and tested on a selected dataset to demonstrate the system performance. Each system has been implemented using a suitable software platform as discussed in the following chapters in detail. The systems designed have all possible capabilities to keep them as independent as possible and to exploit rapid software updating needs.

3.2.6 System Testing

System testing was accomplished by performing a validation of the implementation and demonstrated the expected capabilities set forth as a part of the outcome of this research. Additionally, this study ensures that the system is in compliance with the defined requirements and specifications as envisioned. In this phase, the developed system was intensively tested using historical data of the DJIA and NASDAQ indices for more than twelve years. The study used several error measures to evaluate the prediction capabilities of the proposed systems including Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). The RMSE and MAPE were then compared to assess the precision of the results and performance evaluation. Also, FPMS was tested on DJIA data to construct an efficient portfolio.

3.2.7 Conclusions and Recommendations

The study successfully designed two systems (SPANNS, GANNS) to predict stock market price movements and a third (FPMS) for active portfolio management. The hybrid systems consisted of the signal processing combined with ANN and GA with ANN techniques. The FPMS combined quantitative finance model formulation using goal programming (GP) and fuzzy set theory. The proposed systems should enhance the effectiveness of decision making for both individual investors as well as practitioners.

3.3 DATA DESCRIPTION

Since the focus of this study is to design and develop forecasting and portfolio management system, the study did not require any primary data. Therefore, secondary data of Dow Jones Industrial Average (DJIA) and National Association of Security Dealers Automated Quotations (NASDAQ) was collected from the United States Market. The characteristics of the data consisted of seven features: Date, Low, High, Open, Close, Volume and Adjacent Close for forecasting systems. The variables of data for web based portfolio management system (FPMS) included Stock, Beta, Dividend, P/E Ratio, Analyst Rating, 1 Year, 3 Year, and 5 Year Return.

3.3.1 Data Collection

Data used in developing the models was collected from the online source Yahoo Finance (http://www.finance.yahoo.com/) and covers the period from March 01, 2000 to Feb 02, 2012.

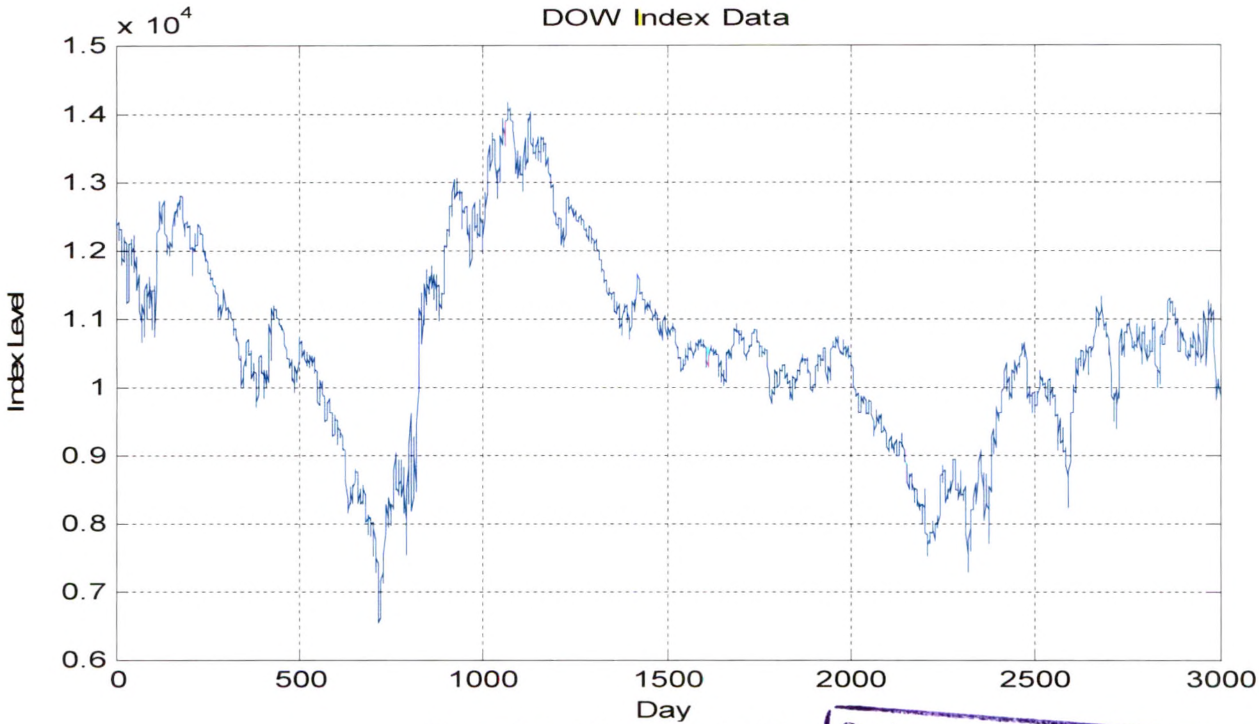


Figure 3.2: DOW Historical Data.

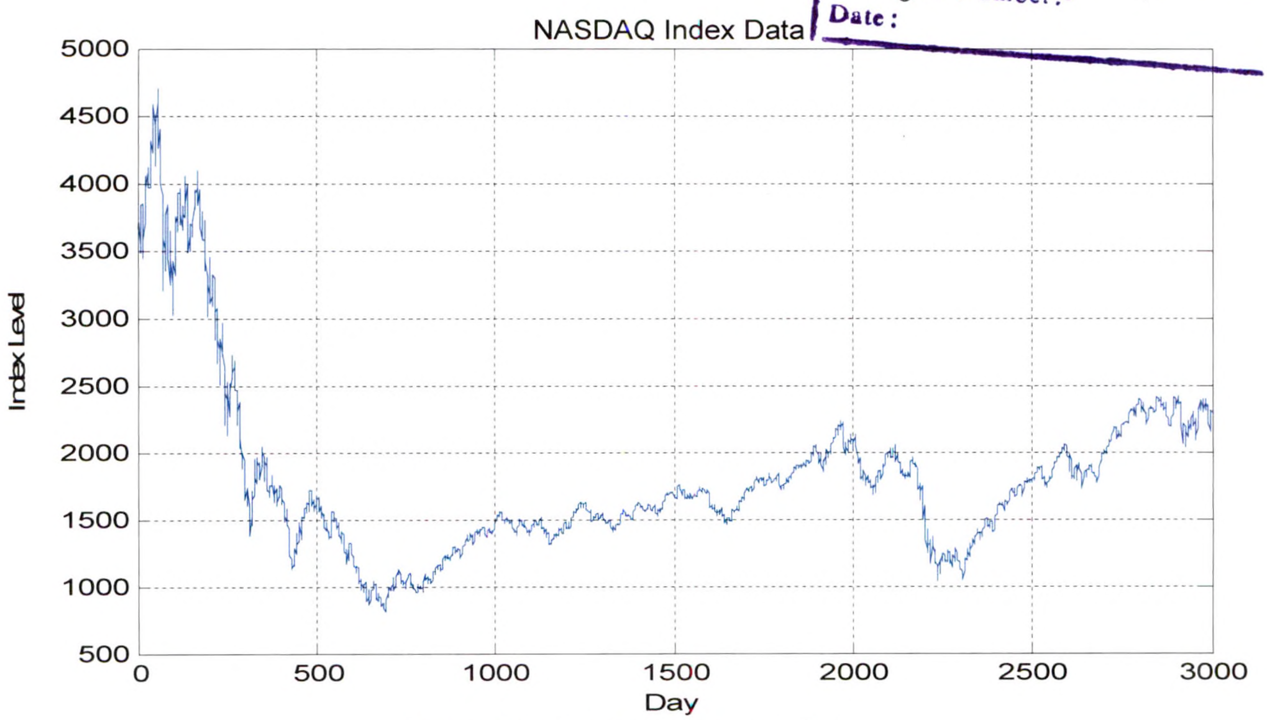


Figure 3.3: NASDAQ Historical Data

The historical trends and patterns of selected data set are given in Figures 3.2 and 3.3. The study attempts to replicate such treads by combining techniques in proposed forecasting models so that investors can make a better decision to invest in the stock market.

The trends in time series data are used to understand past behaviors, as well as, forecasting and planning. A sample data set of DOW30 and NASDAQ100 for the stock market forecasting systems is shown in Tables 3.1 and 3.2 respectively. A financial data set for fuzzy portfolio management is given in Table 3.3. Trends of historical data as shown in Figures 3.2 and 3.3 exhibited highly nonlinear trends, which are difficult to predict using techniques like ARIMA. Although techniques like ARIMA is applied successfully for short term forecasting, yet do not capture long term trends precisely, as discussed in the previous chapter. Therefore, proposed forecasting systems used two combined techniques for improved forecasting.

Table 3.1

A Sample Data of DOW30

Date	Open	High	Low	Close	Volume	Adj. Close
2/2/2012	12716.54	12785.49	12650.24	12705.41	4120920000	12705.41
2/1/2012	12632.76	12826.51	12632.76	12716.46	4504360000	12716.46
1/31/2012	12654.78	12756.05	12542.85	12632.91	4235550000	12632.91
1/30/2012	12659.32	12679.83	12492.18	12653.72	3659010000	12653.72
1/27/2012	12733.72	12749.24	12591.21	12660.46	3860430000	12660.46
1/26/2012	12757.48	12884.63	12679.00	12734.63	4522070000	12734.63
1/25/2012	12673.78	12794.95	12537.25	12756.96	4410910000	12756.96
1/24/2012	12708.44	12753.02	12551.78	12675.75	3693560000	12675.75
1/23/2012	12720.17	12806.98	12620.20	12708.82	3770910000	12708.82
1/20/2012	12623.83	12763.84	12568.35	12720.48	3912620000	12720.48
1/19/2012	12578.19	12678.62	12518.48	12623.98	4465890000	12623.98
1/18/2012	12474.77	12607.71	12424.33	12578.95	4096160000	12578.95
1/17/2012	12423.12	12607.44	12423.12	12482.07	4010490000	12482.07
1/13/2012	12469.96	12469.96	12288.44	12422.06	3692370000	12422.06

Table 3.2						
A Sample Data of NASDAQ100						
Date	**Open**	**High**	**Low**	**Close**	**Volume**	**Adj Close**
2/2/2012	2854.10	2868.23	2849.40	2859.68	1913430000	2859.68
2/1/2012	2830.10	2855.73	2825.19	2848.27	2125720000	2848.27
1/31/2012	2825.76	2830.45	2798.77	2813.84	1786550000	2813.84
1/30/2012	2790.40	2816.85	2782.44	2811.94	1668970000	2811.94
1/27/2012	2797.66	2821.55	2797.24	2816.55	1707350000	2816.55
1/26/2012	2828.78	2834.30	2794.78	2805.28	1998970000	2805.28
1/25/2012	2803.23	2822.79	2788.95	2818.31	1918040000	2818.31
1/24/2012	2771.58	2788.38	2766.34	2786.64	1620690000	2786.64
1/23/2012	2786.21	2804.99	2769.82	2784.17	1652940000	2784.17
1/20/2012	2776.04	2787.20	2775.87	2786.70	1949660000	2786.70
1/19/2012	2779.74	2793.35	2777.17	2788.33	1959950000	2788.33
1/18/2012	2731.16	2769.71	2730.05	2769.71	1968940000	2769.71
1/17/2012	2736.34	2742.73	2721.03	2728.08	1664210000	2728.08
1/13/2012	2707.41	2712.93	2689.58	2710.67	1655960000	2710.67

3.3.2 Data Preprocessing

Data preprocessing includes data inspection, cleaning and selection. Before data is fed into an algorithm, it must comply with the quality and requirements set forth in a study. The success of a system outcome depends on data quality and preparation, and, therefore, setting up appropriate data filters is essential for redistribution, missing values, outliers, and any other irregularities. Since a system can exploit only certain data features, it is important to detect which data pre-processing and presentation works best. Data pre-processing steps are explained in chapter 4.

Table 3.3 Financial Data for Portfolio Management						
Stock	**Beta**	**Dividend**	**P/E Ratio**	**1 Year Return (%)**	**3 Years Return (%)**	**5 Years Return (%)**
AA	2.17	0.12	-13.87	58.57	-24.39	-11.21
AXP	2.11	0.72	27.08	67.18	-10.13	-0.53
BA	1.28	1.68	39.03	87.72	-5.47	6.36
BAC	2.4	0.04	-62.21	100.34	-26.56	-13.38
CAT	1.8	1.68	44.75	81.39	-1.96	9.97
CSCO	1.22	0	24.84	34.73	-0.89	8.55
CVX	0.63	2.72	14.64	19.15	2.44	11.37
DD	1.41	1.64	19.74	40.53	-4.70	-0.69
DIS	1.15	0.35	20.31	61.25	1.17	6.95
GE	1.59	0.04	17.8	47.73	-17.44	-9.51
HD	0.7	0.95	20.89	27.06	-1.83	0.89
HPQ	1.02	0.32	16.04	48.75	8.85	22.06
IBM	0.76	2.2	12.88	26.62	9.76	12.63
INTC	1.18	0.63	29.14	45.78	4.03	1.30
JNJ	0.57	1.96	14.95	28.62	3.52	1.64
JPM	1.13	0.2	20.17	36.11	-2.72	7.62
KFT	0.59	1.16	14.97	34.82	0.49	2.15
KO	0.6	1.76	18.88	31.89	4.83	7.89
MCD	0.62	2.2	16.27	29.53	15.06	21.28
MMM	0.77	2.1	18.57	49.37	3.19	4.50
MRK	0.84	1.52	6.68	61.41	-6.18	6.45
MSFT	0.97	0.52	16.07	47.63	1.15	4.70
PFE	0.7	0.72	13.81	33.67	-8.72	-4.48
PG	0.58	1.76	17.12	30.91	1.84	5.53
T	0.69	1.68	12.36	5.73	-8.36	6.59
TRV	0.65	1.32	8.42	34.51	2.49	11.20
UTX	0.98	1.7	18.17	54.71	5.49	9.87
VZ	0.64	1.9	24.38	7.04	-1.97	2.75
WMT	0.23	1.21	14.95	12.71%	7.15	5.18
XOM	0.42	1.68	17.07	2.94%	-3.56	5.35

3.4 SYSTEM DESIGN AND DEVELOPMENT METHODOLOGY

The system development research methodology can be categorized as applied science and belongs to developmental or formulative research. Software engineering and operations research is the specialty of system research with a focus on the design, development, analysis, measurement, and improvement of software systems (Nunamaker et al., 1991). The proposed methodology specific for system designing and development was implemented after the careful study of previous research work related to the topic. The quantitative research techniques for forecasting trends in the financial industry, specifically security markets including artificial intelligence (AI) techniques such as artificial neural network and genetic algorithm based systems are being developed for stock market prediction. The design of the systems was accomplished through the detailed design analysis and planning, as discussed in the following chapters.

This study comprises of three independent systems, and the design and development of each system is presented in separate chapters. Chapter 4 discusses a technique that combines signal processing and neural networks for designing and developing a predictive system for stock price movements. Chapter 5 proposes an intelligent system by combining an ANN with GA for stock prediction. The proposed system was compared with ANN system to demonstrate the effectiveness and robustness of the system using sample data. Chapter 6 suggests a web based fuzzy portfolio management system (FPMS), which combines a goal programming (GP) mathematical model and fuzzy set theory to accommodate the impreciseness of a real world portfolio management problem.

3.5 SUMMARY

This chapter highlights main components of the research methodology used in completing this study including research methodology description, data description, system design and implementation planning. The details of system designing and implementations are discussed in the following chapters. The chapter presents a planning for presenting a technique that combines signal processing and neural networks to develop a predictive model for stock market movements (Chapter 4); an intelligent system by combining an ANN with GA for stock prediction (Chapter 5); and a web based fuzzy portfolio management system incorporates the goal programming (GP) to formulate the mathematical model of the portfolio management problem, and fuzzy set theory to incorporate impreciseness in the model (Chapter 6).

CHAPTER 4

SPANNS FOR STOCK MARKET FORECASTING

4.1 INTRODUCTION

Stock market prediction involves the interaction of many variables, making forecasts very difficult and complex. Various techniques like the traditional statistical methods and expert systems have been used to predict stocks. However, these models require some basic assumptions or continued review and refinement as economic condition change; they have not proved to be very reliable (Trippi and Turban, 1996). Artificial Neural Networks (ANN) have demonstrated its capability of addressing problems with a great deal of complexity. An ANN was specifically designed to take a pattern of stock price data and generalize from it; this enhances the investor's forecasting ability (Trippi & Turban, 1996).

Several studies have shown that ANN provide a promising alternative approach to time series forecasting (Trippi and Turban, 1993; Sharda and Patil, 1990). The ANN's ability to forecast in a fuzzy sense is more appropriate than the other forecasting methods. Both Box-Jenkins models and ANN perform well for time series with long term memories. However, Box-Jenkins models provide slightly better results for short-term forecasting. However, with short-term memory, neural networks are found to outperform Box-Jenkins (Tang, et al., 1991). For cases of irregular time series, a neural network provides excellent forecasting. Neural networks can be trained to approximate the underlying mapping of the series. However, the accuracy of approximation depends on a number of factors such as neural network structure, learning method, and training procedure.

Signal processing uses adaptive filters widely for efficient filtering of signals. However, adaptive filters for of financial signals have not received much attention, and the area of "financial signals predictive models", signal processing theory has been rarely exploited and explored (Nair et al., 2010). Therefore, the investigation of the effectiveness of signal processing-based techniques in addressing predictive models for financial signals was very motivating for designing and developing systems for this area . Additionally, the testing of the robustness of ANN combined with signal processing techniques, especially stock market price movements would be an interesting and challenging opportunity. The proposed system will use the input feature vectors to the Multi-Layer Perceptron (MLP) network as k-element vector of stock index close day entries. The classes of vectors are modeled as the last entry in each vector, after mapping them to a suitable representation that meets MLP input output layer requirements. An archived data, of Dow 30 and Nasdaq 100 indices for more than twelve years, was used for training and testing the proposed model. The results strongly supported the effectiveness of the proposed model.

Thus, the proposed system combines signal processing and neural networks to develop a predictive model for tracking stock market movements and forecasting. Additionally, the study advanced the model to develop an integrated system that is capable of handling different decision making situations such as stock price movements of open, close, low and high. Furthermore, the study ensured the extension of n-day future prediction, effect of signal processing on the prediction reliability and the accuracy.

4.2 DESIGN AND DEVELOPMENT OF SPANNS

This study proposes a Signal Processing based Artificial Neural Network System (SPANNS). It incorporates Signal Processing/Gaussian Zero-phase (GZ) filter and Artificial Neural Networks/Multi-Layered Perceptron (ANN-MLP) for forecasting of stock price movements. The overall framework of the proposed approach is shown in Figure 4.1.

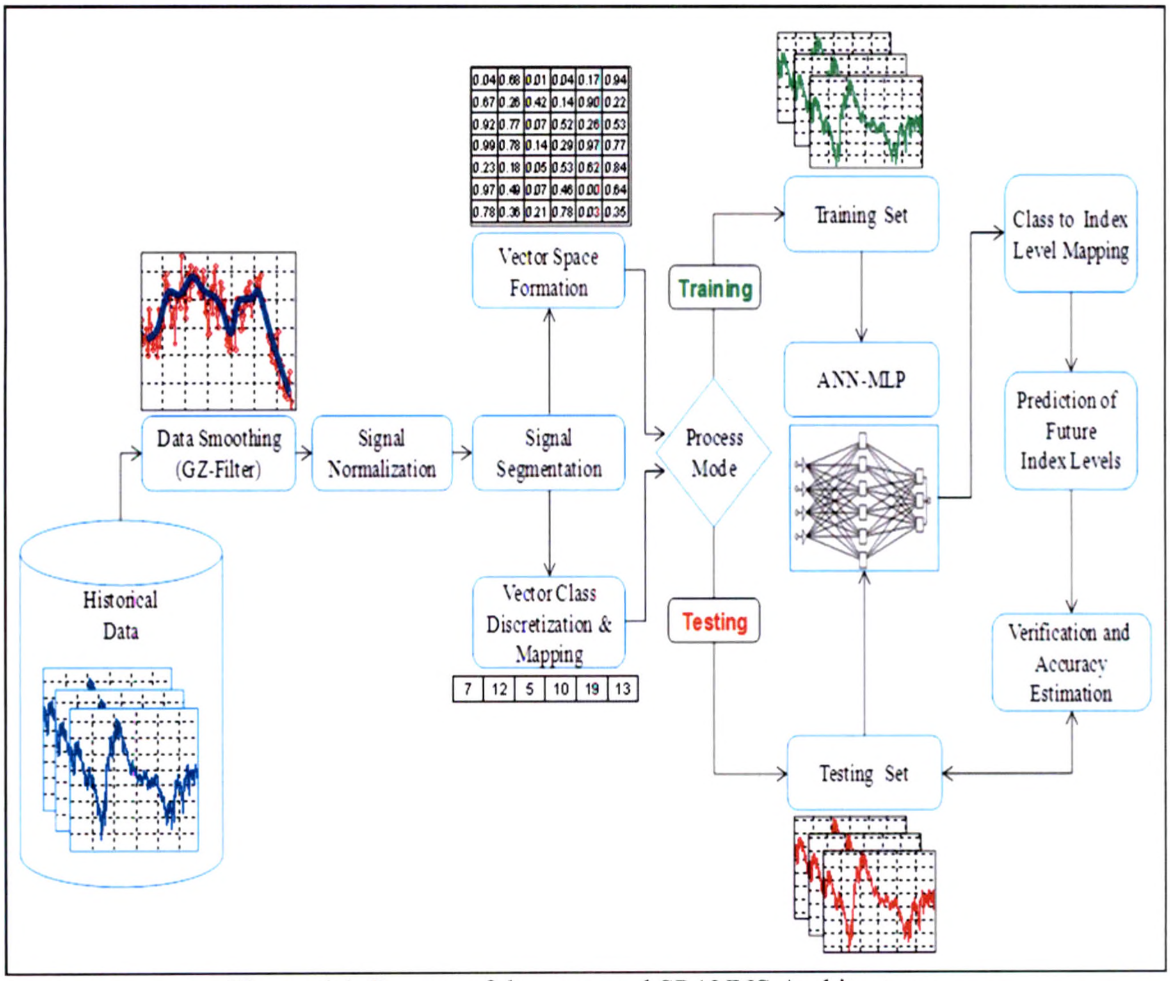


Figure 4.1: Process of the proposed SPANNS Architecture.

4.2.1 Signal Processing

Time-series analysis is similar to Statistical Digital Signal Processing (Signal Processing) in modern times. However, there are some differences exist at certain levels, but both techniques are identical for all practical purposes (Proakis & Manolakis, 2005). Signal processing is one of the time-series analysis technique which involve processing of single and multi-dimensional time series via a spectrum of techniques, filters and algorithms. Depending on the sought objective, input signal can be processed with low-level, intermediate, and high-level processing methods. Low-level methods are concerned with mainly noise reduction (filtering), signal analysis, decomposition, etc. Linear/non-linear filters, convolution, segmentation are some examples of low-level methods. On the other hand, intermediate-level methods include signal modeling, feature extraction and dimensionality reduction. The examples of this technique are Fast Fourier Transforms (FFT), wavelet decomposition, probabilistic/statistical-based, principal component analysis (PCA). The high-level methods are concerned with clustering, classification and recognition problems; examples include: K-Means, soft-computing, AI methods, etc.

The fundamental concept of digital-signal filtering is a convolution, a mathematical way of combining two signals to form a third signal, which is considered one of the single most important techniques in the Signal Processing. Since a convolution relates the three signals of interest: the input signal, the output signal, and the impulse response, which provides the mathematical framework for Signal Processing (Smith, 2002). Mathematically, convolving is the operation of multiplying the coefficients of two polynomial functions. Where, the coefficients of two functions can be denoted as the two vectors u and v. Additionally, the lengths of these two vectors can be denoted as m and n

respectively. Consequently, the output vector of the convolution operation of the two input polynomials will be a length of $m+n-1$ and the kth element in this output vector can be expressed as:

$$w(k) = \sum_{j} u(j)v(k+1-j) \tag{4.1}$$

Based on the convolution theory (MatLab, 2012), the convolution of two sequences can be obtained by the product of their Fourier transform as follows:

Assuming x as the first sequence, y as the second sequence, where it assumed that both sequences have the same length, otherwise they need to be aligned by the zero-padding operation. Further, let X, Y be the discrete Fourier transform (DFT) of the sequences, respectively, then the convolution operation of these two sequences can be obtained as:

$$w = FFT^{-1}(X \bullet Y) \tag{4.2}$$

Where, W is the output signal of the convolution operation; FFT^{1} is the inverse Fourier transform, and X•Y is the element-wise product of the two signals.

The digital-signal filtering utilizes the convolution theory by designing a filter impulse response (FIR) denoted as h, and convolving it with the input signal x to produce the filtered signal y as follows:

$$y(k) = h(k) * x(k) = \sum_{l=-\infty}^{\infty} h(k-l)x(l) \tag{4.3}$$

In this study, we are investigating the low-level methods based on convolution by utilizing the Gaussian Zero-Phase Filter (GZ Filter).

4.2.2 Data Smoothing

Data (Signal) smoothing is a way to eliminate "noise" and extract real trends and patterns in a historical data series. Gaussian Zero-Phase Shift filter (GZ-filter) is a very effective digital signal filter for data smoothing (Rababaah, 2009). Therefore, a GZ-filter is proposed to be used as the smoothing model of the stock market data signal as the first step before further processing of segmentation, feature vector modeling, training and classification, etc. The concept of GZ-filter is to estimate the signal level at each time instance by computing a kernel of Gaussian-weighted neighborhood of the surrounding data points. A kernel size of 3 was demonstrated using the Gaussian PDF to modulate the original signal as a linear combination of the kernel Gaussian weights by the neighboring data points (Figure 4.2). According to the formula (4.4) below:

$$GZ(S(t), \Delta t) = \sum_{t-\Delta t}^{t+\Delta t} G_{pdf}(t) S(t) \tag{4.4}$$

Where, *S(t)*: the input noisy signal, *t*: time, Δt: time interval considered to compute the de-noised signal, G_{pdf}: Gaussian probability distribution function. The uniqueness of the GZ filter lies in retaining is the phase of the original signal as opposed to conventional filters such as moving average or median filters. This means the peaks of the original signal are guaranteed to align with the filtered signal which could be critical if one is interested to identify the exact instances where the signal has abrupt changes. Figure 4.2 demonstrates this fact by illustrating the process diagram of the GZ filter.

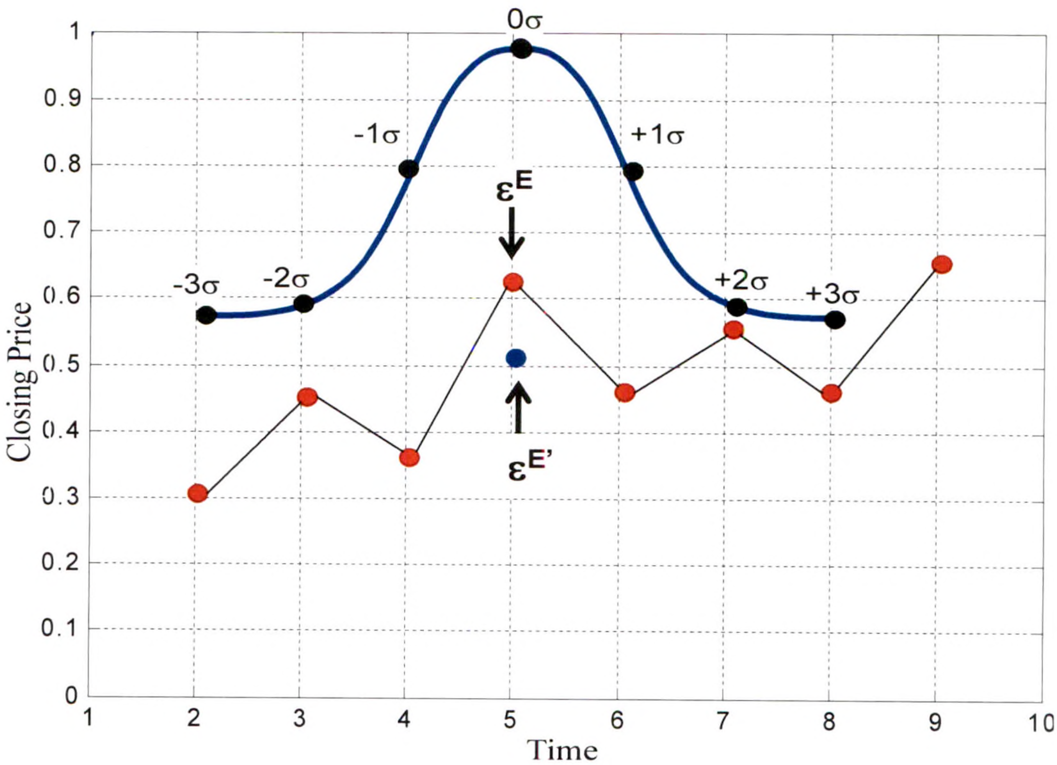


Figure 4.2: The GZ filter Kernel.

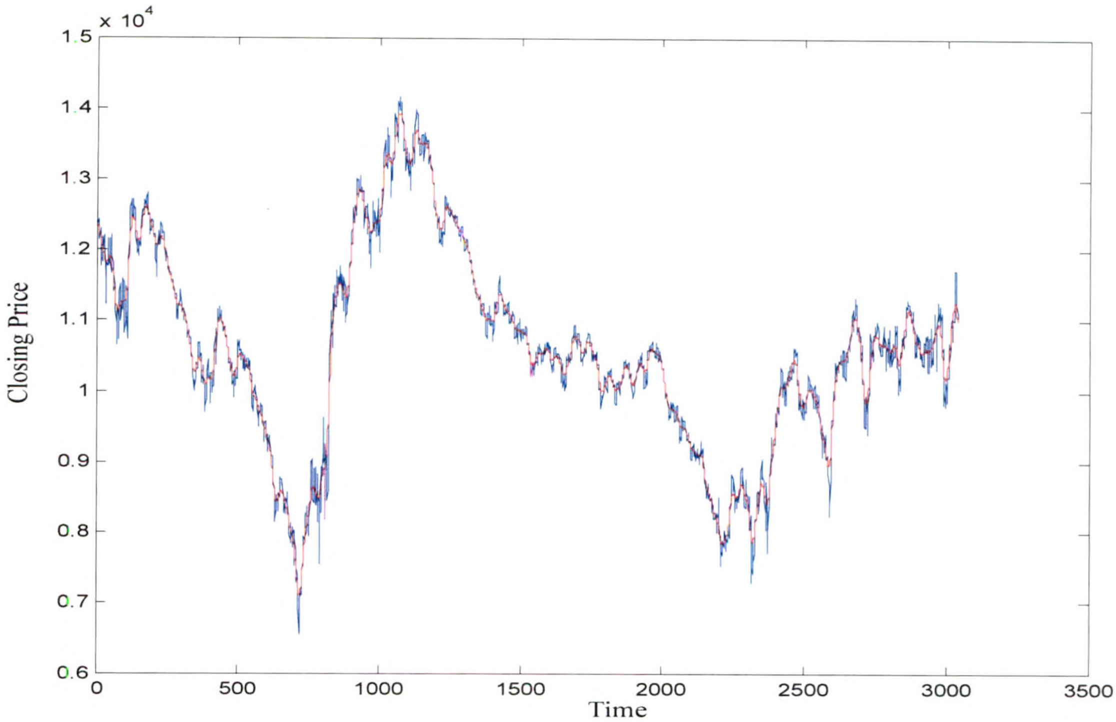


Figure 4.3: Index Data Smoothing Results with GZ-Filter.

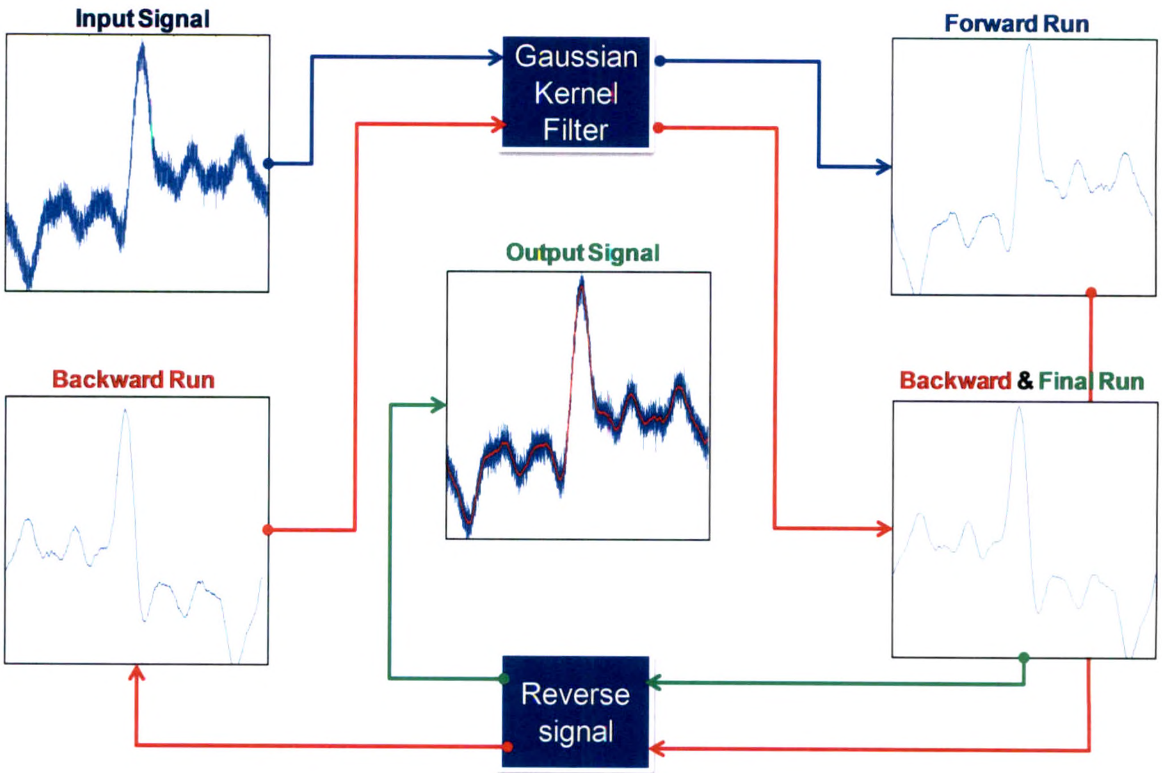


Figure 4.4: The Process Diagram of the GZ Filter.

4.2.3 Data Normalization

In this step, the data are normalized (Figures 4.5 & 4.6) to the range [0, 1]. This is important since the Artificial Neural Network – Multi-Layered Perceptron (ANN-MLP) model requires normalized input vectors. Mathematically, the normalization is expressed as:

$$S(i) = \frac{S(i)}{\max(S)} \tag{4.5}$$

Where, *S(i)* is the signal level at index *i* and *S* is the entire signal and *max* is the maximum level of the signal.

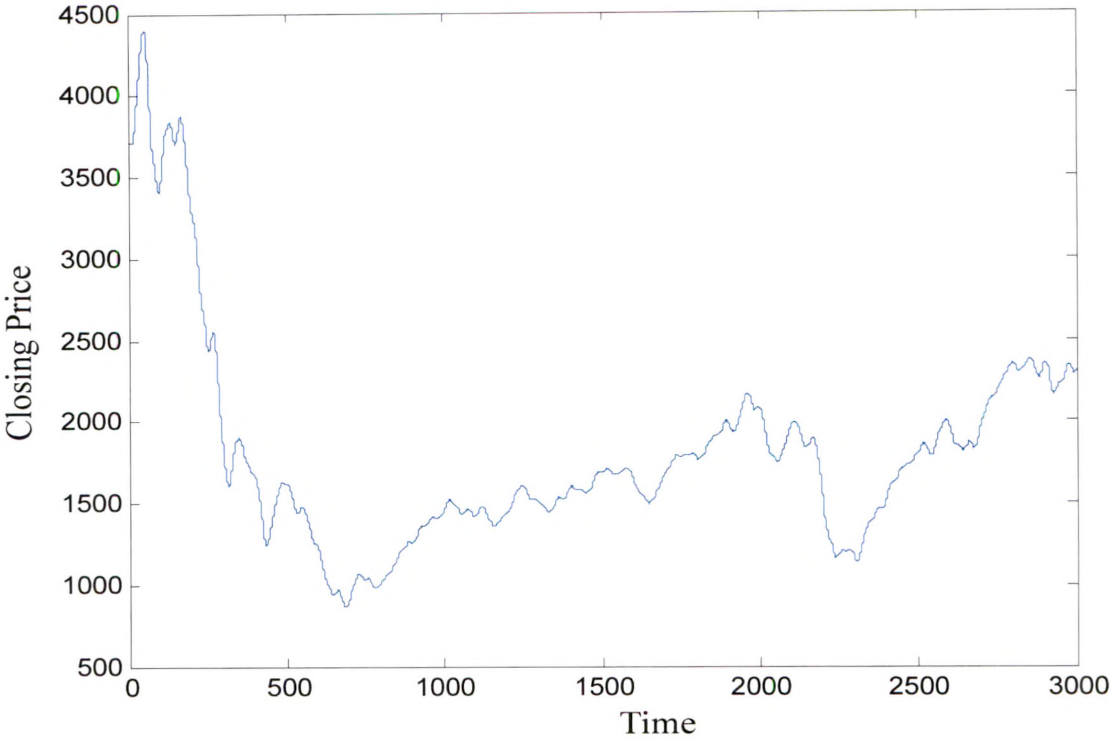


Figure 4.5: The Data before Normalization.

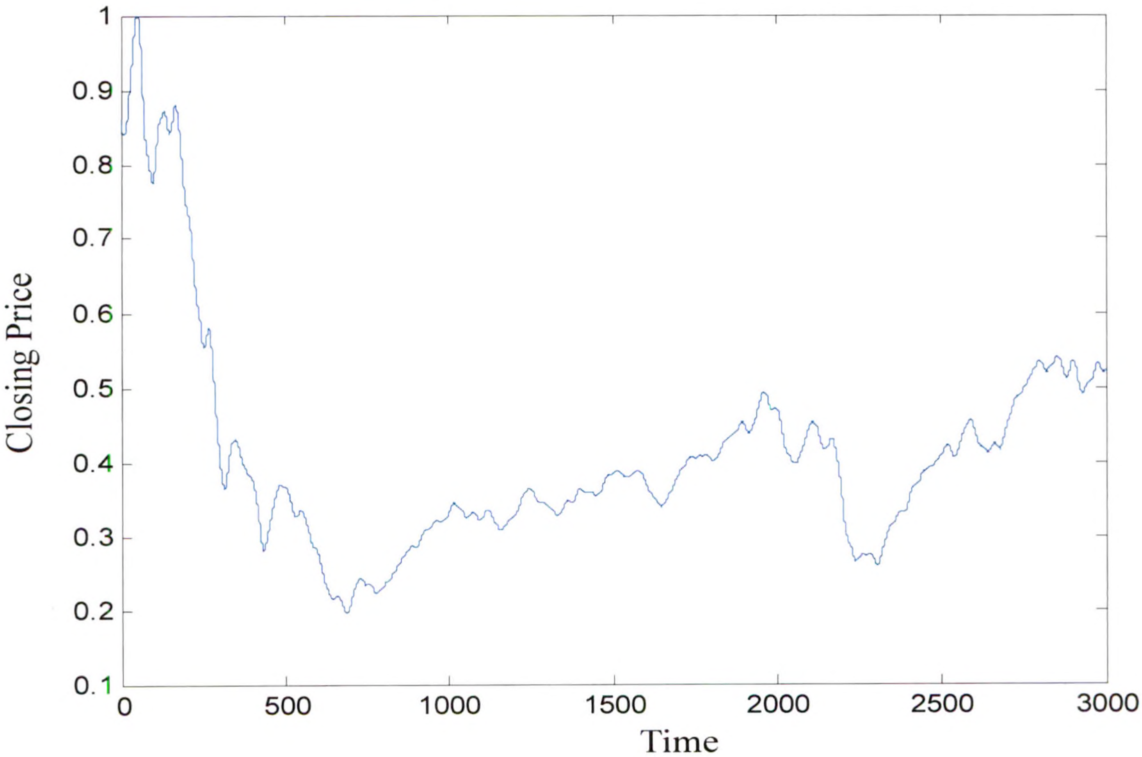


Figure 4.6: The Data after Normalization.

4.2.4 Data Segmentation

The data are then segmented into m-sized (Figure 4.7) vectors that represent the feature vectors used to train, and test the ANN-MLP model. *Vector Space Formation*: in this step, the first m-1 elements in the segmented vectors are used as input feature vectors and the m^{th} element is used as the vector class in supervised training.

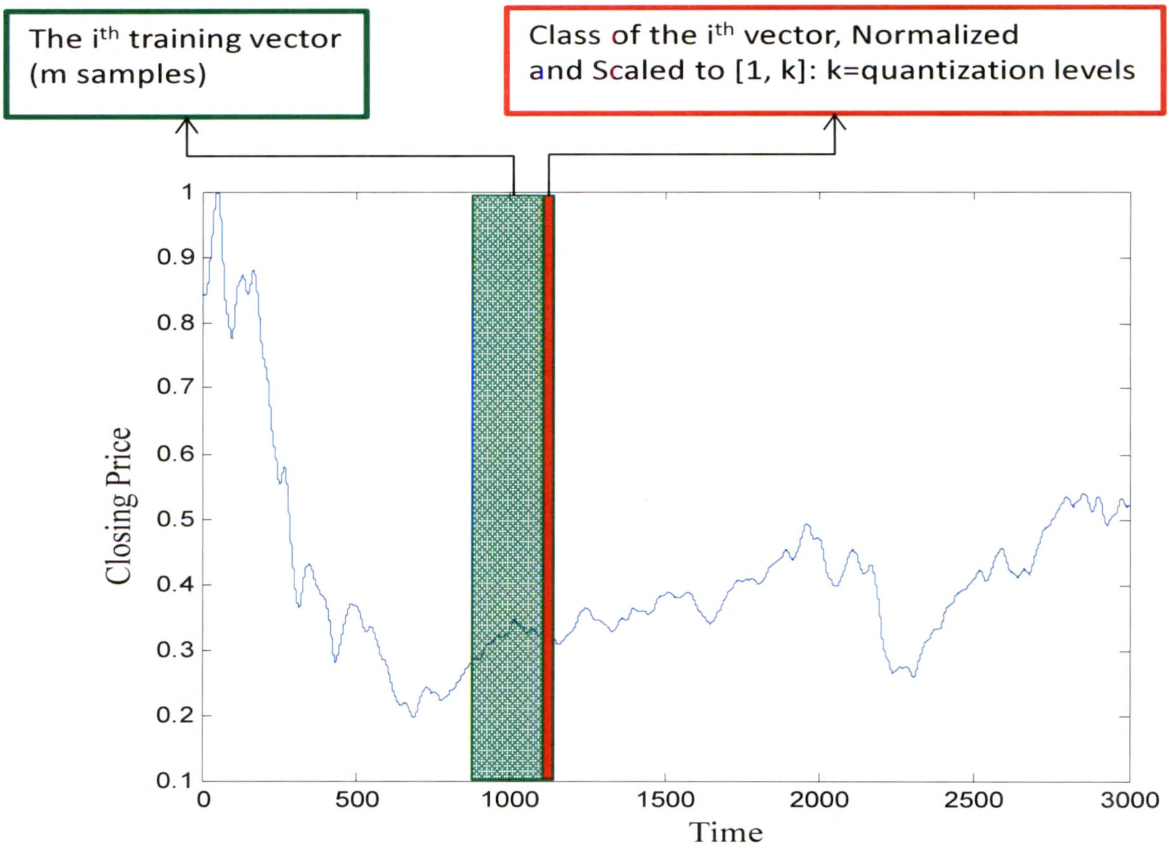


Figure 4.7: Data Segmentation Stage to Generate the Training/Testing Sets for ANN.

4.2.5 Vector Class Discretization

After normalizing the data (signal) level to the range [0, 1] and segmenting it into vectors, we need to assign each vector a class label. The range [0, 1] is continuous, therefore, depending on the desired resolution; a set of k-classes can be established. In this study, we assumed 20 classes as follows: [0, .05) → class 1, [0.5, 0.1) → class 2, …, [0.95, 1] → class 20. The formula to map the index level into a discrete training class is given as:

$$S_{\min} = \min(S),\ S_{\max} = \max(S),\ D_{index} = \frac{S_{\max} - S_{\min}}{k},\quad C(i) = \left\lfloor \frac{S(i) - S_{\min}}{D_{index}} \right\rfloor \tag{4.6}$$

Where, D_{index} is the uniform increment in index levels, k is the number of levels/classes, $C(i)$ the mapped ith class from the ith index level $S(i)$. Figures 4.8-4.11 illustrates samples of signal discretization with different k-levels.

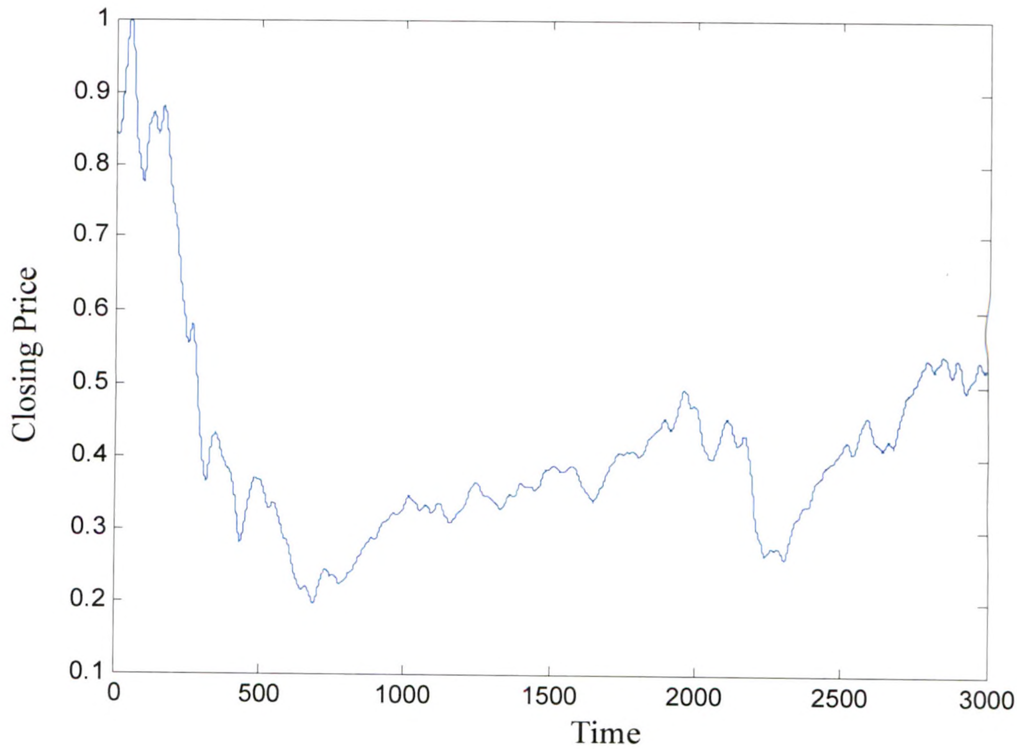


Figure 4.8: Signal Discretization with 10 k-levels.

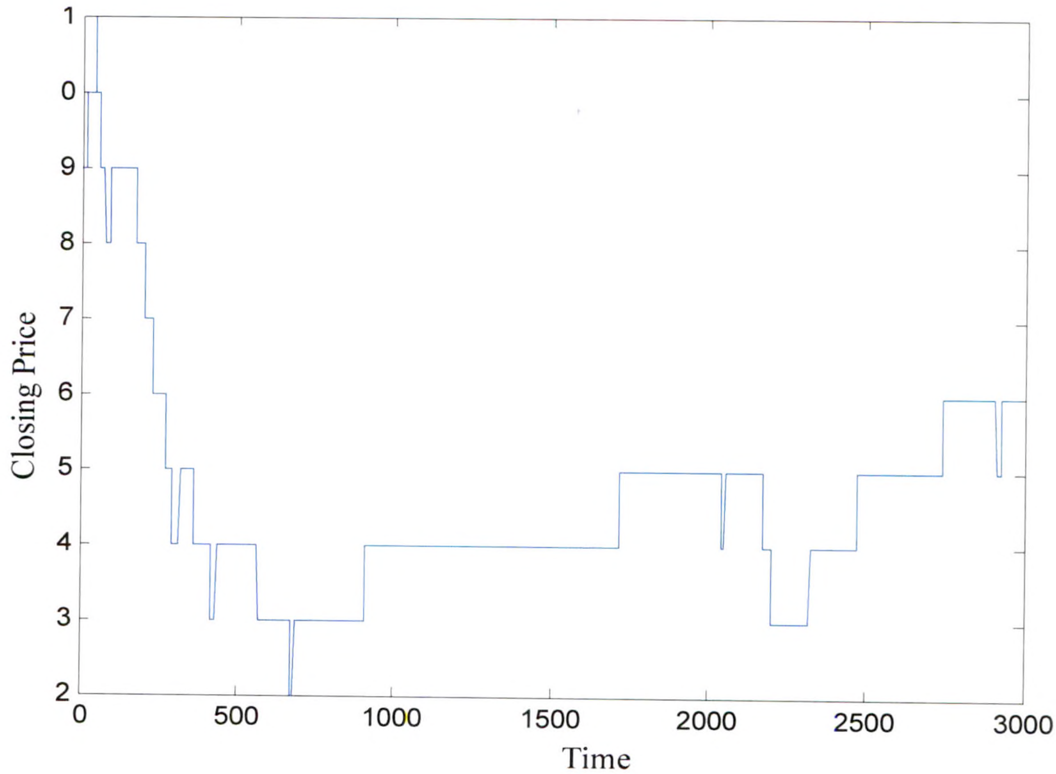


Figure 4.9: Signal Discretization with 40 k-levels.

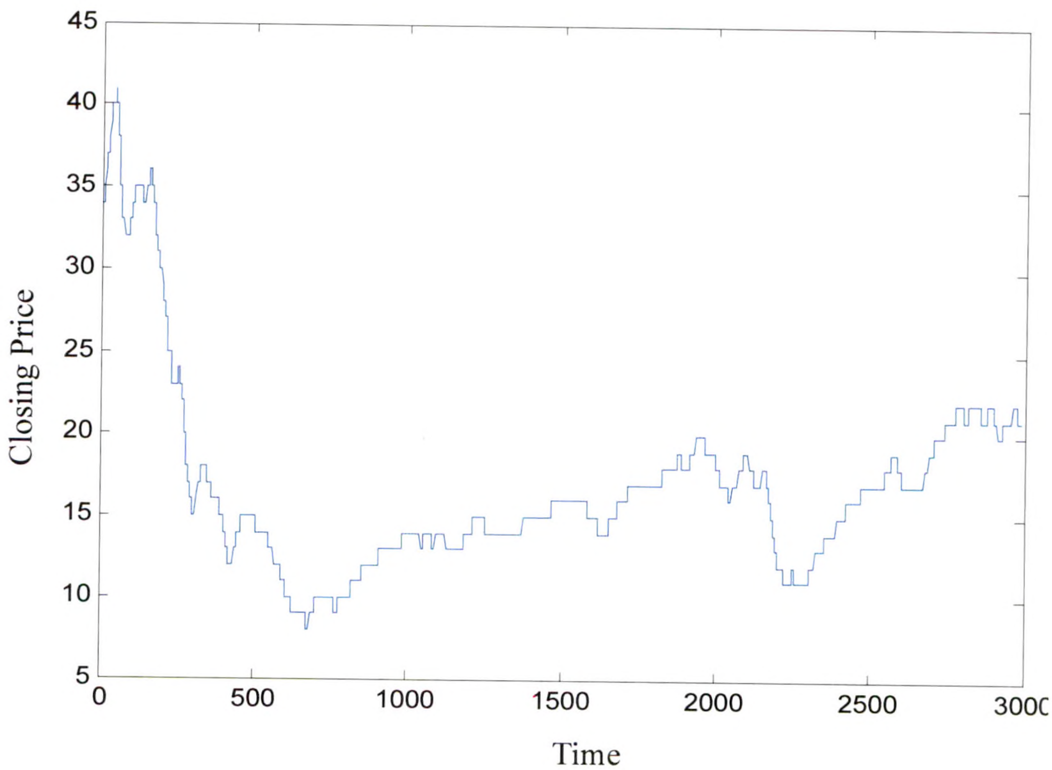


Figure 4.10: Signal Discretization with 80 k-levels.

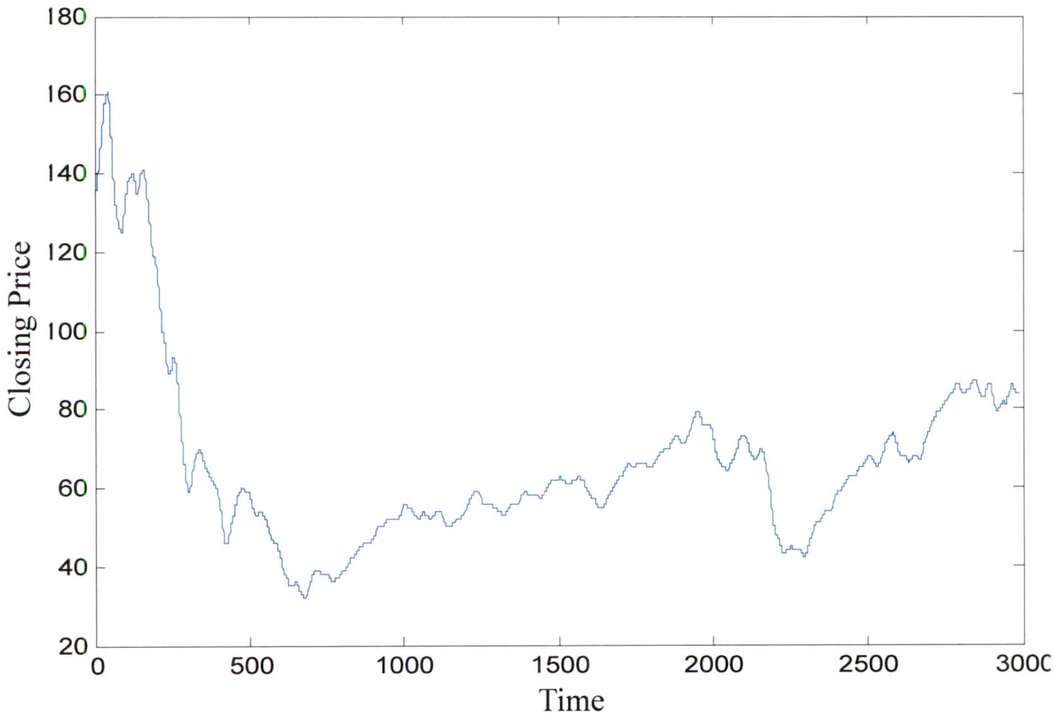


Figure 4.11: Signal Discretization with 160 k-levels.

The preceding stage or phase of data signal processing (DSP) discusses the process of data transformation from raw data into the desired form for the next stage of MLP for training and classifying the data. This process is done sequentially because the model developed is a sequential model, as opposed to parallel processing model. In other words, the MLP processing stage begins after DSP processing stage has successfully completed.

4.2.6 Artificial Neural Networks

A multilayer perceptron (MLP) is a feed-forward artificial neural network model that trained using a supervised training algorithm. The basic functional unit in the network architecture of MLP is the perceptron (Figure 4.12), which computes weighted sum of the components of the input vector and subtracts a threshold value (θ) from it. The result is then passed to an activation function, which can be Hard-limiting, or Sigmoid as shown in Figure 4.13. The sigmoid function is very essential in the learning process as it has the property of being differentiable which is a must requirement for the derivative-based optimization techniques such as the gradient descent (Hush & Horne, 1993).

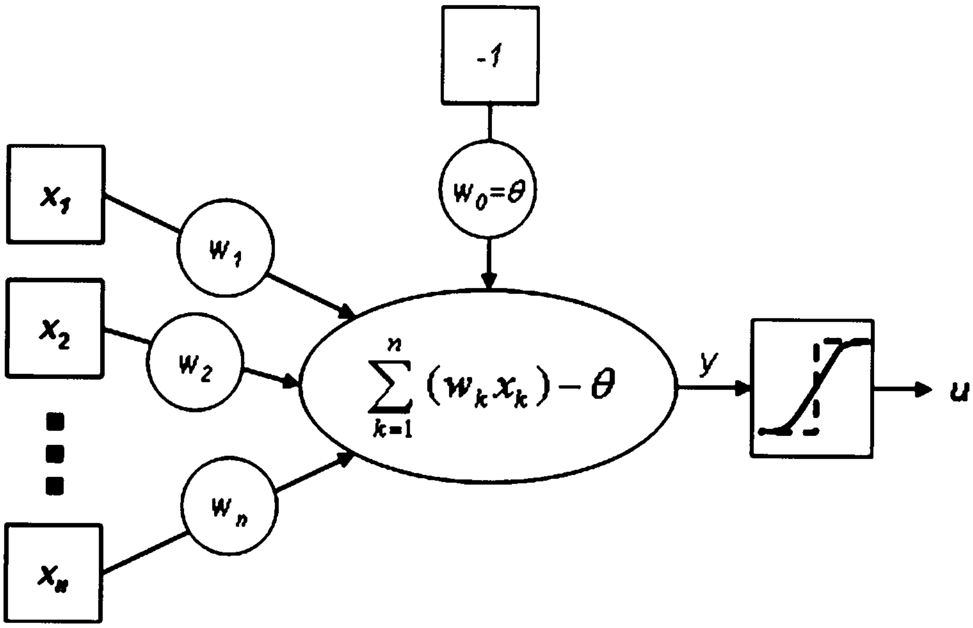


Figure 4.12: The Perceptron, the functional unit in ANN.

The basic functionality of a perceptron involves being as a discriminant function in a pattern recognition problem, where it performs a nonlinear transformation from the input space into the output space. Also, it is used as a binary logic unit that is capable of implementing many logic functions including AND, OR, and NOT. The capabilities of a single perceptron are limited to problems that are linearly separable, i.e., the boundaries of different classes can be separated by a linear function as depicted in figure 4.14.

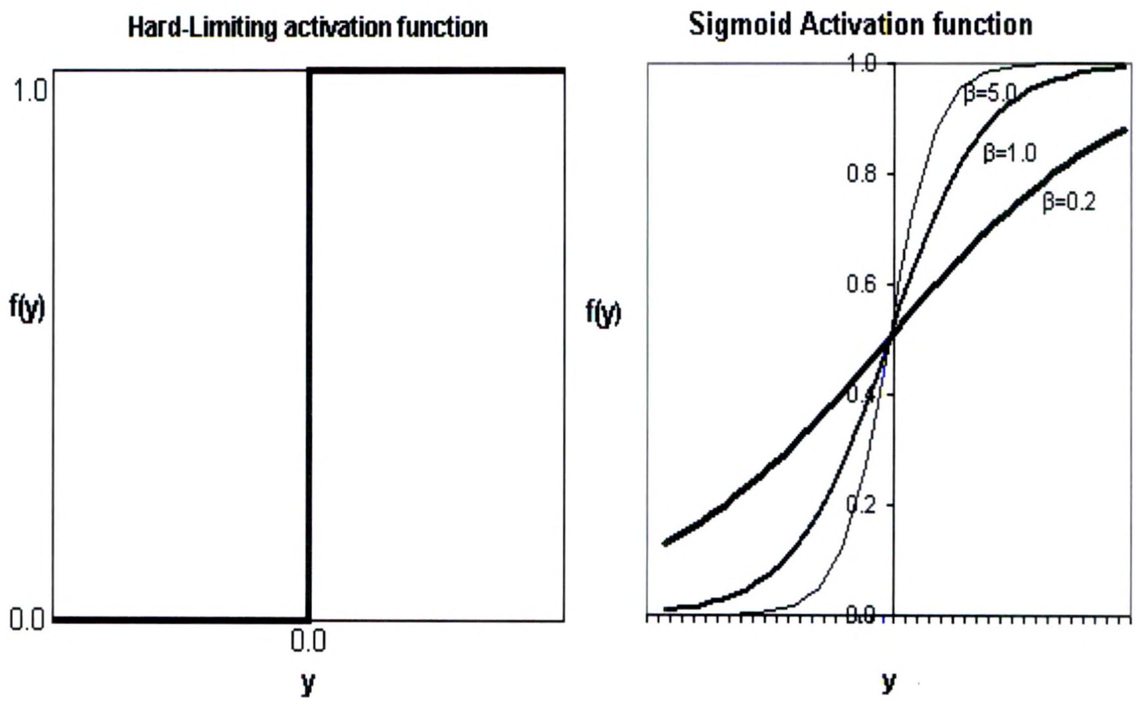


Figure 4.13: Two types of Activation Functions in MLP Neural Networks.

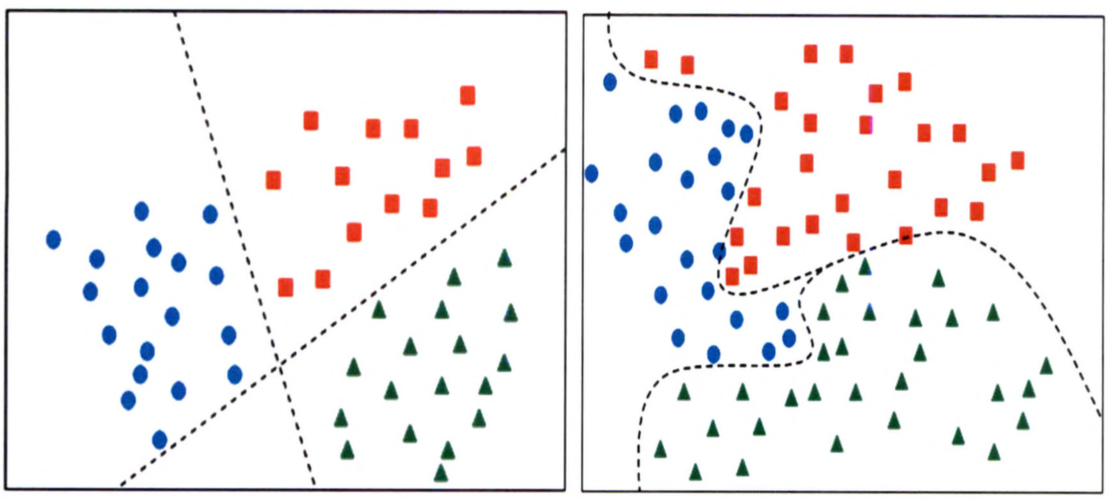


Figure 4.14: Input feature spaces that demonstrate, Left: linearly separable, right: linearly inseparable vector space.

The power and capabilities of the perceptron is greatly extended by the multi-layered architecture with the back propagation learning algorithm. This architecture is illustrated in figure 4.15.

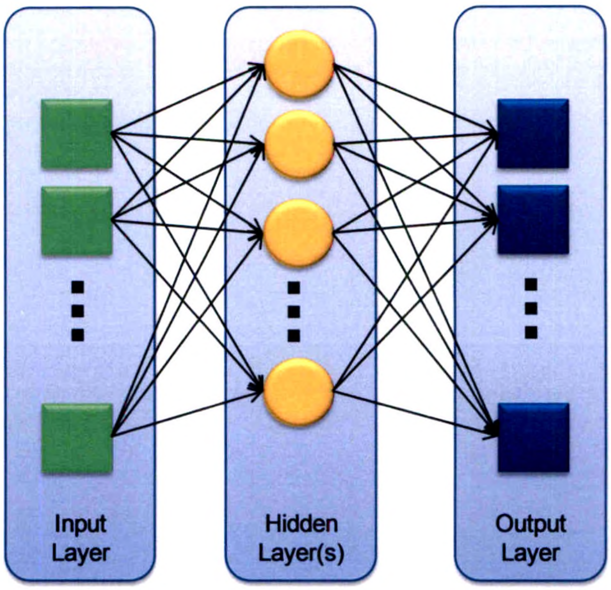


Figure 4.15: ANN Typical Architecture.

The structure of the MLP (Figure 4.15) consists of three parts: Input layer, the first layer of perceptrons that receives the input vector. Hidden Layers, located between the input and the output layer; the output of the input layer is fed into the first hidden layer; the output of the first layer is fed into the next hidden layer and so on. The number of hidden layers needed varies based on the complexity of the application. Often the nodes (perceptrons) of the adjacent layers are fully connected. Output Layer, the multiple nodes in the output layer typically correspond to multiple classes for multi-class pattern recognition problem. The most common approach in the learning process is the gradient descent algorithm, in which a gradient search technique is used to find the network weights that minimize a criterion function. The criterion function to be minimized is the Sum-of-Square-Error. The convergence of the algorithm depends on a threshold error. The MLP outputs one class [1-20] corresponding to a particular index level [0, 1], which is the Class to Index Level Mapping.

4.2.7 MLP Learning Algorithm (Back Propagation)

The most common approach is the gradient descent algorithm, in which a gradient search technique is used to find the network weights that minimize a criterion function. The criterion function to be minimized is the Sum-of-Square-Error (Haykin, 2003).

In the training process, the system is presented with an input vector and paired with an output vector; this process is called the supervised learning. In training, the network is given a preliminary set of data from which it self organizes, detects patterns, and essentially reams. Once trained, the system is functional and ready to be applied to case data. During the training process, input data is fed to the network through the processing nodes in the input layer. Training occurs in several steps and over several iterations. The following training procedure summarizes the back propagation learning algorithm (Haykin, 2003).

Step 1: Initialization of Weights

Weights are initialized, and all synaptic weights and thresholds are set to be small random numbers.

Step 2: Presentations of Training Examples

After the initialization step, present the network with an epoch of training examples. For each example in the set, step 3 and 4 are repeated.

Step 3: Forward Feed

Let a training example in the epoch be [x(n), d(n)], where x(n) is the input vector, and d(n) is the desired output vector on the output layer. The activation potential and function signals of the network are computed, proceeding forward through the network, layer by layer, using the following relation system:

$$v_j^{(l)}(\text{n}) = \sum_{i=0}^{p} w_p^{(l)}(n) y_i^{(l-1)}(n) \tag{4.7}$$

$$w_0^{(l)}(n) = -1, \quad y_0^{(l-1)} = \theta$$

Where, $v^{(l)}$ is Vector of net internal activity levels of neurons, $w^{(l)}$ is synaptic weight vector of a neuron, $y^{(l)}$ is Vector of function signals of neurons, and $\theta^{(l)}$ is the Threshold of a neuron.

$$y_i^{(l)}(\text{n}) = \frac{1}{1+\exp(-v_j^{(l)}(n))} \tag{4.8}$$

If the neuron is the first hidden layer, then

$$y_i^{(0)}(\text{n}) = x_j(\text{n}) \tag{4.9}$$

If the neuron is in the output layer (l = L), then

$$y_i^{(L)}(\text{n}) = o_j(n) \tag{4.10}$$

Hence, the error is computed as

$$e_j(n) = d_j(n) - o_j(n) \tag{4.11}$$

Where, e_j is the j^{th} error vector where, j = 1, 2, 3, …, n

Step 4: Back Propagation

Compute the local gradients of the network, proceeding backward, layer by layer.

In the output layer

$$\delta_j^{(L)}(n) = e_j^{(L)}(n)o_j(n)[1 - o_j(n)] \tag{4.12}$$

Where, $\delta^{(l)}$ is a Vector of local gradients of the neurons.

In a hidden layer

$$\delta_j^{(l)}(n) = y_j^{(l)}(n)[1 - y_j^{(l)}(n)]\sum_k \delta_j^{(l+1)}(n)w_{kj}^{(l+1)}(n) \tag{4.13}$$

Hence adjust the weights:

$$w_{ji}^{(l)}(n+1) = w_{ji}^{(l)}(n) + \alpha[w_{ji}^{(l)}(n) - w_{ji}^{(l)}(n-1)] + \eta\delta_j^{(l)}(n)y_j^{(l-1)}(n) \tag{4.14}$$

Where, η is the learning-rate parameter and α is the momentum constant.

The tradeoff of η is a rough approximation for faster processing, or a Better approximation for slower processing. In the case where a high learning-rate is chosen, α is introduced to stabilize the system.

Step 5: Iteration

Iterate the computation by presenting new epochs of training examples to the network until the free parameters of the network stabilize their values with minimum average squared error for the entire trained set. The order of presentation of training examples should be randomized for all epochs. The momentum and the learning-rate parameter are typically adjusted (and usually decreased) as the number of training iterations increases.

Some points need to be considered in MLP model:

- The weights typically are initialized to small random values, which gives the algorithm a safe start.
- A simple heuristic technique is used to choose learning rates, which is to make the learning rate for each node inversely proportional to the average magnitude of vectors feeding to that particular layer.
- Termination process may include any of the following criteria:
  - A target of minimum gradient is reached;
  - The Sum of Squared Error falls below a fixed threshold;
  - All training samples have been correctly classified;
  - A fixed number of iterations has been performed; and
  - A cross validation has been successful.

As usual, the available input space is randomly partitioned into a training set and a test set. The training set is further partitioned into two subsets: a subset used for estimation the model (model training), and a subset used for evaluation the performance of the model (model validation); the validation subset is typically (10 to 20)% of the training set. The goal of this technique is to validate the model on a data different from the one used for model estimation. The best model is chosen after this validation phase, then the chosen model is trained using the full training set (Haykin, 2003).

It is worth mentioning that the last approach (Cross Validation), which is not sensitive to the choice of the parameters as compared to all other approaches. This approach not only avoids premature termination, but also improves the generalization performance. However, this approach requires intensive computational.

At this point, the data is conditioned to be fed into the training stage where typically 80-90% of the data is utilized for training the MLP and 10-20% of the data is used for testing.

4.2.8 Verification

In the verification and accuracy estimation step, the output of the MLP and the real index levels are compared to estimate the prediction accuracy. The prediction accuracy is expressed as:

$$Accuracy = 1 - \frac{\sqrt{\sum_{i=1}^{n} [C_T(i) - C_P(i)]^2}}{n} \tag{4.15}$$

Where, C_T is the true (real) class of the ith vector, C_P is the predicted class of the ith vector and n is the number of sample vectors in the testing set. The training/testing data set generation and ANN training are depicted in Figure 4.16.

During the ANN training stage, finding an optimal vector size is important, where the mean squared error (MSE) is minimize. After conducting several experiments, a vector size of 20 yielded the minimum MSE. The results of these experimenters are plotted in Figure 4.17.

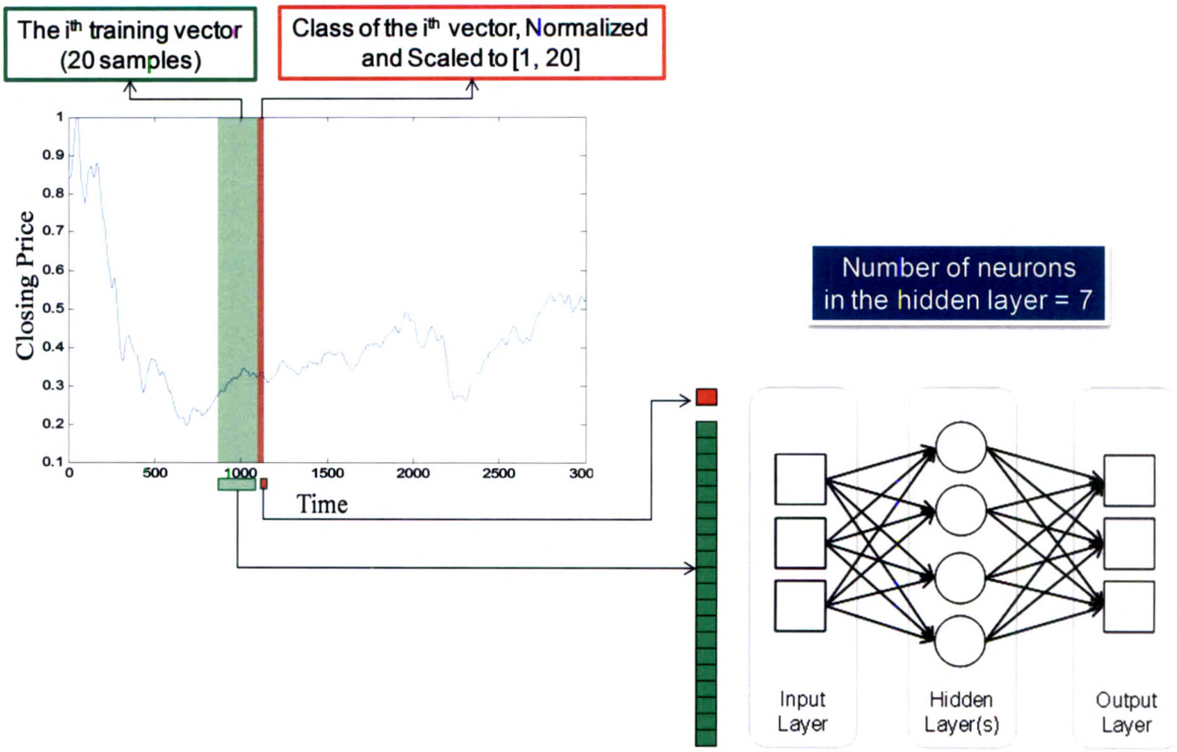


Figure 4.16: Training/Testing Vector Data Sets Generation and ANN Training.

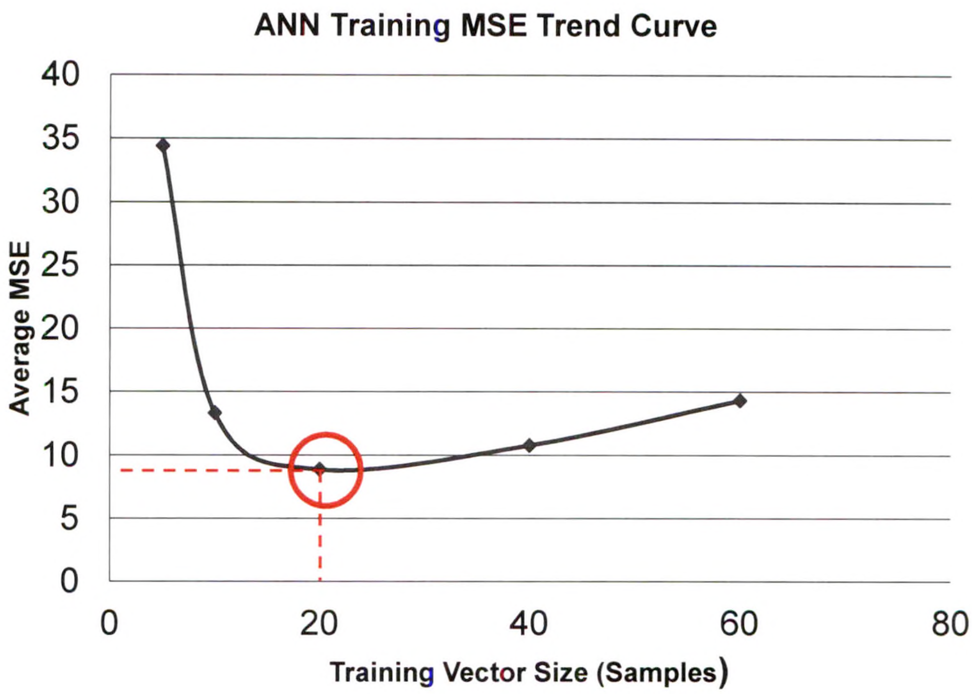


Figure 4.17: Finding the Optimal Input Size Vector for Training and Testing Sets of ANN.

4.2.9 Evaluation Criteria

There are several error measures used to evaluate the prediction models including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). In this study, we have used MAPE and RMSE to evaluate the performance of the proposed system and are as follows:

$$MAPE = \frac{1}{N}\left[\sum_{i=1}^{N}\frac{|AV_i - PV_i|}{AV_i} \times 100\right] \tag{4.16}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(AV_i - PV_i)^2} \tag{4.17}$$

Where, AV_i and PV_i are actual value and predicted value respectively for i^{th} instance and N is the total number of instances. If you lower the value of all the above measures, it will give better performance. MAPE is a measure which gives more stable result and is clear to understand and evaluate the models.

4.3 IMPLEMENTATION

The flow diagram of the system implementation is shown in Figure 4.18. As it can be observed, the system consists of four integrated stages of data processing.

Signal Processing

This stage is concerned with transforming the raw input signals into a consumable form that can be fed to the next stage of ANN. This stage contains four different operations: historical data, data smoothing with GZ-filter, signal normalization and signal segmentation. All of these operations are implemented as MatLab M-Files. These M-Files are connected to the GUI which will be discussed later in this section.

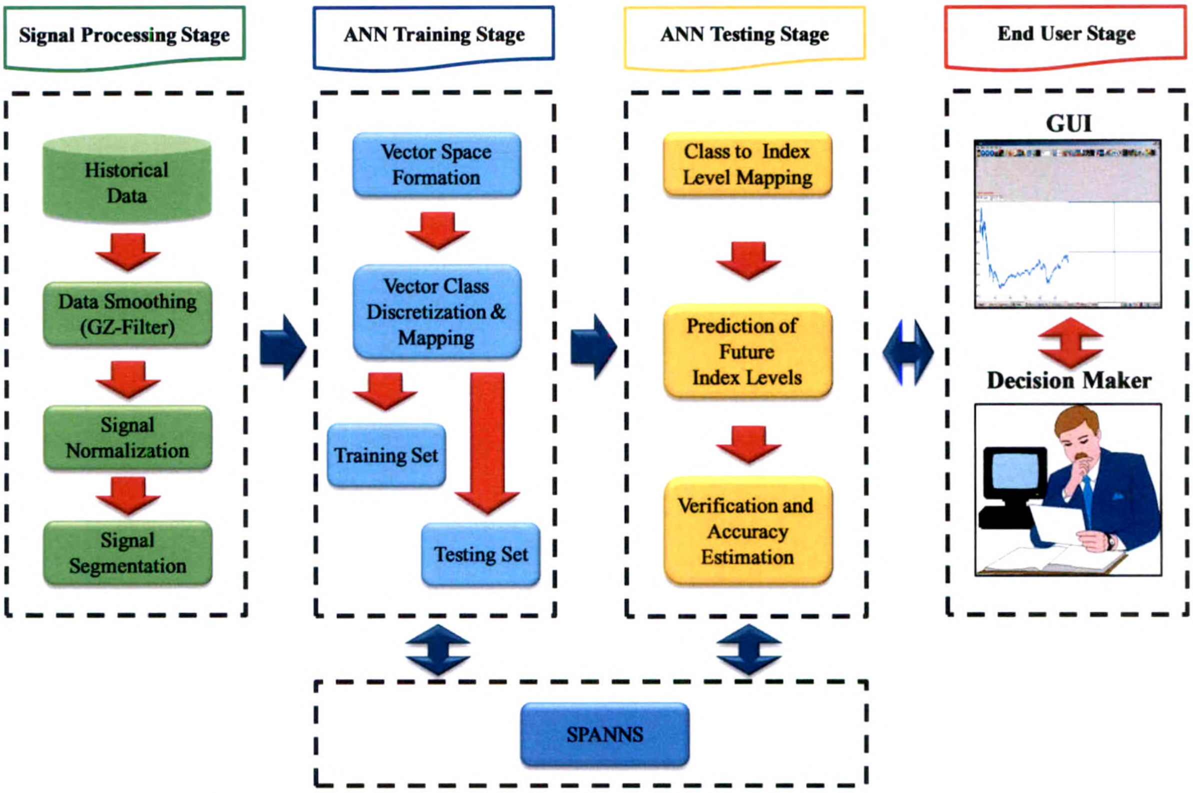


Figure 4.18: SPANNS Prototype Implementation Architecture.

ANN Training & Testing

The ANN training and testing stages are a customized implementation of the MatLab library/toolbox. To automate the training and testing, we developed two M-Files as wrappers of the native libraries to facilitate vector space generation, training/testing sets partitioning, testing and plotting the results, computing the error and accuracy of the predictive models. These M-Files are also connected to the GUI.

End User Stage

In this stage, the GUI of the system is designed to facilitate the user-system interaction activities. Figure 4.19 depicts the developed GUI. The following are the components of GUI:

- **Pop Up Menu**:
  - Pop up lists available options that are linked to functions including load a signal from a text file, load a signal from a spreadsheet, plot signal, build vector space, train the ANN model, test the model, etc.
- **Control Panel**:
  - Control panel enables the experimentation with different parameters such as, vector size, quantization levels, training set size, etc.

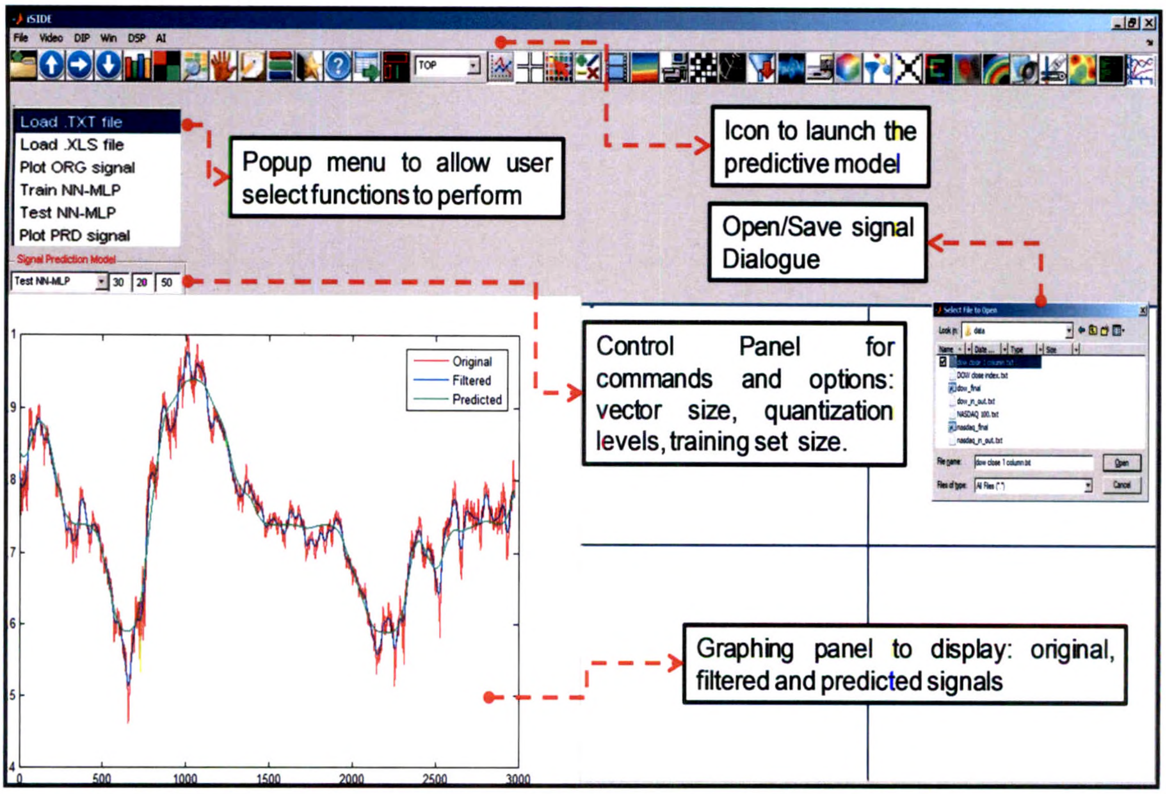


Figure 4.19: The Graphical User Interface of SPANNS.

- **Graphing Panel**:
    - Graphing panel provides the means to plot the original and predicted signals. Open/Save Dialogue: allows the user to select a path/file to read/save the signal. To develop the GUI and the underlying functions, Matlab guide was used for GUI development. The main libraries used to implement the different functions and algorithms are: Signal Processing toolbox, Neural Network toolbox and Plotting interface.

4.4 SUMMARY

In this chapter, the study proposed a hybrid system that combines signal processing and neural networks to develop a predictive system for stock market indices. The proposed integrated system is capable of handling different decision making situation including stock index individual price, open, close, low and high signals, n-day future prediction, the effect of signal processing on the prediction reliability and the impact of the accuracy measure used to evaluate the system performance. The study further believes that this work is unique in terms of comprehensiveness in investigating many aspects of the development and testing the proposed system and presenting a research methodology approach on how to develop, integrate and test similar systems.

CHAPTER 5

GANNS FOR STOCK MARKET FORECASTING

5.1 INTRODUCTION

Traditional statistical techniques such as auto regressive integrated moving average (ARIMA), exponential smoothing, and expert modeler have been used for stock market forecasting for a long time. Artificial intelligence techniques including Artificial Neural Networks (ANN) and Genetic Algorithms (GA) are also being applied for forecasting stock prices for nonlinear time series. Most of the systems have been designed using a single technique. Any single technique has some strengths and weaknesses (Branke, 1995; Yao, 1999; Kwon & Moon 2007). Therefore, there is a need to develop hybrid systems using two or more techniques to combine the strengths. The stock market movements can be predicted better combining more than one technique instead of a single forecasting technique because of multiplicity of the variables.

The purpose of this study is to design and develop a Genetic Algorithm based Artificial Neural Network System (GAANS) to accommodate the current needs of investors and portfolio professionals for investment decision making using the forecast of the next day's closing price of the Dow30 and NASDAQ100 indices. The system has both GA and ANN modules. GA is used to optimize the weights of inputs used for forecasting by the ANN. Also, the proposed system is capable of comparing the results and trends of actual and predicted values.

5.2 DESIGN AND DEVELOPMENT OF GANNS

This section describes a proposed hybrid intelligent system that combines ANN with GA. The next section entails a brief introduction of ANN concepts, followed by detailed descriptions of GA and finally, the discussion of GANNS system development.

5.2.1 Artificial Neural Network

A biological nervous system, such as the power of brain processing information, inspires the development of an ANN (Shivanandan & Pai, 2011; Zurada et al., 1994), which is an information-processing model. An ANN is composed of a large number of highly interconnected processing elements (neurons) used to solve specific problems. The aim of the neural network is to train the net to achieve a balance between the net's ability to respond and its ability to give reasonable responses to inputs that similar to but not identical to those used in training. The nonlinear nature of stock time series data makes ANN the preferred model because it is able to map as input with pattern with a corresponding output pattern accurately.

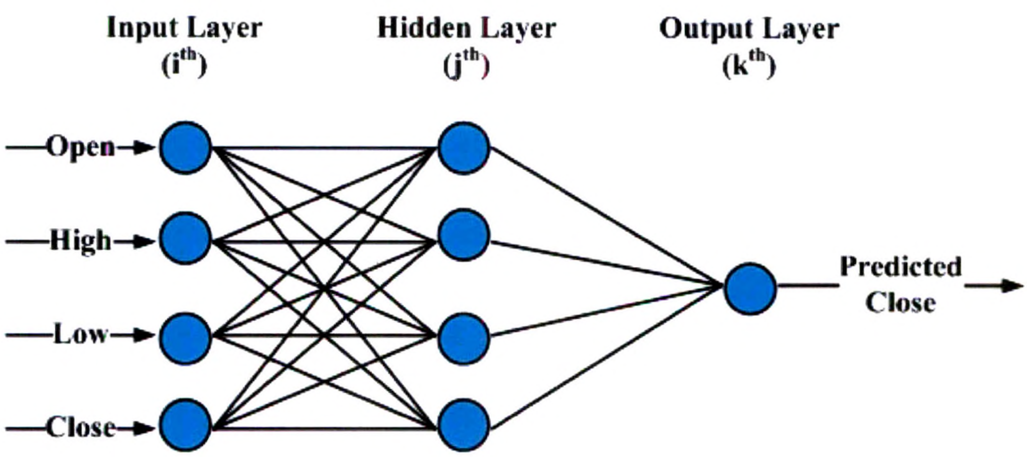


Figure 5.1: A simple architecture of Artificial Neural Network for stock price.

An ANN architecture with three layers, as shown in Figure 5.1, is sufficient to solve a complex nonlinear problem such as a stock index forecasting. A simple architecture of ANN with an input of four neurons, and a hidden layer in each neuron, and one neuron in the output layer is constructed. Let the three layers input, and hidden output layer of above ANN be identified as i^{th}, j^{th}, and k^{th} layer.

An ANN model can be developed using two phases: Training and Testing. For the training, Error Back Propagation Algorithm (EBPA) is most widely used. The network is known as Back Propagation Artificial Neural Network (BPANN); the back propagation learning algorithm is one of the most important developments in neural networks. The author applied this learning algorithm to a multilayered feedforward network consisting of processing elements, which have continuous, differentiable, and activation functions. For a given set of input-output pair, this algorithm provides a procedure for changing the weights in a BPANN to predict the given input correctly. The basic concept for this weight updated algorithm is simply the gradient-descent method as used in the case of simple perceptron networks with differentiable units. This is a method where error is propagated back to the hidden unit and weights are updated, and finally ANN can be tested with unseen data (Testing data), to verify the prediction accuracy of the model.

The training process of BPANN consists two phases: feed forward phase in which output is calculated and feed backward phase in which calculated error is propagated back to the network to adjust the weights this algorithm is described by the following steps:

Step 1: Weight Initialization

Weight can be initialized in randomize or expertise way. Setting all weights and node threshold to small numbers, select initial arbitrary values of weight vector $W = [w_1, w_2, w_3 \ldots w_n]$.

Step 2: Calculation of the activation

Calculaticn of the activation values using the activation function as linear or nonlinear function. Sigmoid function is one of the most widely used activation function cf the form:

$$f(net) = \frac{1}{1+e^{-net}} \tag{5.1}$$

where, net is the total input to the neuron which can be expressed with following formula:

$$\text{net} = \sum_{i=1}^{n} W_{ji} X_j \text{ for j=1,2,3...m} \tag{5.2}$$

where, W_{ji} is weight from i^{th} to j^{th} layer and X_j is input to j^{th} layer

Step 3: Weight adjustment

If the desired output from the network is not achieved, then weights are adjusted by various weight adjustment formulae, starting with the output units and working backward to the hidden layers recursively. The weight change equation is written as:

$$\Delta W_{ji} = \alpha \delta_j O_j \tag{5.3}$$

Where α is learning rate ($0< \alpha <1$) and δ_j is the error gradient and O_j is the output at unit j, finally weight can be adjusted by the following formula:

$$W_{ji}(t+1) = W_{ji}(t) + \Delta W_{ji} \qquad (5.4)$$

where, $W_{ji}(t)$ is the weight from unit i to unit j at time t (or t^{th} iteration) and ΔW_{ji} is the weight adjustment.

Step 4: Error gradient

The error gradient can be calculated using following two formulas separately in hidden and output layer:

(a) For the output layers

$$\delta_k = O_k(1 - O_k)(T - O_k) \qquad (5.5)$$

Where T, is the desired output (Target output) and O_k is an actual output from k^{th} layer.

(b) For the hidden layer

$$\delta j = O_i(1 - O_i)\sum_k \delta k\, W_{kj} \qquad (5.6)$$

Where, δ_k is the error gradient at unit k to which a connection points from hidden unit j.

Step 5: Repeat

Repeat the iteration until convergence in terms of the selected error criterion is obtained.

This research work uses a three layer back propagation artificial neural network of type 4-4-1, with default control parameters (learning rates, momentum etc.) and log sigmoidal activation function in both the layers (hidden and output) for forecasting stock index price.

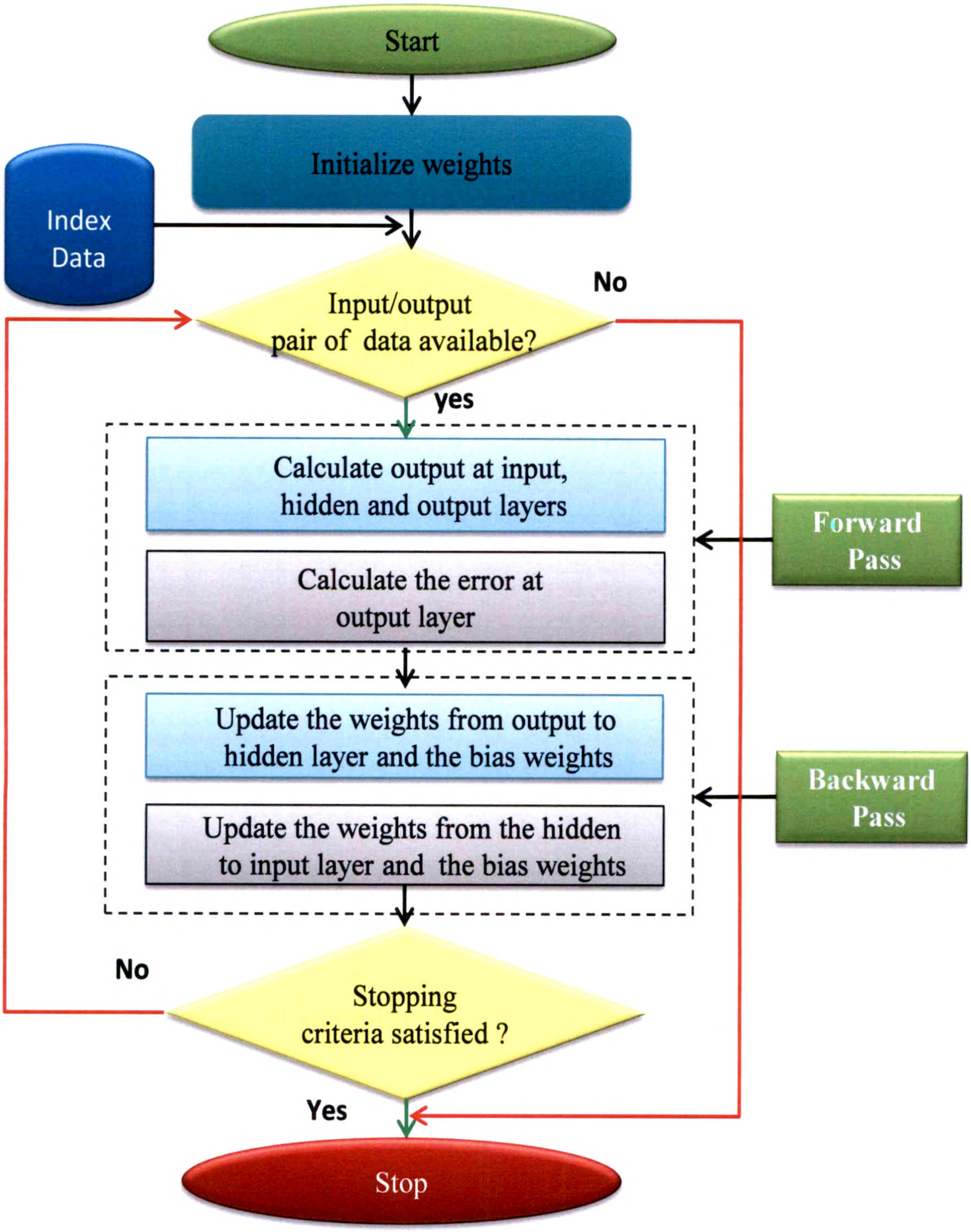


Figure 5.2: Flow Diagram of the ANN Learning Algorithm.

5.2.2 Genetic Algorithms

Genetic Algorithms (GA) technique is a stochastic heuristic optimization search method. GA follows the natural selection process in biological evolution, to arrive at optimal or near-optimal solutions in complex decision making problems (Holland, 1975). An initial population of individuals representing possible solutions is created when this technique is applied to a problem. Each of these individuals has certain characteristics that make them more or less fit as members of the population. The fittest members will have a higher probability of mating than lesser fit members, producing offspring that have a significant chance of retaining the desirable attributes of their parents (Sharma & Jana, 2009). The basic cycle of genetic algorithm is shown in Figure 5.5 and the steps of GA (Goldberg, 1989) are as follows:

Step 1: Initialization.

This step generates the initial population of chromosomes by generating uniform random numbers. A pre-specified interval corresponding to each decision variable, is defined to generate a uniform random number. The process continues until all chromosomes are feasible or converged. The details of generating uniform and other random numbers can be found in Gentle (2004).

Step 2: Evaluation.

This step evaluates each chromosome via a user-defined fitness function. The fitness value of each chromosome or string is an index generated by GA based on the design suitability and survival of reproduction probability.

Step 3: Selection.

Two parent chromosomes are selected to generate new population using the selection procedure. The various methods used to select parent chromosomes, are: roulette wheel selection, Boltzmann selection, Tournament selection, Rank selection, and steady-state selection. Roulette wheel selection method of two parent chromosomes is one of the most reliable selection method, which is based on the fitness value of each chromosome. A Chromosome having higher fitness value has a higher probability of selection. The total fitness value of all the chromosomes is calculated first. This step is repeated until the number of chromosomes selected is equal to the number of the population.

Step 4: Crossover.

The crossover is a powerful and important operation in the GA that allows the search process to fan out in diverse directions and look for a new solution. Crossover proceeds in three steps. First, the reproduction operator selects a random pair of two individual strings for mating, then a cross-site is selected at random along the string length and the position values are swapped between two strings. The single point crossover operation is presented in Fig. 5.3.

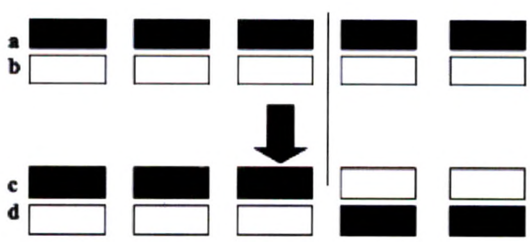


Figure 5.3: Single-point crossover operation.

Step 5: Mutation.

Mutation operator is an optional but is an important operator the main objective of this operator is to preserve the chromosomes having more potential with low mutation probability, so that in the next generation a better population can be produced. The mutation operation introduces random variations into the population. It is performed on a bit-by-bit basis. The bit-by-bit mutation operation is shown in Figure 5.4.

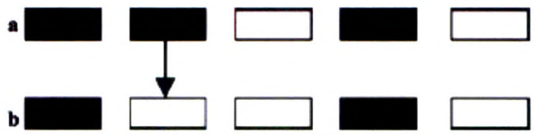


Figure 5.4: Bit-by-bit mutation procedure operation

Step 6: Termination

The last step is the verification of a termination criterion. The execution of the whole process terminates when any of the predefined stopping criteria satisfies or GA converged towards the global optimal solution. However, successful convergence of GA does not guarantee that optimal solution has been achieved. On the other hand setting algorithm specific parameters of GA like mutation probability, crossover probability, deciding selection operators and crossover strategy and others are complicated task and again required to apply optimization of these parameters.

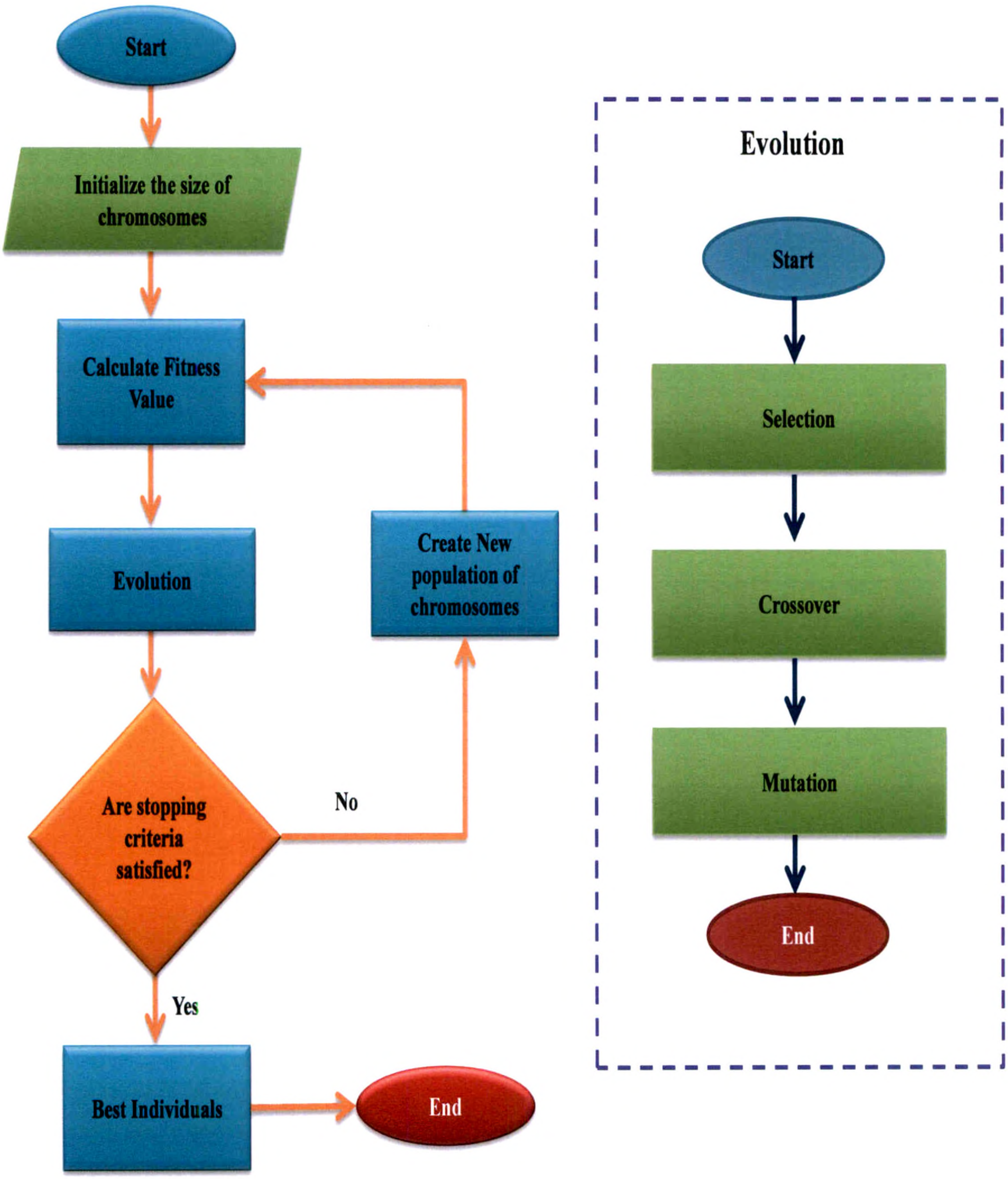


Figure 5.5: Basic Cycle of Genetic algorithm.

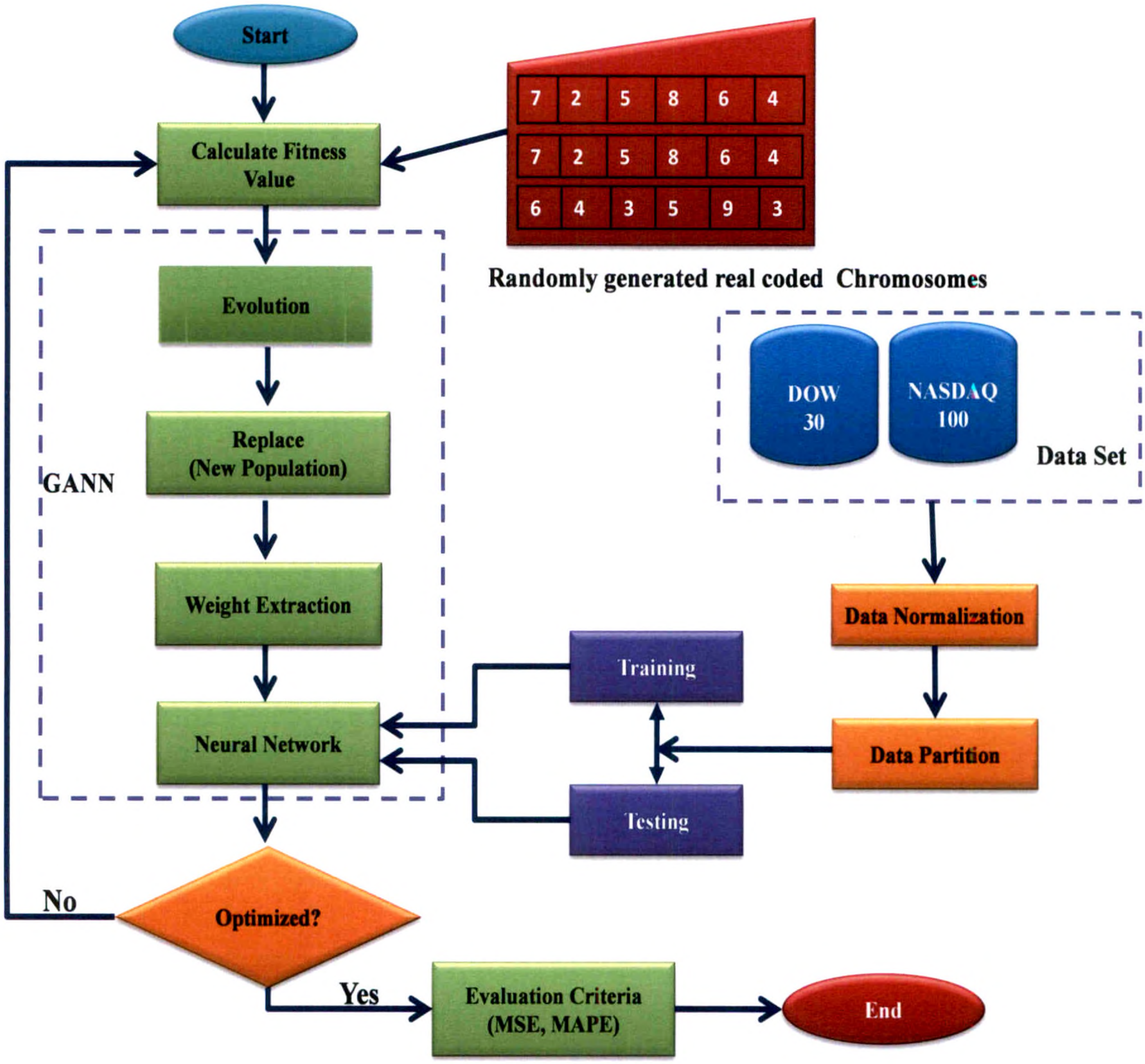


Figure 5.6: Process of Proposed GANNS Approach.

5.2.3 Genetic Algorithm based Artificial Neural Network System

Back Propagation Artificial Neural Network (BPANN) may face a problem of local minima as well as network paralysis, which affects the accuracy of the system. The network is not able to adjust the weights towards global minima. On the other hand, GA does not guarantee for an optimal solution. A suitable integration of ANN with GA may overcome the problems of both techniques, where ANN is used for learning while GA is used for optimization of weights (Rajasekaran & Pai, 1996). Figure 5.6 shows overall process to apply Genetic Algorithm based Artificial Neural Network System (GANNS) for stock index forecasting. Each of the components of the above Figure is explained as below:

Data Set

The original data set consists of daily index prices of DOW30 and NASDAQ100. In order to feed it to ANN we need to scale the data in the range of [0, 1] to simplify the process of learning and improve the accuracy (Kim et al., 2004). Data are normalized the using standard normalization formula as written in equation (5.7):

$$D(Norm) = \frac{D(i)}{\max(D)} \tag{5.7}$$

Where, $D(i)$ is the i^{th} instance and $\max(D)$ is the maximum value of a particular feature.

Data Partition

Both data sets consist of 3000 instances of daily index prices from March 01, 2000 to Feb 02, 2012. These instances are divided into training and testing sets. These data sets are divided into various portions, as shown in Figure 5.7, to check the robustness (Wang et al., 2011) of GANNS. GANNS is tuned with all the portioned data set one by one and results are analyzed. Partition 1 consists of 1800 training and 1200 testing instances, similarly partition 2 consists of 2250 training and 750 testing instances and so on.

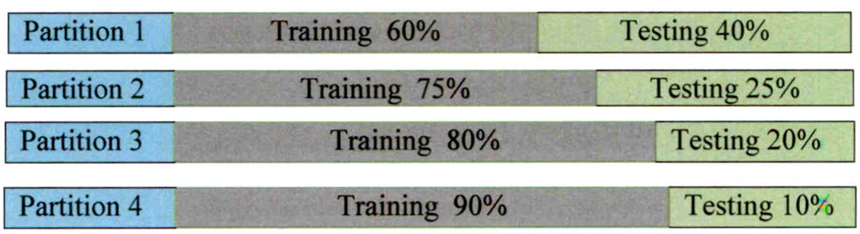


Figure 5.7: Various Data partitions.

Step 1: Initial Population and Coding.

To work with GA an initial population is required (Rajasekaran & Pai, 1996). If we have no idea of the solution, the population is randomly generated so it is spread throughout the search field. Coding usually comes after the mathematical modeling of a given problem. The coding is represented as strings of bits containing all the necessary information to describe a point of space in the population, a gene. These genes are combined together to form a chromosome (string).

Assume a BPANN whose network configuration is l-m-n (l input neurons, m hidden neurons, and n output neurons). The number of weights that are to be determined are (l + n)m. With each weight (gene) being a real number and the number of digits (gene length) in the weight to be d, a string S of decimal values representing the (l + n) m weights and therefore having a string length L = (l + n)md is randomly generated. The string S represents the weight matrices of the input-hidden and hidden-output layers. In the case of the 4-4-1 network considered here for index price forecasting, the number of weights will be (4+1)4=20 without bias. If bias connation to hidden layer and output layer are considered then number of weights will be 25, let us assume gene length d=5 then string (chromosome) length L= (4+1)4*5=25. An initial population of p chromosomes of length 25 is randomly generated where p is referred to as the population size.

Step 2: Fitness Function

The fitness value in this study is calculated with the help of following formula

$$F=\frac{1}{E} \tag{5.8}$$

Where, E is the root mean square of the error of the form given below:

$$E = \sqrt{\frac{(E_1 + E_2 + E_3 + \ldots.. + E_n)}{n}} \tag{5.9}$$

Where, En for i=1,2,….n is the error for the nth instance of the data set.

Step 3: Selection

Chromosomes are selected from the population to be parents to crossover and will produce offsprings. A number of selection operators are available for this selection processes. These are Roulette Wheel, Boltzman, Tournament, Rank and Steady state selection operator. In this study, Roulette wheel selection operator is used.

Step 4: Crossover

As in sexual reproduction two good parents produce a healthy child. The process can be applied to exchange genetic material of two parent chromosomes. The crossover operator reconstructs the genes of individuals within the population to enrich it by crossing the selected couples (pairs) in the selection step. The cross over consists of randomly selecting pairs of parents to be crossed, creating two new chromosomes with a part of the gene pool of their parents. In this phase, the mating pool is formed before the parent chromosomes reproduce to deliver offspring with better fitness. Two point cross over as shown in Figure 5.8 is applied in this study.

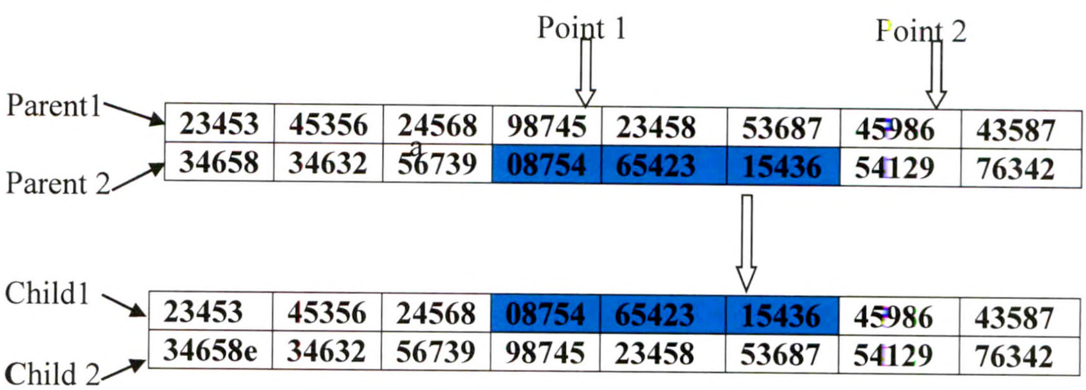


Figure 5.8: Two point crossover (Real coded genes).

Step 5: Mutation

This is an optional operator which permits to change a small part of chromosomes to give something new to the individual with very low mutation probability. We have applied two points mutation operator in the evolution process to optimize the weights of ANN.

Step 6: Replace

A worst fit chromosome in the population is replaced with best fit chromosome in order to produce better set of chromosomes for the next generation.

Step 7: Weight Extraction

In order to train the ANN, weights must be extracted from each of the chromosomes from the current population (Rajasekaran & Pai, 1996). Using the weights obtained all the training data set is supplied to the ANN which checks for the error. If the results are not satisfactory, the process will be continued. Let x1, x2, ...xd, ..., xL represent chromosomes and xkd+1 ,xkd+2..., x (k + 1)d represent the kth gene (k>=0) in the chromosome. The weight extraction formula is given by the following formula:

$$w_k = \begin{cases} + \dfrac{X_{kd+2}\, 10^{d-2} + X_{kd+3}\, 10^{d-3} + \cdots + X_{(k+1)d}}{10^{d-2}} & \text{if } 5 \leq X_{kd+1} \leq 9 \\ - \dfrac{X_{kd+2}\, 10^{d-2} + X_{kd+3}\, 10^{d-3} + \cdots + X_{(k+1)d}}{10^{d-2}} & \text{if } 0 \leq X_{kd+1} \leq 5 \end{cases} \quad (5.10)$$

5.2.4 Evaluation Criteria

This study considers the mean square error (MSE) and mean absolute percentage error (MAPE) to evaluate the ANN and GANNS. However, other error measures can also be used to evaluate the performance of the same systems. These measures are as follows:

Mean Absolute Percentage Error: $MAPE = \frac{1}{N}\left[\sum_{i=1}^{N}\frac{|AV_i - PV_i|}{AV_i}\times 100\right]$ (5.11)

Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(AV_i - PV_i\right)^2} \qquad (5.12)$$

Where, AV_i and PV_i are actual value and predicted value respectively for i^{th} instance, and N is the total number of instances. If you lower the value of all the above measures, the model will give better performance. MAPE is a measure which gives more stable result and is clear to understand and evaluate the models.

5.3 IMPLEMENTATION

The GANNS was implemented using JAVA programming language. This framework integrates various web technology tools and intelligent techniques like ANN and GA (Sonar, 2006). The system can be deployed and run under any environment in a standalone machine and can be viewed and discussed according to the layer formed. The system comprises of five layers in all, each of the layer are discussed below.

Physical layer

This layer tells about physical data storage in secondary media in the form of flat file, each file contains the number of instances as first row, and the rest of the rows of files contain instances of the DOW30 and NASDAQ100. The four different files are created for both training and testing data of both the indices. These physically stored files are known as I/O files.

Data Access Layer

In order to process data by system engine (Optimization layer), it is necessary to retrieve it from the files using I/O API (Application Program Interface). Thereafter, the data pass to the higher layer, i.e., optimization layer for further processing.

Optimization Layer

This layer is an important component of the system which consists of two sub components GA and ANN, coded with the help of basic features provided by JAVA. This is the layer where weights of ANN is optimizes by GA and ANN become enough intelligent to forecast index prices. A suitable selection of various tuning parameters of ANN and GA may give better results than using individual techniques. To start training ANN through GA, an initial population with a constant size is required, which is generated by JAVA's random function feature. Since population for weight optimization is randomly generated, the result will vary in different cycle of the system and accuracy will change accordingly.

Presentation Layer

Presenting data, in proper and attractive format, are an essential job of any system. To do so various web technology tools such as XML (Extensible Markup Language), HTML(Hyper Text Markup Language), XSLT (XML Stylesheet Language Transformation) and CSS (Cascading Style Sheet). Data stored in XML is prepared in proper format using XSLT and CSS, and presented in the form of HTML, a web page, which contains input and output along with various error measurements.

Application Layer

This is the layer where user can interact to perform the desired task. To design interactive graphical user interface (GUI) AWT (Abstract Window toolkit) and Swing API of JAVA are used. The role of JavaScript in this layer is to validate the data provided to the system.

The flow diagram of the system implementation is shown in Figure 5.9.

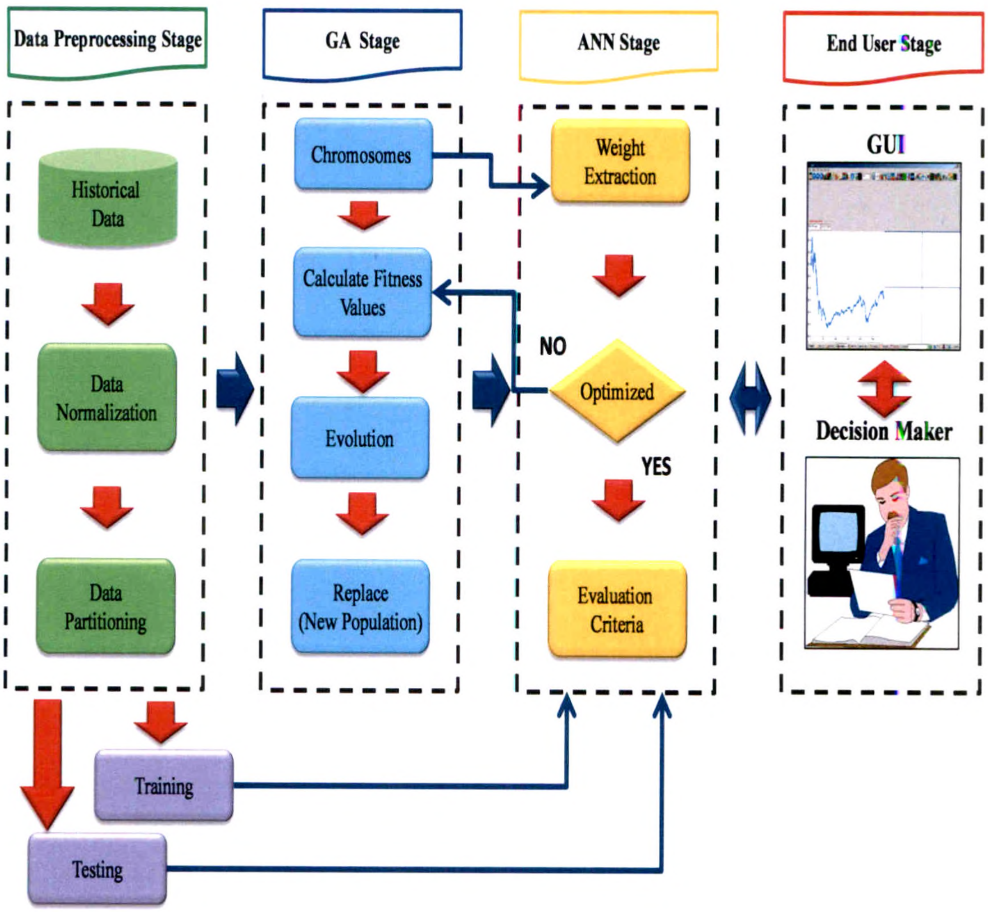


Figure 5.9: GANNS Prototype Implementation Architecture.

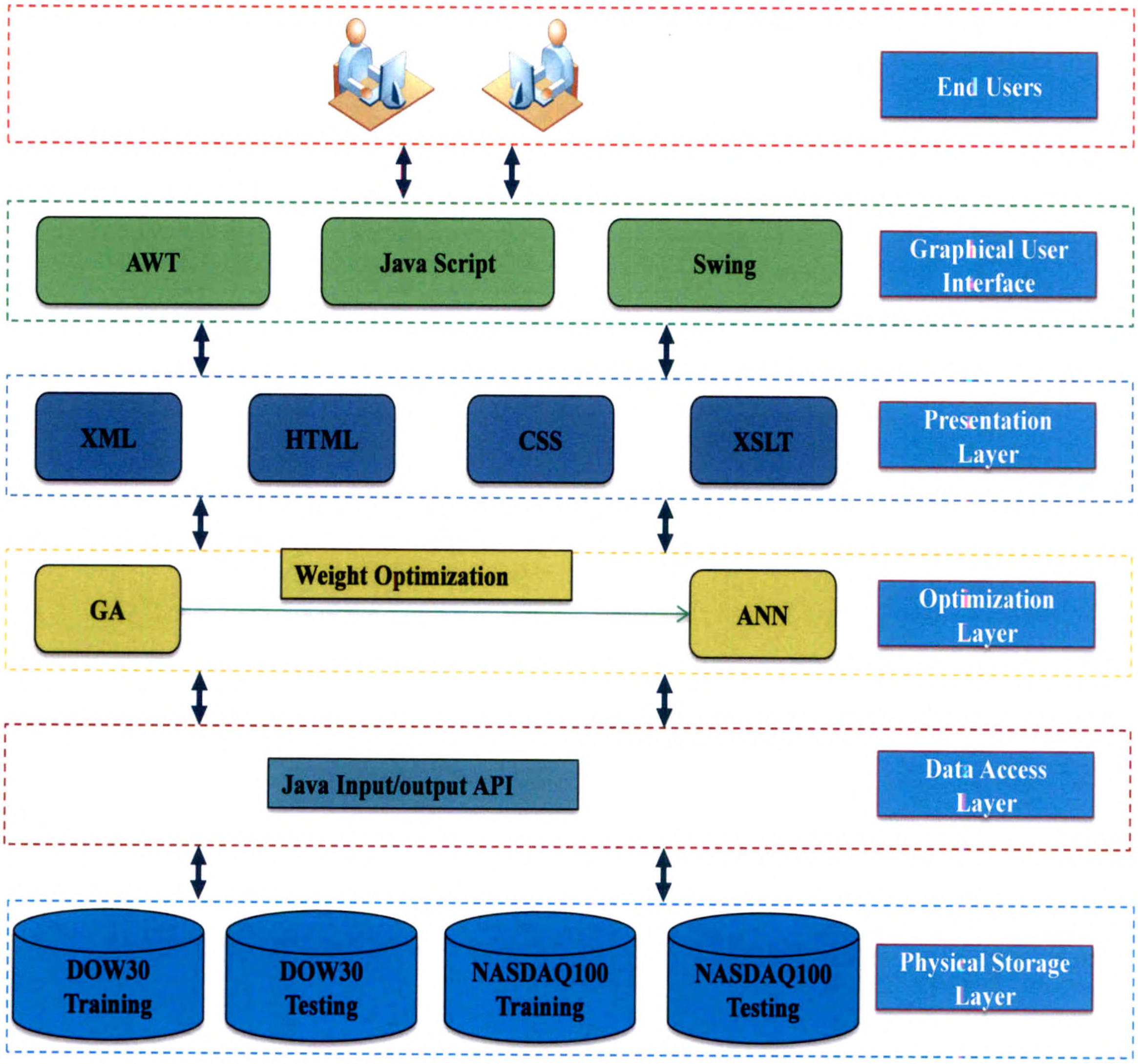


Figure 5.10: Framework of GANNS.

As we start the system, a welcome screen with login and password options will appear. A pre-created user account validates the data to provide system authenticity. However, a new user who wishes to utilize the system can create his/her own account by providing the various necessary information. The GANNS performs training and testing with the help of four steps.

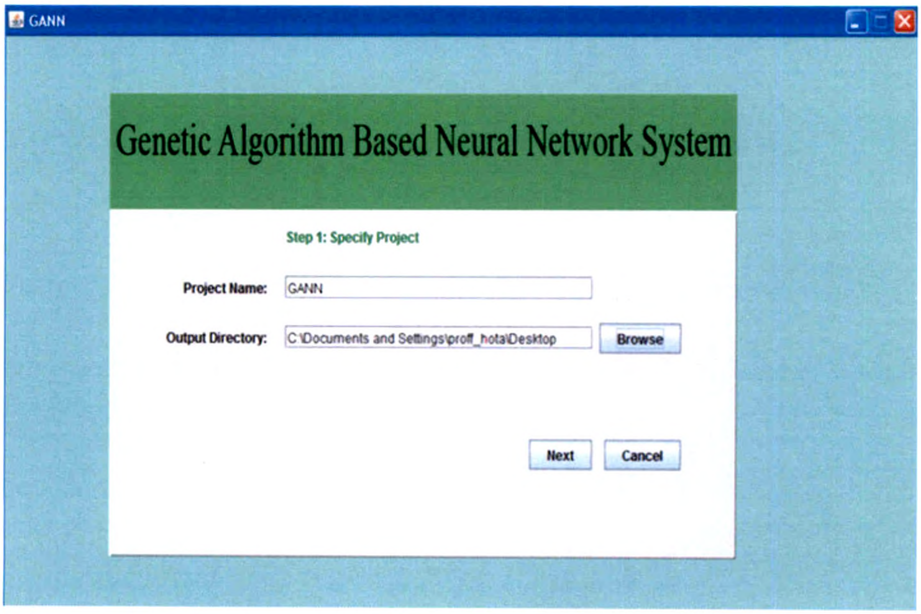


Figure 5.11: Provide project name and location.

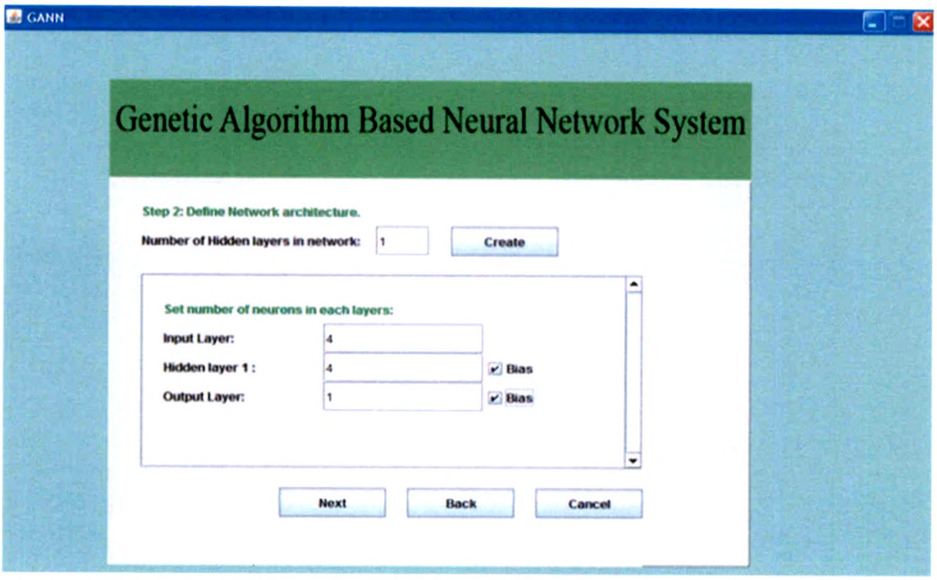


Figure 5.12: To design ANN architecture.

After validation of the User ID and password a new screen as shown in Figure 5.11 will appear where the user provides name of the project and the location where system generated HTML files containing result will be stored. The four files are actually generated by the system which contains initial and final population used for optimization of weights, training and testing result with actual and predicted data along with Mean absolute percentage error (MAPE) and optimized weights from input to hidden and hidden to output layer.

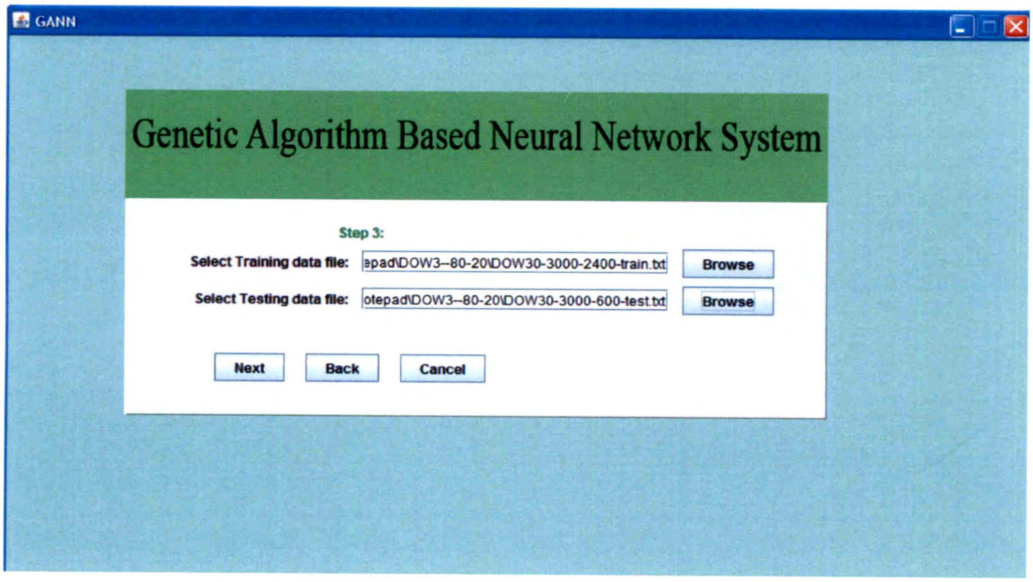


Figure 5.13: To feed input /output file.

The next screen will ask about the number of layers to design ANN architecture with optional tuning parameter bias as shown in Figure 5.12. This system provides a facility to create architecture of any type with any number of hidden layers. We have created ANN architecture of 4-4-1. There are four input parameters and 1 output parameters available in the dataset by clicking the next button; a new screen as shown in Figure 5.13 will appear which asks about the files containing training and testing data set. Finally, a screen as shown in Figures 5.14 shows all the setting parameters, and soon after the training process will start.

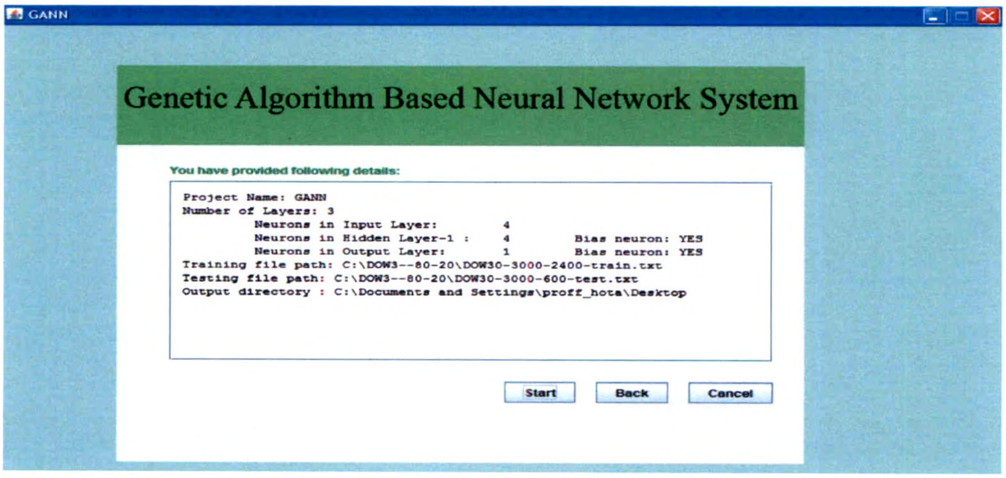


Figure 5.14: Training process.

The system generates the training data through GA, using an initial population provided. This randomly generated population may change every time and hence the time required to optimize the weights of ANN may also vary. Also, the set of weights may be different in different time. We have considered the best set of weight for which the prediction accuracy is higher. The genes of the chromosome are real coded.

Initial population, which is generated by the system automatically with a constant population size of 40 in each iteration. Each cell represents a single gene while each row represents a single real coded chromosome. In this chromosome, there are 25 genes where one gene is required to represent the weight of one connection of network. We have obtained similar chromosome in the final population as a result of optimization, which show that GA has converged successfully for optimization of weight.

Network was trained with training data set and final weight obtained for different connection of input to hidden and hidden to the output layer along with the bias weights in case of least MAPE for the training set of DOW30 and NASDAQ100 data sets (Tables 5.1 & 5.2). These weights are extracted from the final chromosome using equation (5.10)

Table 5.1 Final Weights of ANN optimized by GA for Partition 3 of DOW30 Data			
Input to Hidden Layer (From all the neurons of input layer to j^{th} neuron of hidden layer)	Bias to Hidden Layer	Hidden to Output Layer(From all the neurons of hidden layer to k^{th} neuron of outer layer)	Bias to output Layer
3.918,4.453,2.612,2.999	-8.125	0.694	-0.133
-1.760,5.779,0.215,6.344	-9.468	2.402	---
5.836,-1.081,0.332,3.466	-8.780	1.880	---
-3.398,4.675,2.898,-1.490	-7.258	-0.576	---

Table 5.2 Final Weights of ANN optimized by GA for Partition 1 of NASDAQ100 Data			
Input to Hidden Layer (From all the neurons of input layer to j^{th} neuron of hidden layer)	Bias to Hidden Layer	Hidden to Output Layer(From all the neurons of hidden layer to k^{th} neuron of outer layer)	Bias to output Layer
-7.935,-2.097,-2.106,-2.980	0.610	-6.184	-0.863
0.204,-2.774,9.680,1.499	-7.751	0.921	---
-3.420,7.986,5.672,7.080	-6.981	0.991	---
0.508,-3.976,3.637,1.690	-6.615	2.259	---

5.4 SUMMARY

This chapter discusses the integration of artificial neural network (ANN) based Back Propagation Neural Network (BPNN) model and Genetic Algorithm (GA). The combined system called Genetically Tuned Artificial Neural Network System (GANNS). GANNS and ANN are tested on DOW30 and NASDAQ100 data sets. This system provides us, with the facility of graphical user interface (GUI), to work in an interactive manner. Results obtained from both models, are compared in terms of MAPE and RMSE, and it is found that GANNS is performing well. The data set is partitioned into four different partitions, to check the robustness of GANNS. GANNS performs well in training, for three data partitions, while ANN performs well, for one data partition. Due to the problem of local minima, sometimes BPANN may fail to optimize the weights of

ANN. In those cases, we can rely on GANNS, because GANNS works in global optimizations. Also, GANNS can capture the nonlinearity situation of stock market in a more intelligent way.

CHAPTER 6

WEB BASED FUZZY PORTFOLIO MANAGEMENT SYSTEM

6.1 INTRODUCTION

In recent years, researchers and practitioners are focusing on sophisticated systems for managing risk of complex investment portfolios effectively. Web technologies are transforming the design, development, implementation and deployment of financial decision support systems (FDSS) for decision-making (Bhargava, 2007). However, developments of web-based FDSS are in the infancy stage. The available systems are providing basic services such as relevant data and information, but lacks analytical decision making tools. With advancements in security and technology, traditional DSS could be improved by migrating them to a web-based system. Traditional windows based DSSs are good for single-user personal computers. The manageability and cross platform support can easily be deployed in web applications to support the end user's needs. Additionally, web-based applications can dramatically lower cost due to reduce support, maintenance and low requirements on the end users systems. The simplified architecture of web-based applications is helpful for streamlining day to day operations of business and end users. However, complexity and uncertainty in portfolio management problems require sophisticated tools such as Web-based DSS that can provide optimum solutions for portfolio management decisions.

Researchers and professionals are focusing on Web-based DSS (Dong et al. 2002; Fan et al., 1999) that is one of the most desirable choices of Web applications. In the area of investments, the mean-variance model is a land mark in Modern Portfolio Theory (Markowitz, 1952).Web-based mean-variance optimization based DSSs are being developed for simplifying stock portfolio management process (Dong et al., 2004). However, the framework for stock analysis and management has addressed inadequately important issues such as flexibility and managerially oriented decision support for stock selection, in general (Bernstein and Wilkinson, 1997; Wood, 2000; Dong et al., 2002 and 2004).

This chapter is an attempt to propose a web-enabled fuzzy portfolio management system (FPMS) that can facilitate some flexibility and managerial issues in portfolio management. The three- tier architecture, of the FPMS consists of the client, application, and database, is designed with the systems and software technology including Java, SQL and TOMCAT Apache web server. Additionally, portfolio selection and management process is enriched by quantitative financial model designed using goal programming (GP) and fuzzy set theory to provide flexibility and accommodate for impreciseness of real world situations.

6.2 DESIGN AND DEVELOPMENT OF FPMS

The FPMS designed, in this work, for portfolio selection of securities includes three subsystems. Subsystem I is stock selection, subsystem II is strategic decisions and model formulation, and subsystem III is knowledge acquisition. Figure 5.1 shows the structure of the FPMS. The main functions of each subsystem are explained as follows:

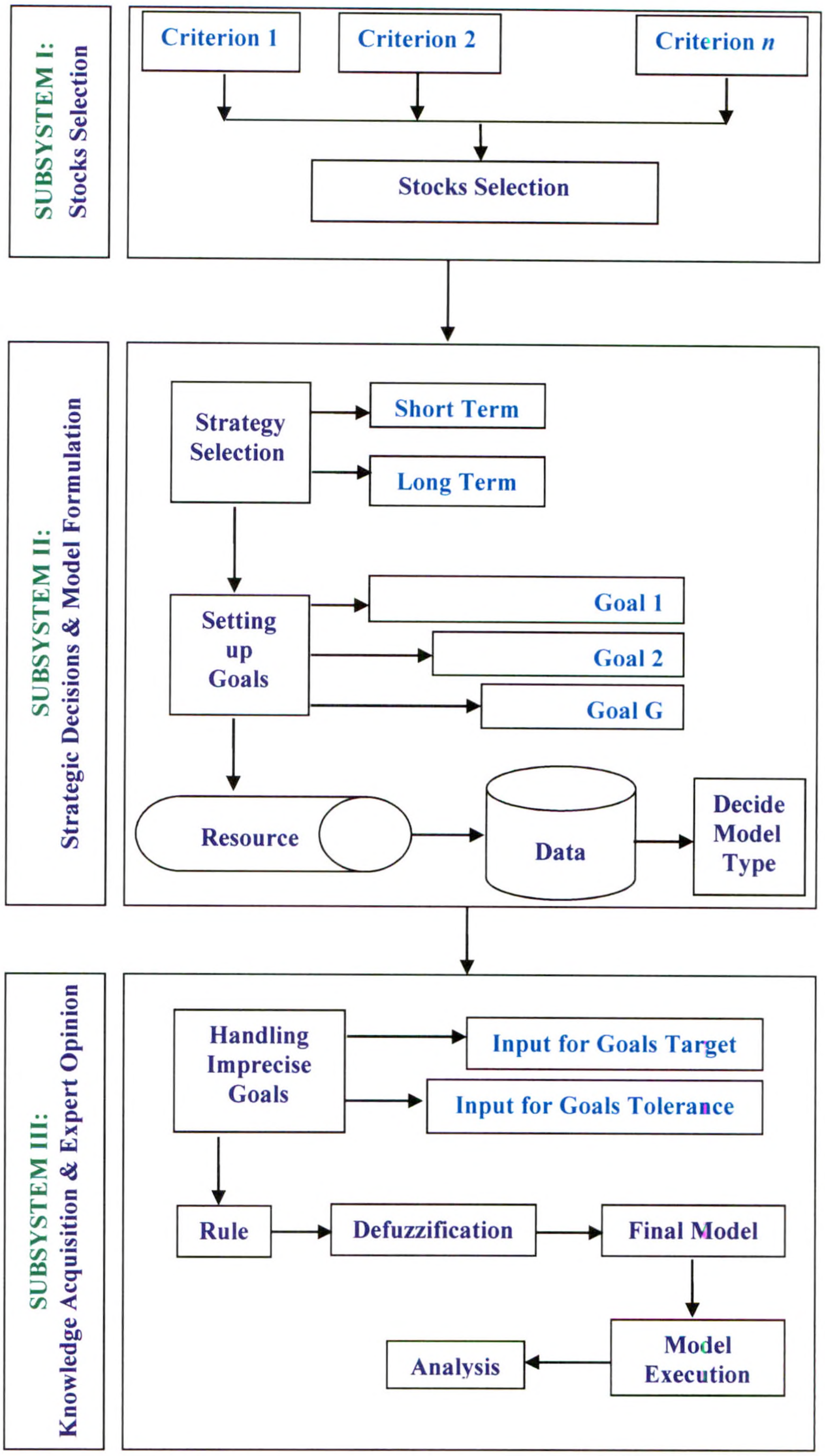


Figure 6.1: DSS Overview for Stock Portfolio Management.

6.2.1 Subsystem I: Stocks Selection

This subsystem deals with identifying the possible securities from all available securities. Depending upon the preferences of an investor, certain criteria are established. The initial selection of stocks depends on these criteria. The subsystem provides an interface to enter criteria such as analysts rating, expected return for a specific time horizons, and risk tolerance measurements. In return, the subsystem provides possible number of securities that are feasible for construction of an optimal portfolio.

6.2.2 Subsystem II: Strategic Decisions and Model Formulation

Subsystem II deals with the strategic decisions including goals and priorities of the investor. Generally, there are short, medium, and long term preferences of the investor. Based on the strategic focus, goals and resources are identified. Then the model incorporating goals, restrictions, and other essential components is formulated. To formulate the FGP model of stock portfolio, the following notations are defined first:

Index

s: index for the proportion of money invested in securities $s \in \{1,2,\cdots,S\}$

Variables and parameters

X_s = proportion of money invested in a security s

R_s^1 = expected annual rate of return from the security s for one year

R_s^3 = expected annual rate of return from the security s for the next three years

D_s = expected dividend on stock s

β_s = estimated measure of risk associated with security s

U_s = maximum proportion of money invested in security s

L_s = minimum proportion of money invested on security s

A_s = analyst rating of stock s

A_{min} = minimum acceptable analyst rating

PE_s = expected price earnings ratio of security s

PE_{max} = maximum acceptable price earnings ratio

R^1_{max} = expected maximum annual rate of return for one year

R^3_{max} = expected maximum annual rate of return for three years

R^5_{max} = expected maximum annual rate of return for five years

D_{max} = expected maximum annual income from dividend

β_{min} = acceptable tolerance of risk of portfolio

Investor's Goals

(i) **Annual return:** In terms of annual return, the objective is to maximize the total return from all securities from the constructed portfolio. This objective is expressed as:

For one year return:

$$\max : \sum_{s=1}^{S} R^1_s X_s ,$$

For three years return:

$$\max : \sum_{s=1}^{S} R^3_s X_s \text{, and}$$

For five years return:

$$\max : \sum_{s=1}^{S} R^5_s X_s$$

(ii) **Portfolio's risk:** The portfolio's beta is called systematic risk and is measured as the sensitivity of a security's returns to the market returns. This objective is

expressed as: $\min : \sum_{s=1}^{S} \beta_s X_s$

(iii) **Annual dividend:** In terms of annual dividend income, the objective is to maximize the dividend income from all securities. This objective is expressed as:

$$\max : \sum_{s=1}^{S} D_s X_s$$

Constraints set forth by the Investor:

(i) **Investment:** The decision maker's intention to investment the maximum funds can be expressed as:

$$\sum_{s=1}^{S} X_s = 1$$

(ii) **Portfolio's price earnings ratio**: The current and expected price earnings ratio of each security can be used as one of the constraint and can be expressed as:

$$\sum_{s=1}^{S} PE_s X_s \leq PE_{\max}$$

(iii) **Analyst rating:** The analyst rating of individual company is a subjective assessment, which could be measure by judging the performance, past records, public image, position of a company within the industry and its financial position. This goal is expressed as:

$$\sum_{s=1}^{S} A_s X_s \geq A_{\min}$$

(iv) **Investment diversification:** To minimize the risk by diversify the portfolio, investor has to decide the maximum proportion in an individual security, the investment diversification constraint may be constructed as follows:

$$X_s \leq U_s, \quad s = 1,2,\cdots,S$$

6.2.3 Subsystem III: Knowledge Acquisition

This subsystem handles the imprecision in the model using the concepts of FGP.

Handling imprecise portfolio goals

This is an important part of the DSS where system helps finding the target and tolerance limits of the desired goals.

Rules

Rules reflect expert's decisions to express vague aspiration levels of an investor. The literature suggests different shapes of membership functions such as such as a linear (Zimmermann 1978), exponential (León and Vercher, 2002), and so on. In this paper, for short term investment study, we use a logistic function (Watada, 1997) which is a nonlinear S-shaped membership function and more appropriate to express vague aspiration levels of an investor. For medium and long term investment studies, we use linear membership function.

Defuzzification

The defuzzification is done by using membership functions. It is mentioned in the previous section that we recommend to using two types of membership functions. The S-shaped membership function is given by:

$$\mu(x)=\frac{1}{1+\exp(-\alpha x)}$$

Where, $0 < \alpha < \infty$ is a fuzzy parameter that measures the degree of imprecision. The linear membership function takes the following form:

$$\mu_{z_k}(x)=\begin{cases}1 & \text{if } z_k(x)\geq b_k, \\ \dfrac{z_k(x)-(b_k-t_k^l)}{t_k^l} & \text{if } b_k-t_k^l\leq z_k(x)<b_k, \\ 0 & \text{if } z_k(x)<b_k-t_k^l\end{cases}$$

for the fuzzy goal of type $z_k(x)\underset{\sim}{>}b_k$, in general, where, t_k^l is the lower tolerance limit whereas for fuzzy goal of type , $z_k(x)\underset{\sim}{<}b_k$ it takes the following form:

$$\mu_{z_k}(x)=\begin{cases}1 & \text{if } z_k(x)\leq b_k, \\ \dfrac{(b_k+t_k^u)-z_k(x)}{t_k^u} & \text{if } b_k<z_k(x)\leq b_k+t_k^u . \\ 0 & \text{if } z_k(x)>b_k+t_k^u\end{cases}$$

Where, t_k^u is the upper tolerance limit.

Security Portfolio Model: Final Form

A maximizing function in FGP model can be developed using the above membership functions corresponding to different stock portfolio goals as follows (Tiwari et al. 1987):

$$\max : \mu_{R^i}(x)+\mu_D(x)+\mu_\beta(x),\ i=1,3,5$$

s. t.

$$\mu_{R^i}(x)\leq\{\textstyle\sum_{s=1}^{S}R_s^iX_s-(R_{\max}^i-R^i)\}/R^i,\ i=1,3,5$$

$$\mu_D(x)\leq\{\textstyle\sum_{s=1}^{S}D_sX_s-(D_{\max}-D)\}/D$$

$$\mu_\beta(x)\leq\{\beta_{\min}+\beta-\textstyle\sum_{s=1}^{S}\beta_sX_s\}/\beta$$

$$0\leq\mu_{R^i}(x),\mu_D(x),\mu_\beta(x)\leq 1$$

$$\sum_{s=1}^{S}X_s=1$$

$$\sum_{s=1}^{S} PE_s X_s \leq PE_{\max}$$

$$\sum_{s=1}^{S} A_s X_s \geq A_{\min}$$

$$X_s \leq U_s, \quad s = 1,2,\cdots,S$$

$$x \geq 0$$

Since all the goals are not equally important for the decision making process in construction of an efficient portfolio, therefore, goals are assigned priorities for achieving the goals. Therefore, objectives with higher priority will also have a higher degree of satisfaction and hence have a higher membership function value (Li et al., 2004). For example, the risk goal has the highest priority, annual return has the second highest priority, and dividend has the third priority then the corresponding constraint in the model can be constructed as follows: $\mu_{\beta}(x) \leq \mu_{R'}(x) \leq \mu_{D}(x), i = 1,3,5$.

6.3 DESIGN AND DEVELOPMENT OF WEB BASED FPMS

The design of the proposed web based FPMS has three tiers to fulfil the client requirement (Figure 6.2). Each tier is connected to subsystems to meet the end users requirements.

The client tier comprises of a user interface from where the user interacts with the application via Web browser. The tier provides a flexible interface to enter criteria such as analysts rating, expected return for a specific time horizon, and risk factor (Figures 6.3 & 6.4). The tier through a web browser provides feasible number of securities for construction of an optimal portfolio. The client tier architecture is designed using FTL (Freemarker tag library), XHTML, JavaScript and Ajax.

The application tier uses Struts 2.0 (Java Framework) to employ the process for the requested data. The process also manipulates the resultant information for user in the application tier and summarizes the result as a solution in the web browser (Figure 6.5).

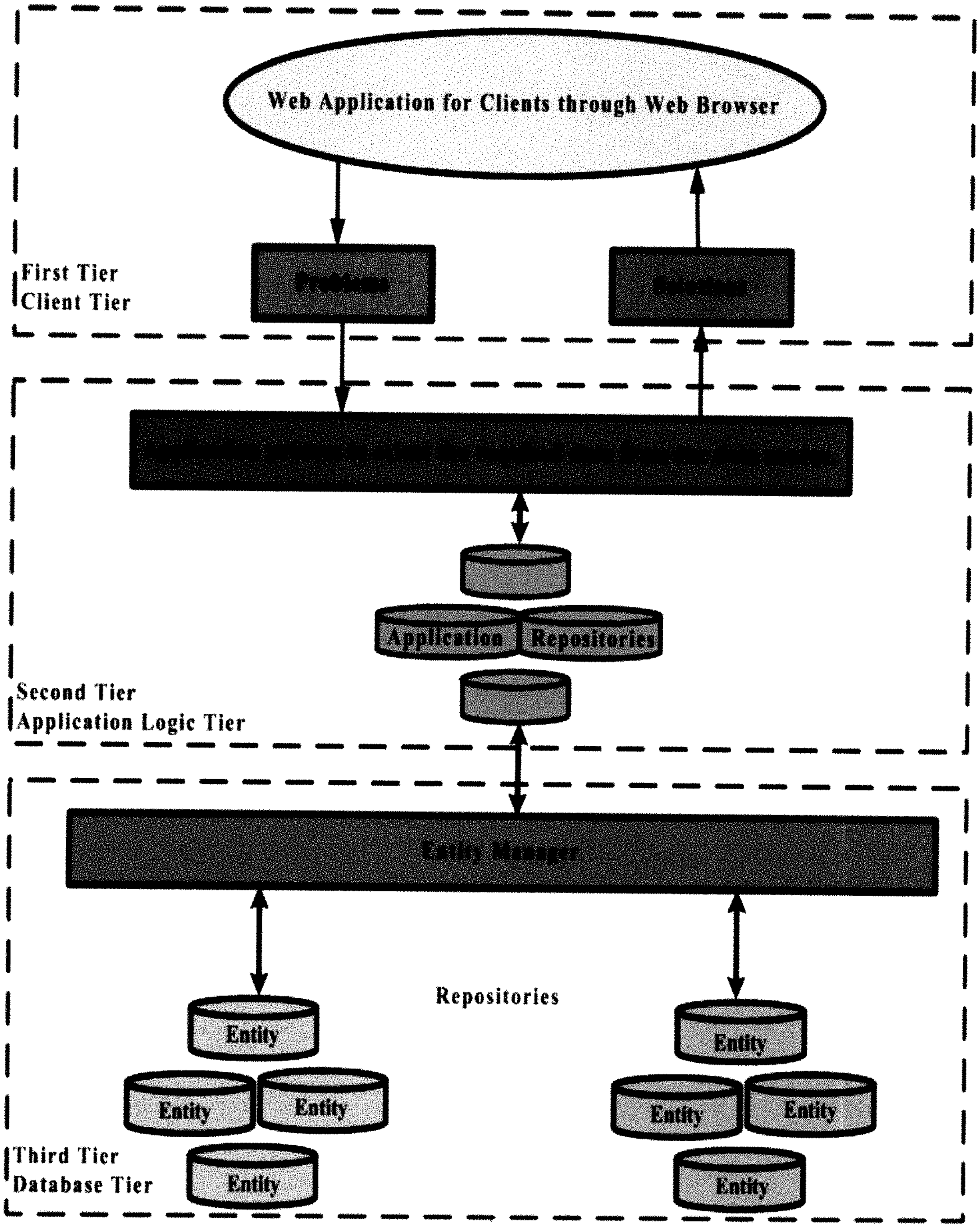
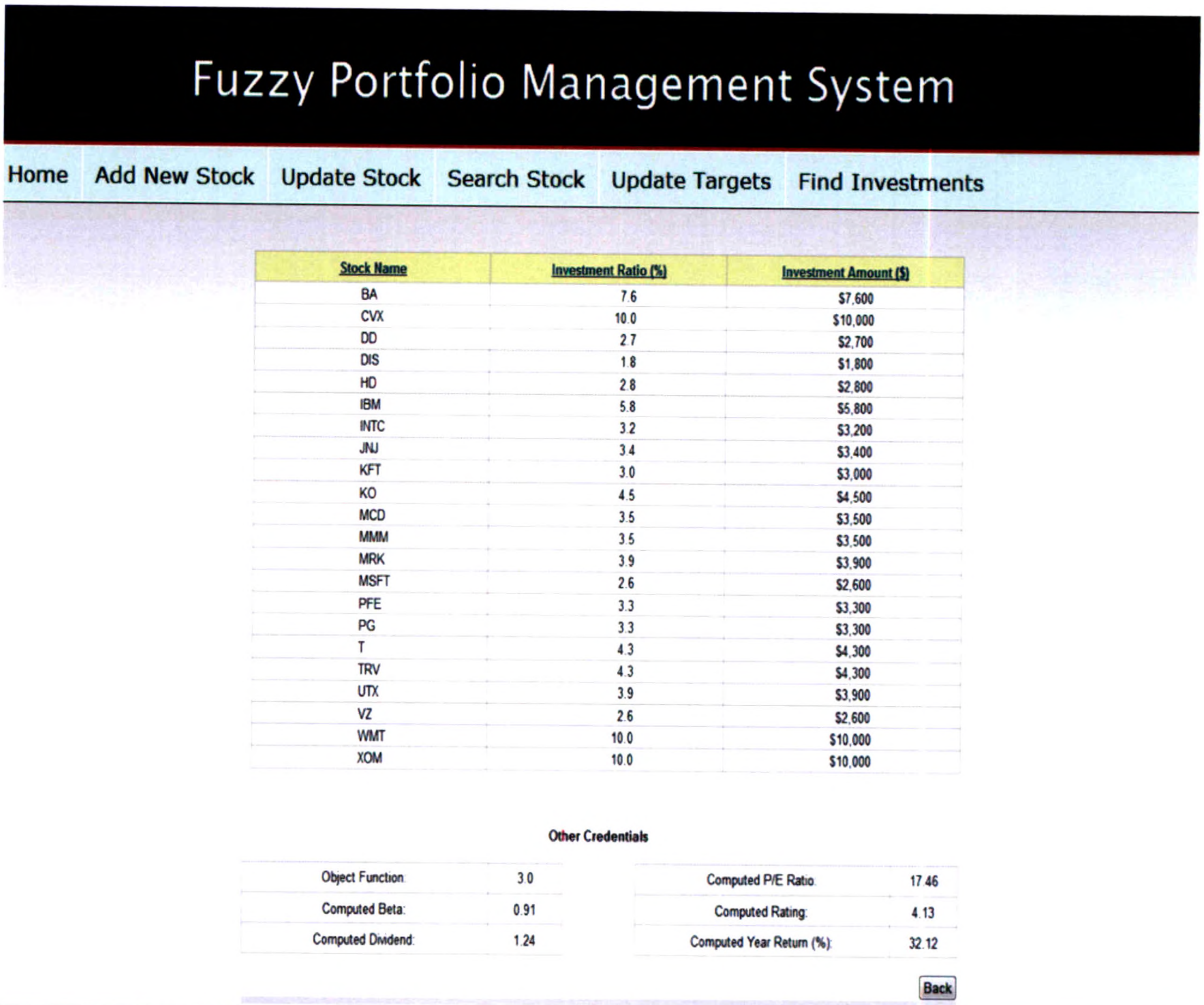


Figure 6.2: System Architecture.

Figure 6.3: FPMS Interface.

Figure 6.4: Updates Investment Targets.



Stock Name	Investment Ratio (%)	Investment Amount ($)
BA	7.6	$7,600
CVX	10.0	$10,000
DD	2.7	$2,700
DIS	1.8	$1,800
HD	2.8	$2,800
IBM	5.8	$5,800
INTC	3.2	$3,200
JNJ	3.4	$3,400
KFT	3.0	$3,000
KO	4.5	$4,500
MCD	3.5	$3,500
MMM	3.5	$3,500
MRK	3.9	$3,900
MSFT	2.6	$2,600
PFE	3.3	$3,300
PG	3.3	$3,300
T	4.3	$4,300
TRV	4.3	$4,300
UTX	3.9	$3,900
VZ	2.6	$2,600
WMT	10.0	$10,000
XOM	10.0	$10,000

Other Credentials

Object Function:	3.0	Computed P/E Ratio:	17.46
Computed Beta:	0.91	Computed Rating:	4.13
Computed Dividend:	1.24	Computed Year Return (%):	32.12

Figure 6.5: Optimal Output.

The database tier handles database management needs, which are accomplished through a software package that controls the creation, maintenance, and use of a database. In this particular system, we have used MySql database because it is available as open source and can easily configure and also widely used in many web application. Moreover, MySql allows the database administrator to conveniently develop databases of stocks from the available data at different web sites. Also, the database administrator controls data access, enforces data integrity and security.

This dataflow diagram (Figure 6.6) shows the complete internal flow of the application.

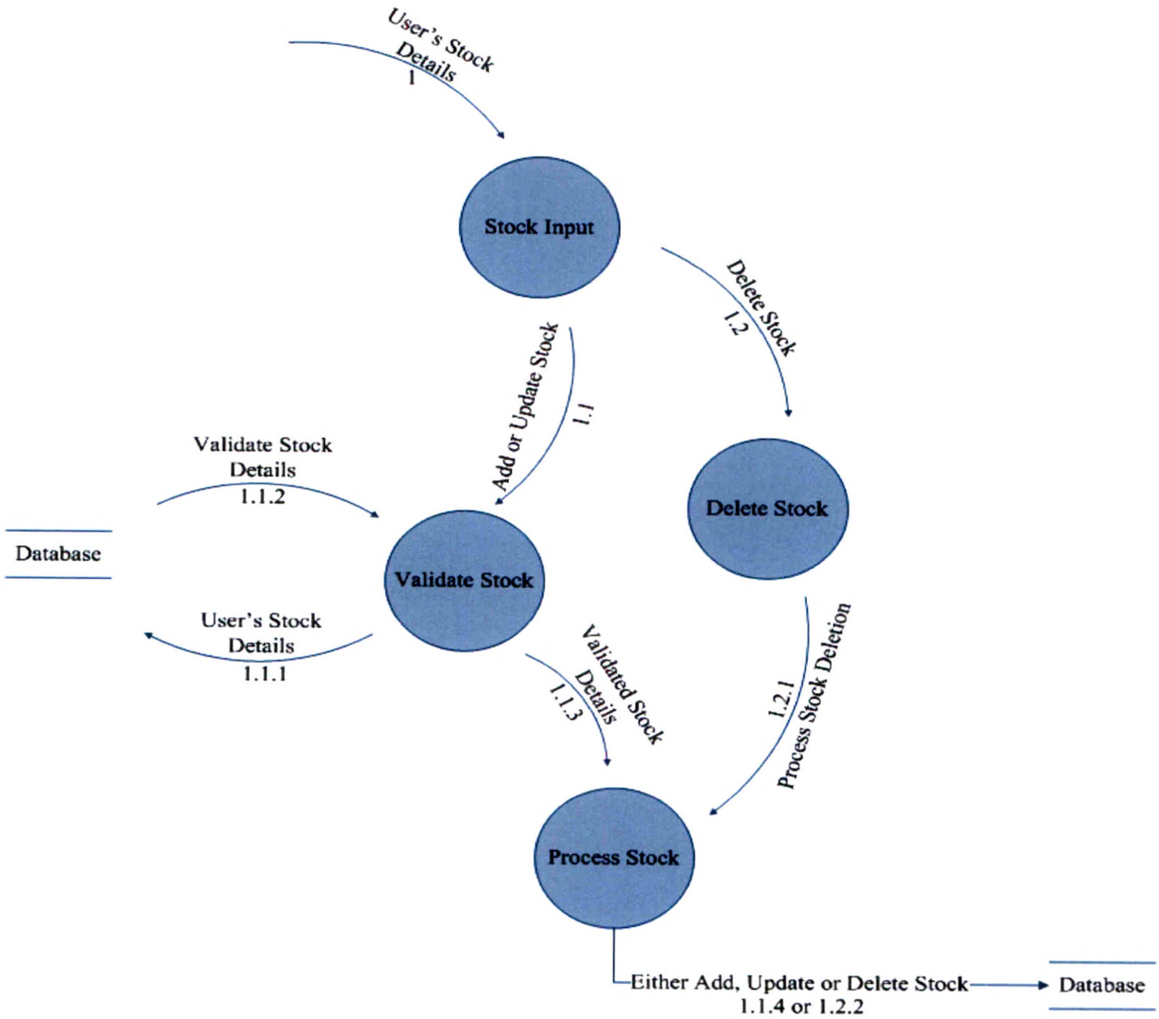


Figure 6.6: Data Flow Diagram.

6.4 IMPLEMENTATION

The prototype of FPMS was implemented within an object-oriented paradigm (Figure 6.7). MYSQL was used for data management. The fuzzy goal programming model (FGP) was implemented using MS Excel and Visual Basic. The prototype was run on the Windows XP. Apache Maven-Jetty was the Web server and FTLs (Freemarker

Tag Library) were used for user interface development. Internet Explorer 8.0/Mozilla Firefox 2.6.13/ Google Crome 10.0.648.151 was selected as the Web browser in the client computers. Lomboz eclipse 3.2 was the Integrated Development Environment (IDE) that is used to develop the whole Interface.

The main body of the FPMS was written using Struts 2.0 framework. To create more functional and interactive Web pages, Ajax was chosen for the server-side script. In the FPMS, validation was performed by the struts 2.0 validation feature. A strut 2.0 is a widely used framework of java. This uses MVC (Model-View-Controller) design pattern. The JPA (Java persistence Application Programming Interface) was selected to communicate with the MYSQL Database because it is compatible with a variety of database systems. The Entity Manager provides the control over the entities. The entity information is retrieved by the EntityManagerFactory (EMF) API, which uses the current Java Transaction API (JTA) Transaction. JTA provide distributed transaction and uses Java Database Connectivity (JDBC) drivers with greater data access power.

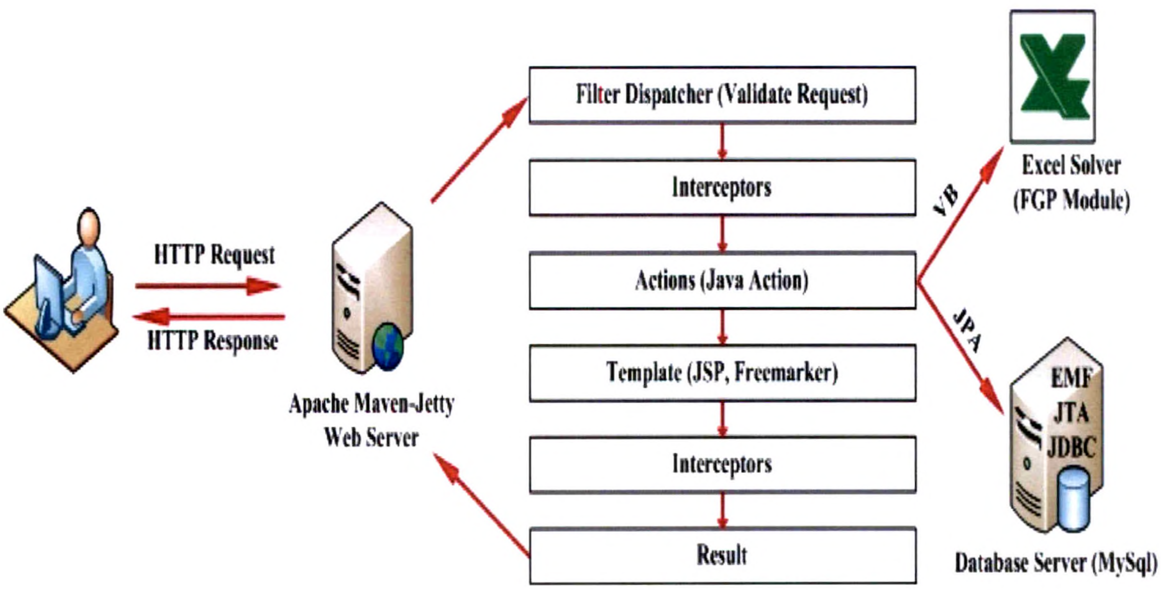


Figure 6.7: FPMS Implementation.

6.5 SUMMARY

This chapter proposes a web-based fuzzy portfolio management system (FPMS). The proposed system incorporates the goal programming (GP) to formulate the mathematical model of the portfolio selection problem, and fuzzy set theory to incorporate impreciseness in the model. The developed system has three tire architecture; client, application, and database for stocks investment decisions. The FPMS has been developed with open source technology including Java, SQL and TOMCAT Apache web server. FPMS accommodate investors' personal characteristics and preferences for different types of decision-making models. It provides flexibility for the decision-maker to refine the tolerance and targets of goals to find a feasible solution based on the current market conditions and forecasts of economic and financial variables.

CHAPTER 7

RESULTS AND FINDINGS

7.1 INTRODUCTION

In this chapter, the study focuses on intensively testing the performance of systems using historical data of the USA stock market indices. The systems, Signal Processing based Artificial Neural Network System (SPANNS) and Genetic Algorithm based Artificial Neural Network System (GANNS), were tested using data of the Dow Jones Industrial Average (DJIA) and National Association of Security Dealers Automated Quotations (NASDAQ) indices for more than twelve years. The performance of FPMS was tested using the DJIA short- and long-terms returns using one, three and five year investment horizon. The results and findings of this research are discussed below:

7.2 RESULTS BASED ON SPANNS

The study investigated five different experiments for the testing. These were: (1) single and multiple inputs, (2) N days future prediction, (3) individual index price prediction: open, close, low and high prices, (4) comparison of ANN and SPANNS, and (5) comparison of RMSE and MAPE for prediction accuracy. These different testing cases are presented in the following sections:

7.2.1 Single and Multiple Inputs

In this section, the study presents experimental work of testing the SPANNS for next day close price. The data set of 3000 observations was segmented into ten consecutive data points and produced 300 vectors for training and testing purposes. Each segment of 300 observations was further segmented into three consecutive data points. Each experiment consisted of 100 vector divided as 75% (75 vectors) for the training stage and 25% (25 vector) for the testing stage.

The results based on a single input (daily closed price) shows that the initial training outcomes were achieved with average accuracy of 96.7% (DOW30: Figures 7.1-7.4, NASDAQ: Figures: 7.5-7.8 and Figure 7.9) on four samples selected for each index. The outcome of final testing, on the entire data of both DOW30 and NASDAQ100 indices, was 98.7%, much higher as compared to that of samples (Figures 7.10-7.13).

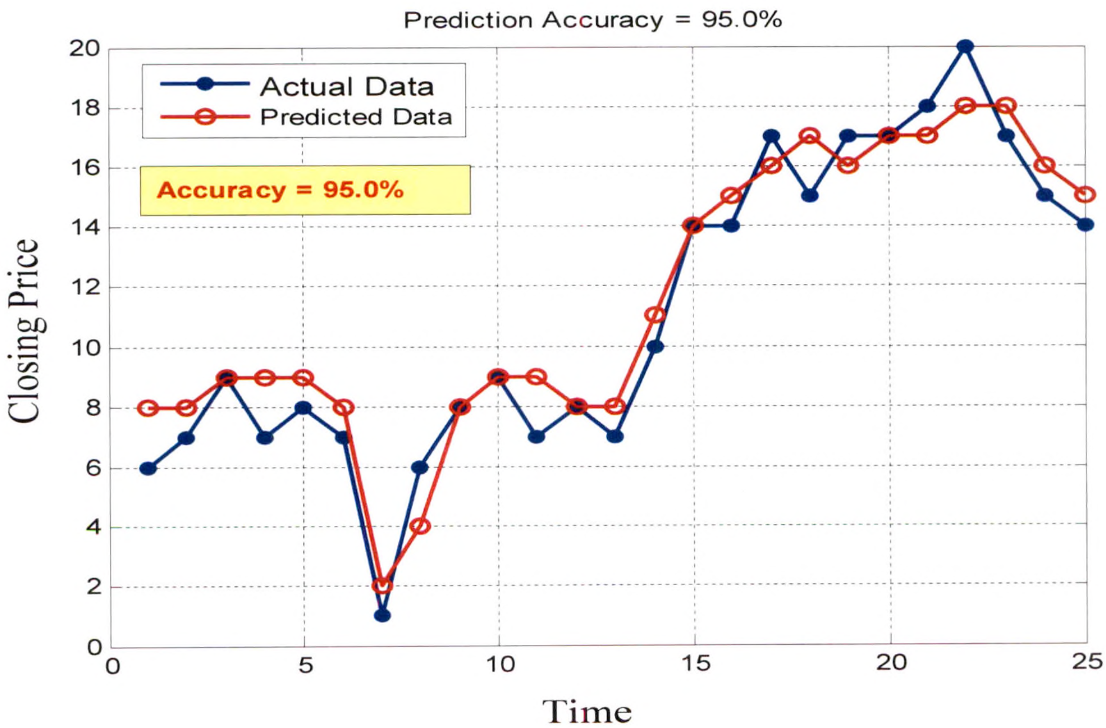


Figure 7.1: Results of the SPANNS for the DOW Index (Sample 1).

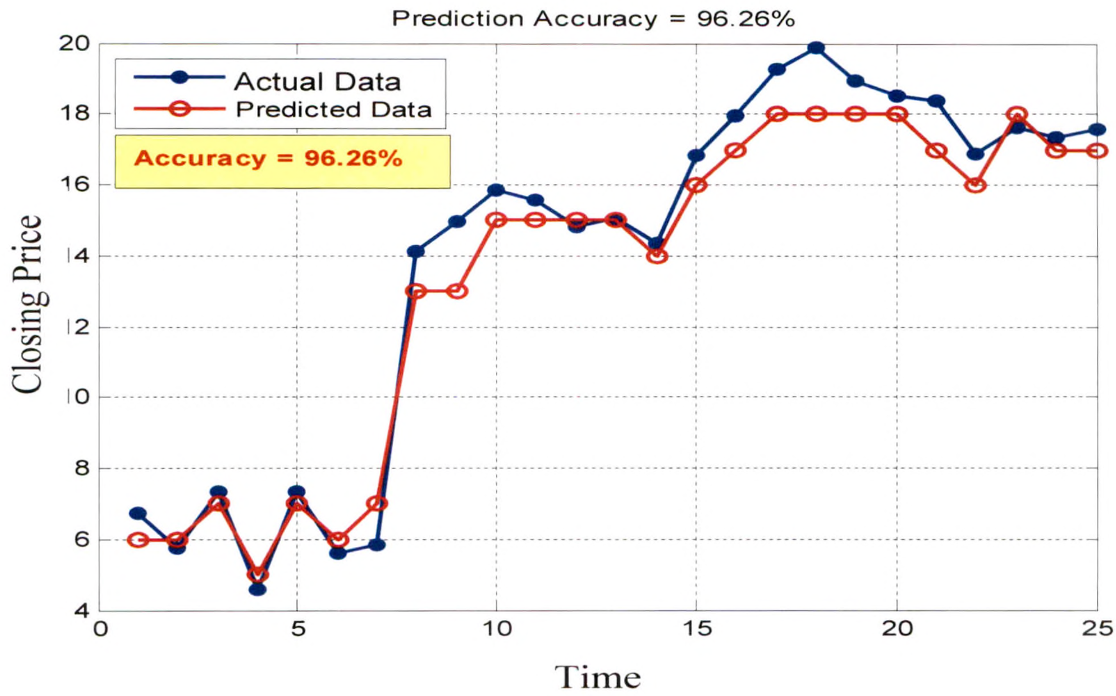


Figure 7.2: Results of the SPANNS for the DOW Index (Sample 2).

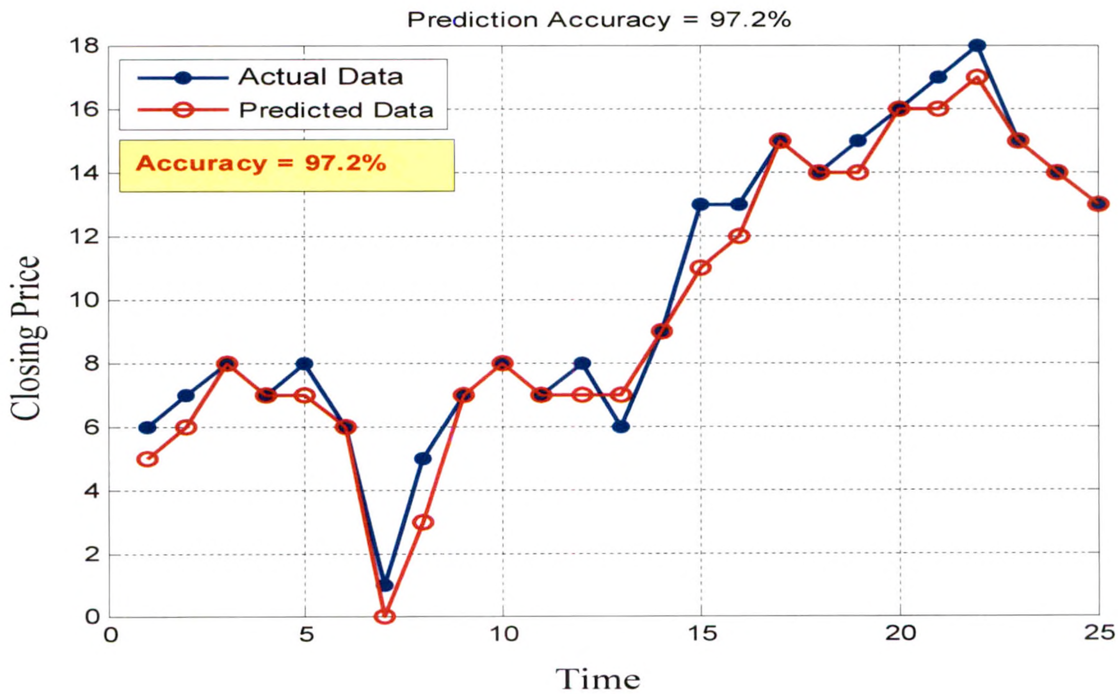


Figure 7.3: Results of the SPANNS for the DOW Index (Sample 3).

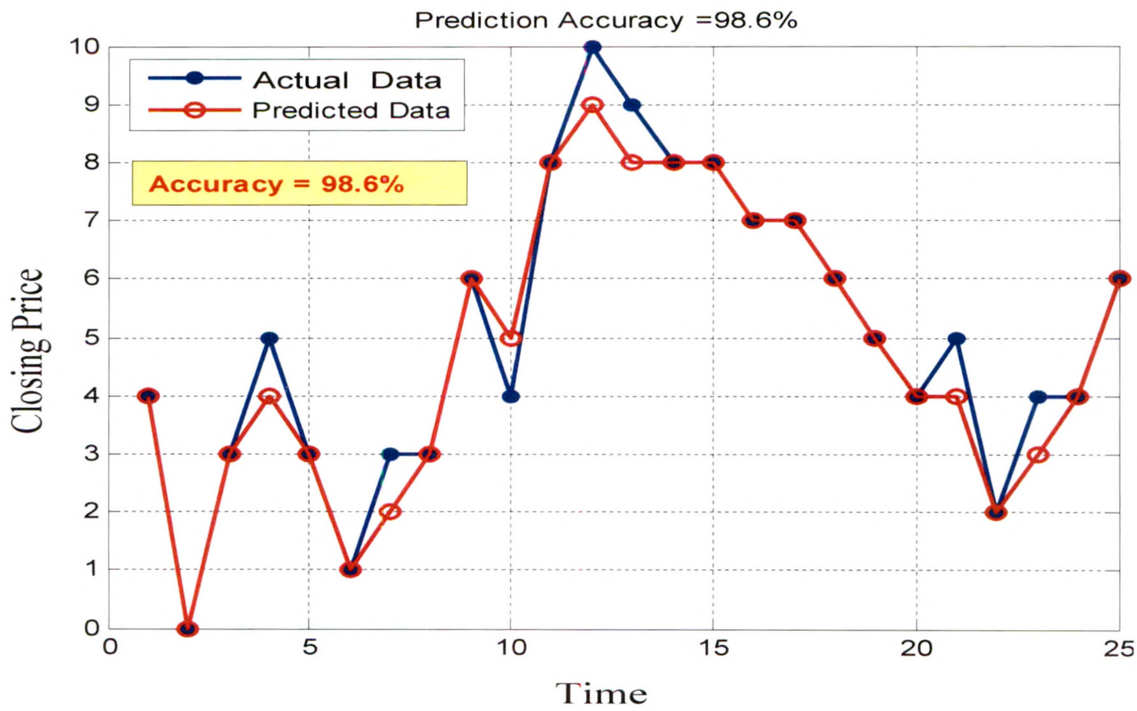


Figure 7.4: Results of the SPANNS for the DOW Index (Sample 4).

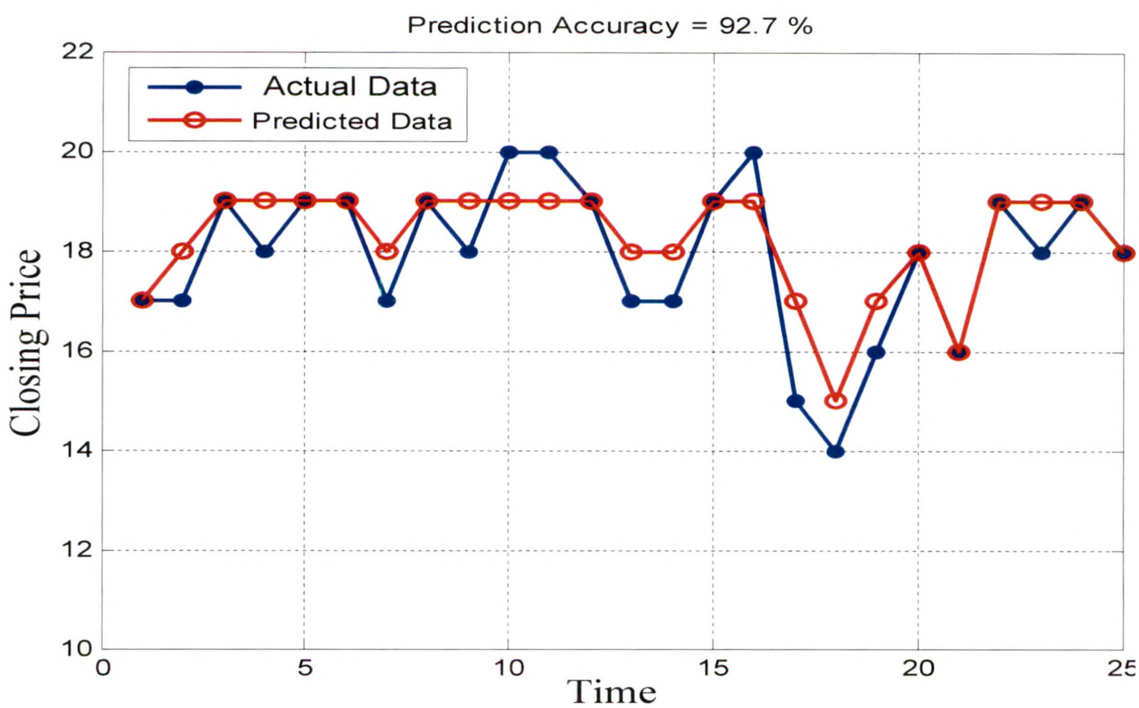


Figure 7.5: Results of the SPANNS for the NASDAQ Index ((Sample 1).

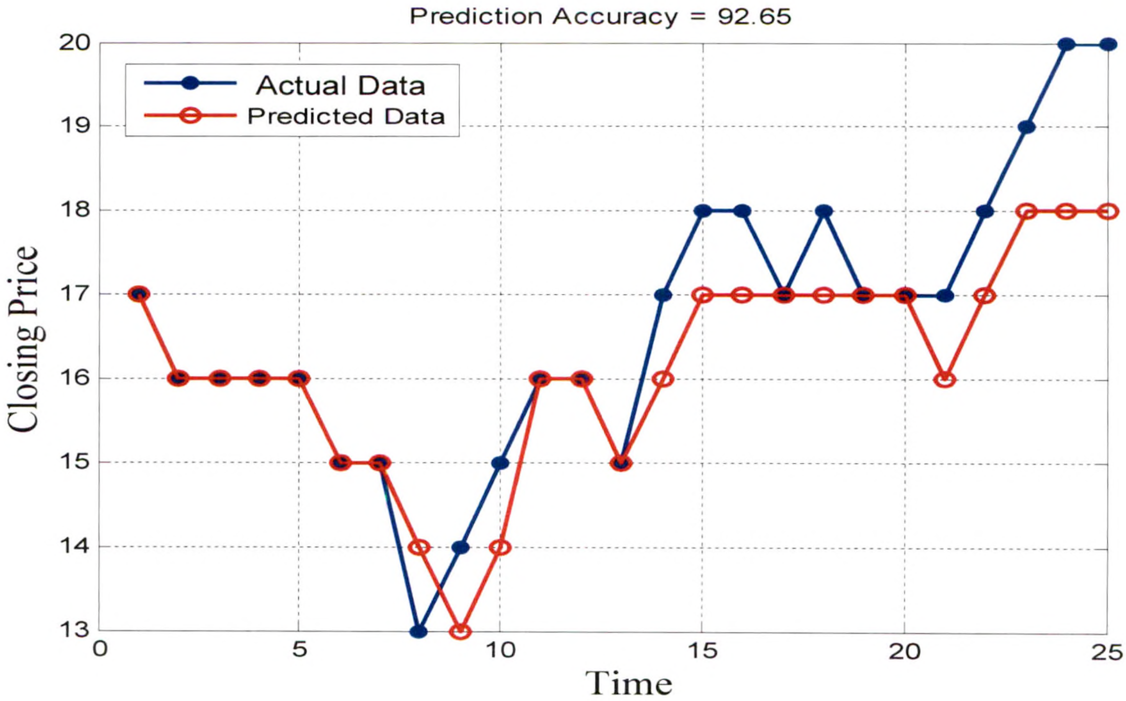


Figure 7.6: Results of the SPANNS for the NASDAQ Index ((Sample 2).

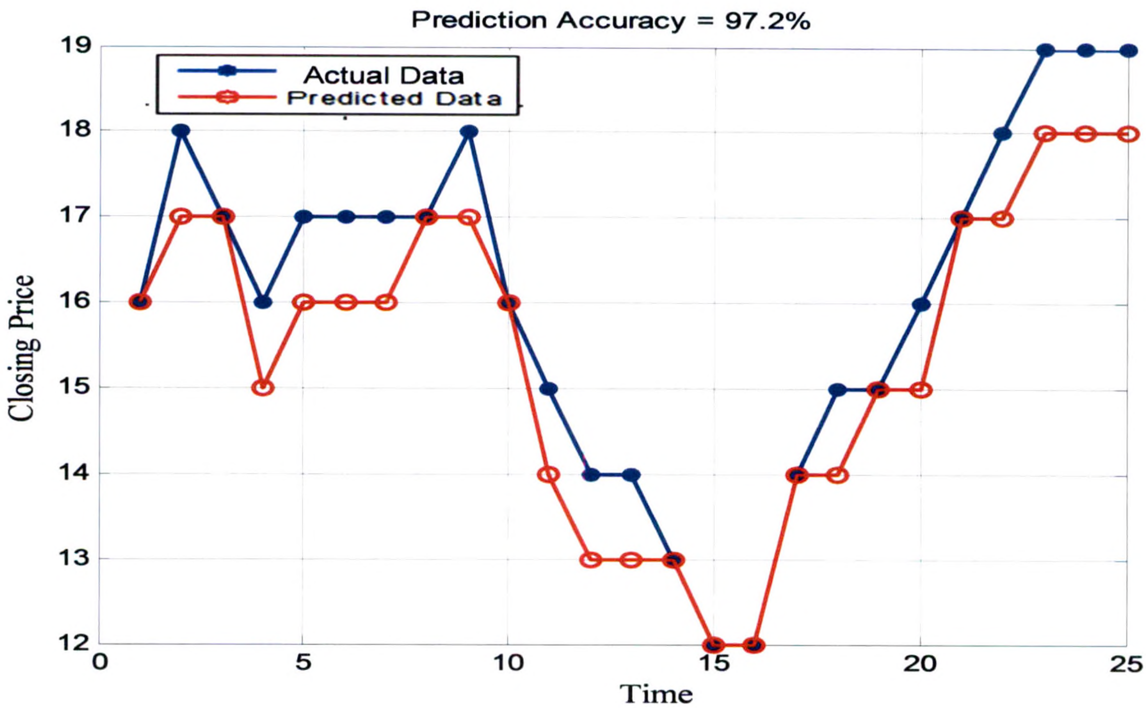


Figure 7.7: Results of the SPANNS for the NASDAQ Index ((Sample 3).

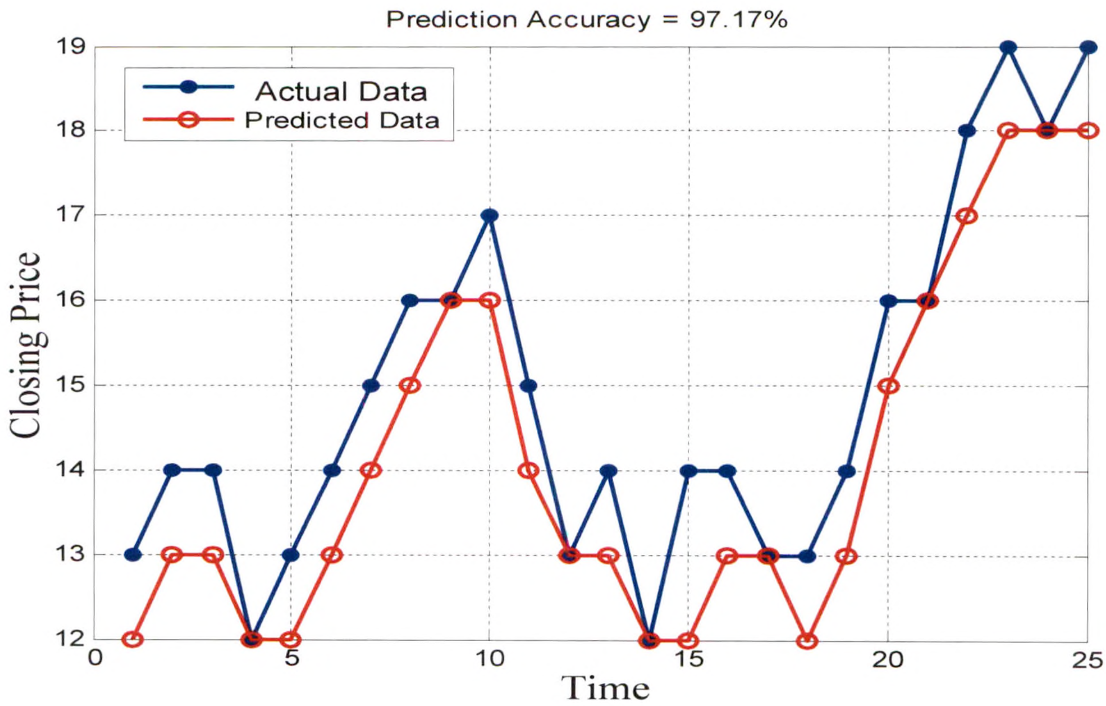


Figure 7.8: Results of the SPANNS for the NASDAQ Index ((Sample 4).

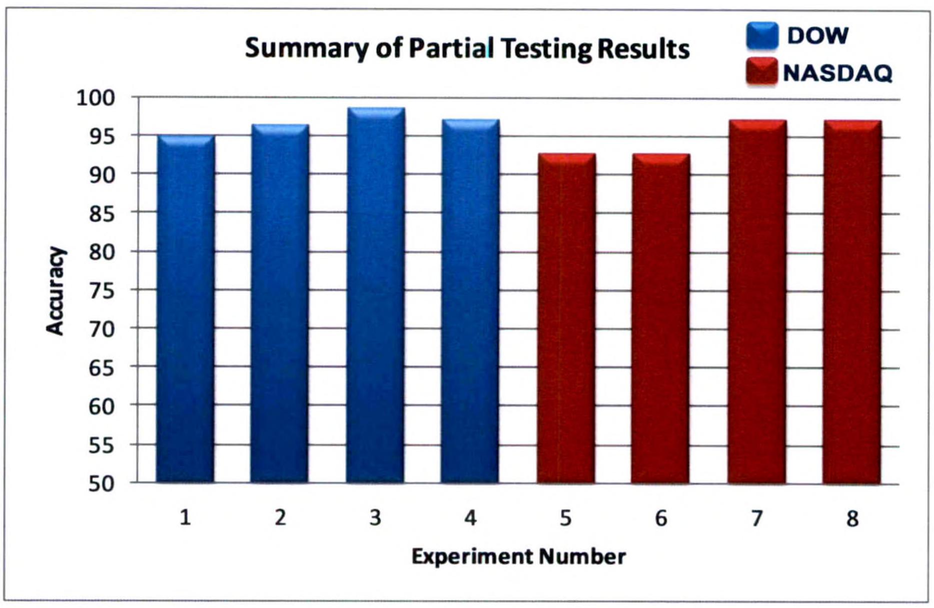


Figure 7.9: Summary of Partial Testing Results of the Two Indices.

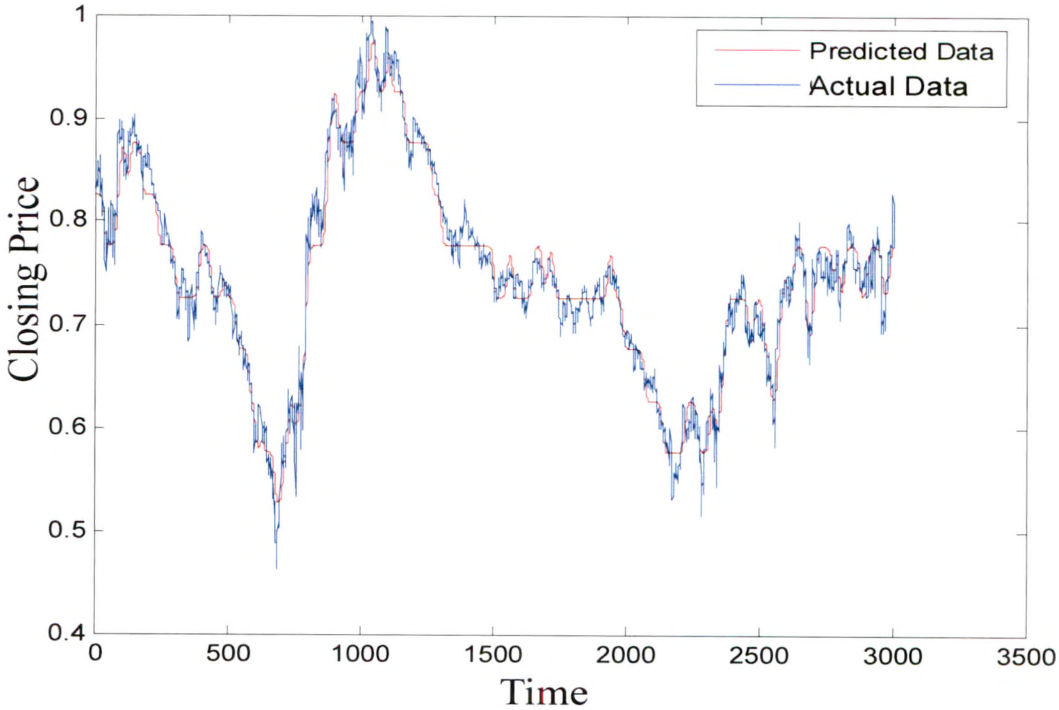


Figure 7.10: Results of the SPANNS for the DOW Index (Entire Data).

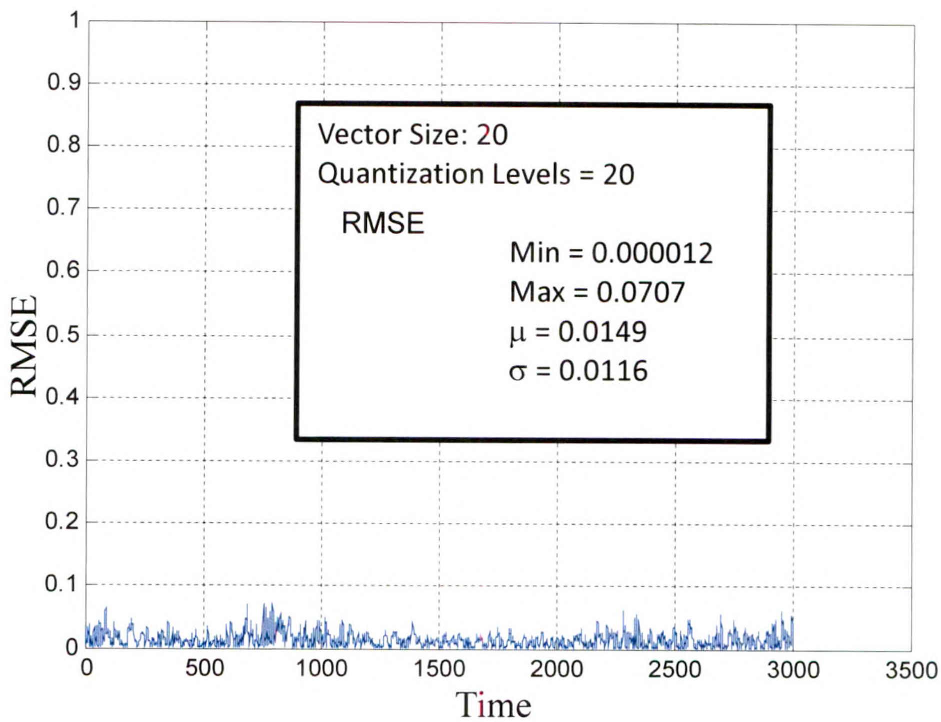


Figure 7.11: Root Mean Square Error Analysis of the DOW index.

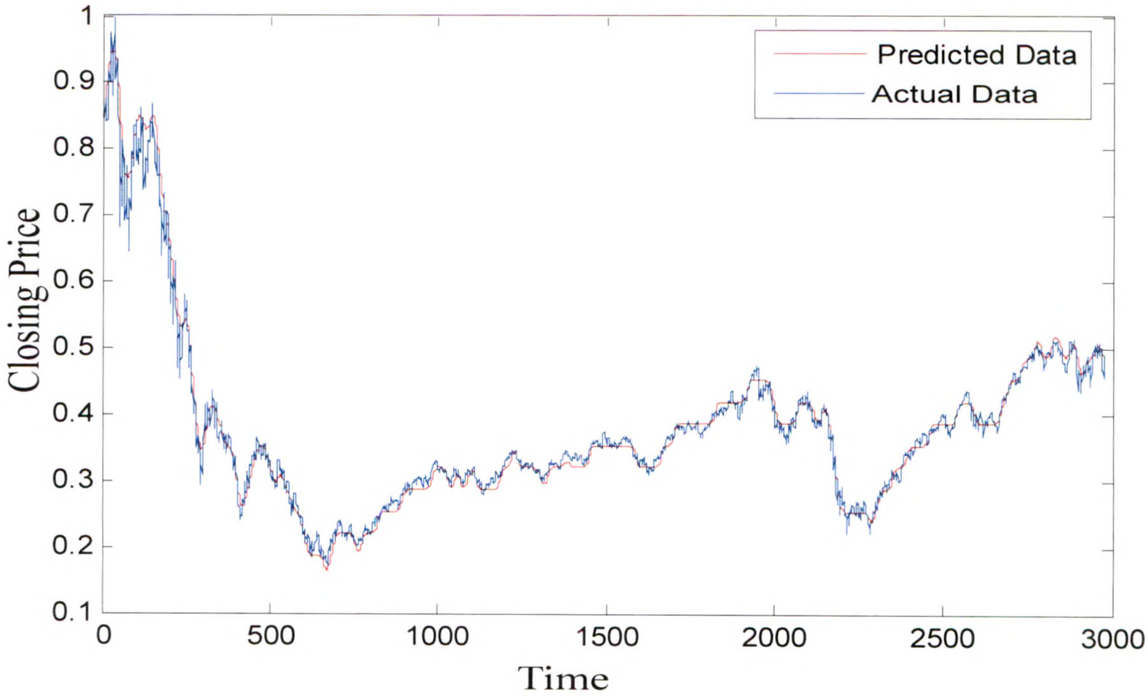


Figure 7.12: Results of the SPANNS for the NASDAQ Index (Entire Data).

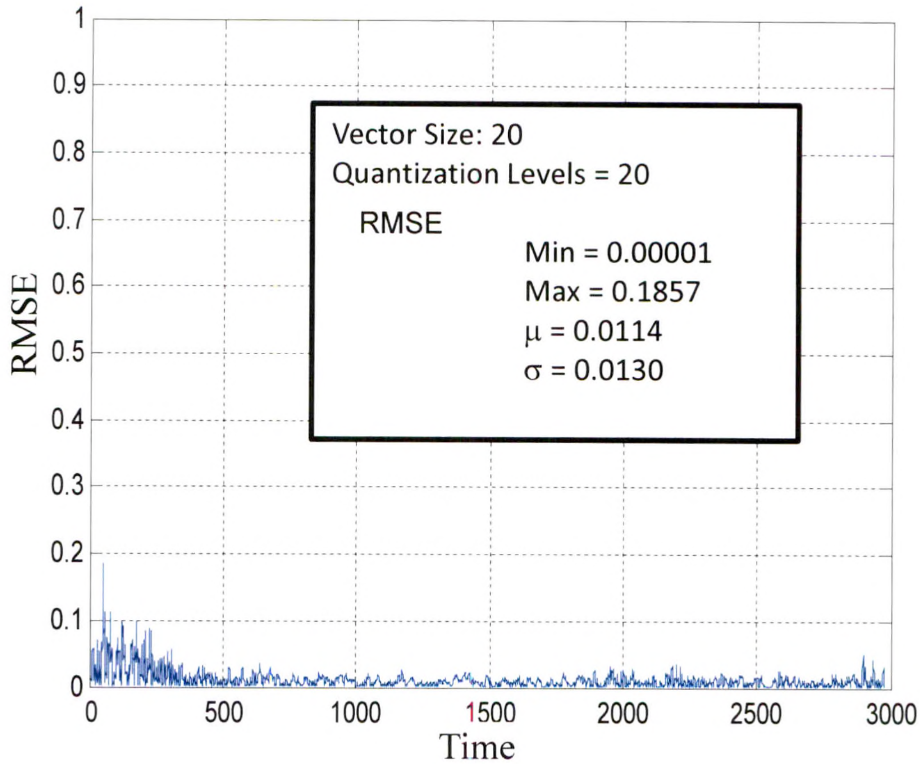


Figure 7.13: Root Mean Square Error Analysis of the NASDAQ index.

The study just demonstrated a single input vectors approach. The next experiment was conducted on multiple input vectors that include equal-sized vectors of open, close, high and low index prices. The results of using multiple-input in the system (Figure 7.14) demonstrated that the average prediction accuracy was 97.24%, while the accuracy of single-input vector was 98.7%. Therefore, the outcome concluded that multiple input-vectors did not enhance the accuracy of the system.

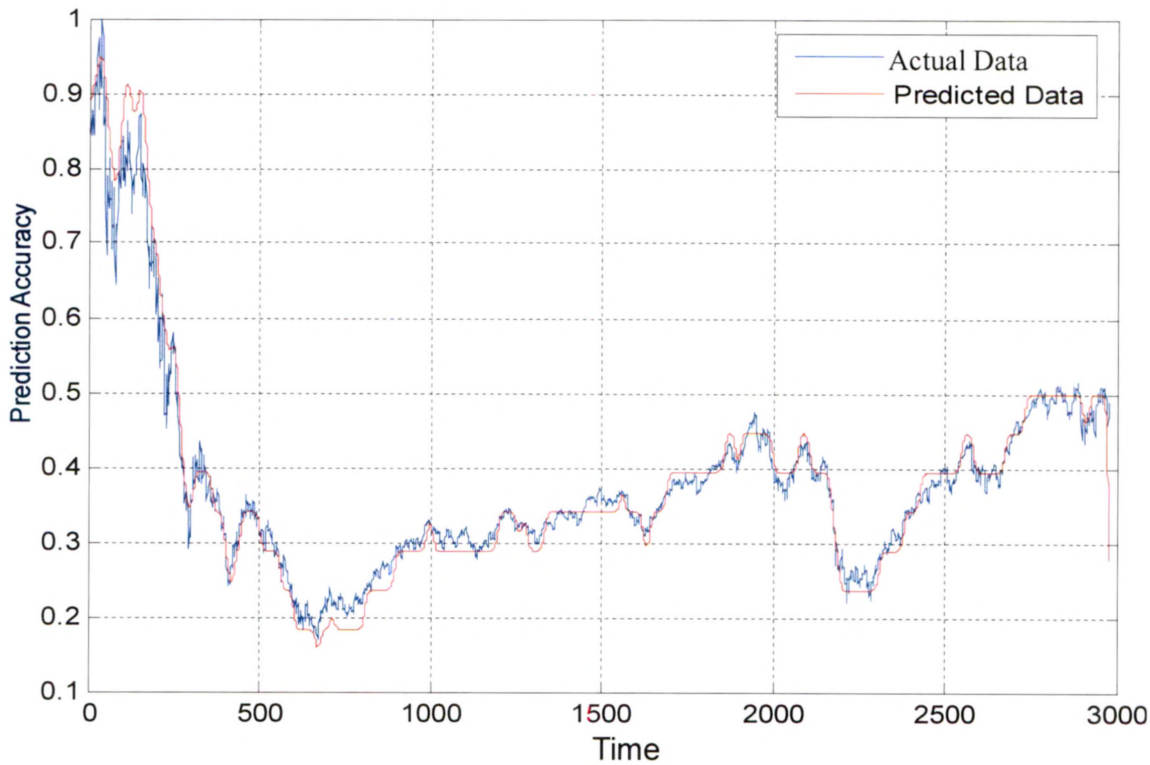


Figure 7.14: Multiple Inputs (Low, High, Open and Close) Results for Nasdaq Index (Accuracy = 97.24%).

7.2.2 N Days Future Prediction

The study further experimented to predict future prices ranging from one day to 30 days and investigated the impact of the prediction accuracy on the future term (number of days). The study started accomplish this task from day one and gradually incremented the term up to thirty days with an increment of five days at a time. The accuracy for each experiment was tabulated for analysis (Table 7.1). The experiment indicated that the accuracy of prediction decreased with the increase of prediction horizon. In other words, the inference of study is that the prediction accuracy is inversely proportional to the prediction horizon. Figure 7.15 demonstrates the prediction accuracy and prediction horizon and revealed a consistent trend for both the indices. However, NASDAQ predictions were less precise with the increase of time horizon.

Table 7.1

N Days Future Prediction

Days	**Accuracy (%)**	
	DOW30	**NASDAQ100**
1	0.980	0.975
5	0.976	0.965
10	0.970	0.960
15	0.974	0.957
20	0.971	0.946
25	0.968	0.932
30	0.953	0.930

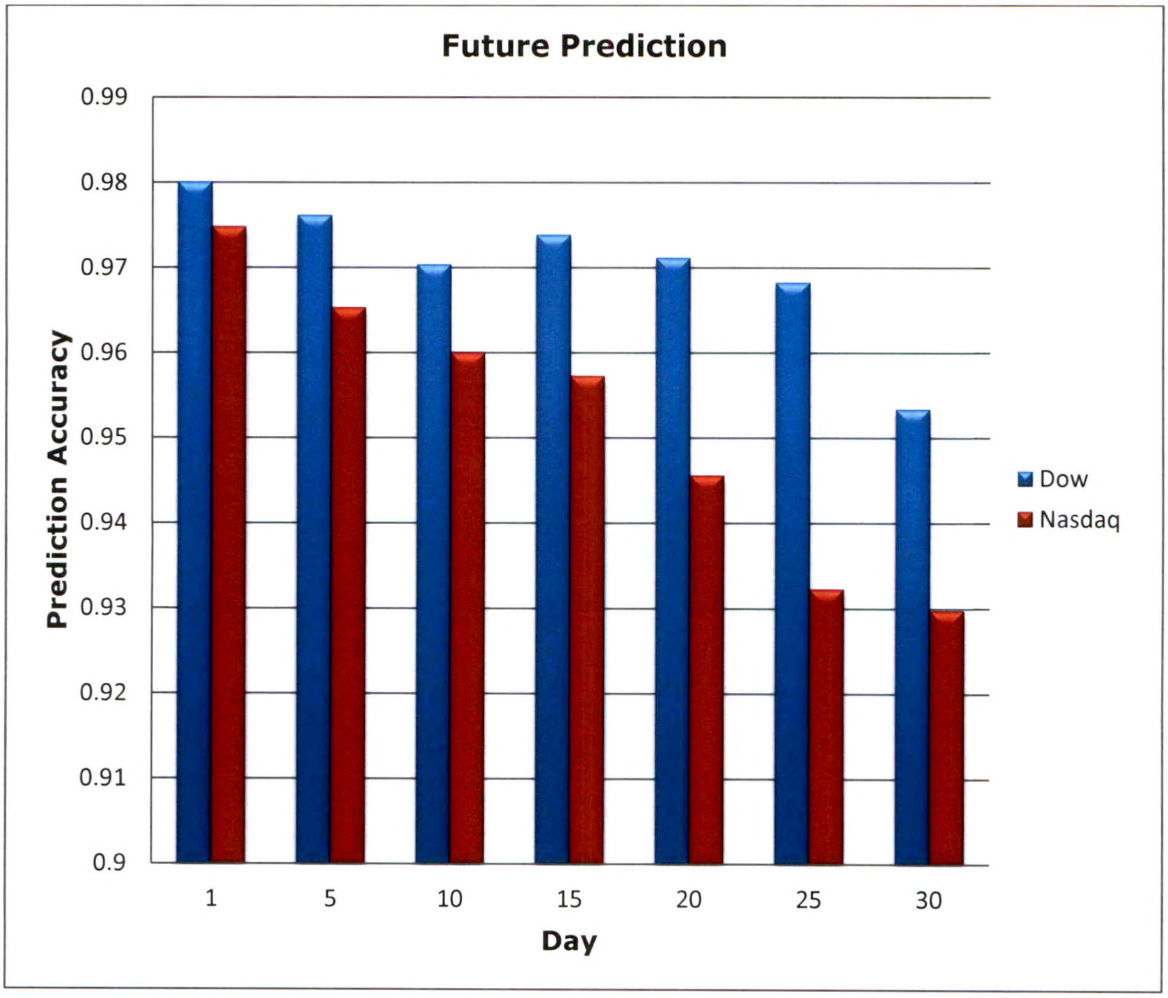


Figure 7.15: Testing N Days Future Prediction Accuracy

7.2.3 Comparison of ANN and SPANNS

The study further investigated the impact of ANN and SPANNS on the prediction accuracy (Figure 7.16). The investigation included testing both systems on the same inputs using two cases for this part: one that uses only ANN without the signal processing (SP) components and the other uses both ANN and SP (SPANNS). The results of all experiments are summarized in the Table 7.2.

Table 7.2 Comparison of ANN and SPANNS				
INDEX	ANN		SPANNS	
	RMSE	MAPE	RMSE	MAPE
NASDAQ	0.9622	0.9549	0.9750	0.9748
DOW	0.9639	0.9727	0.9797	0.9801

The results clearly support the importance and significance of using SPANNS (Table 7.2 and Figure 7.16). It can be observed that the accuracy of SPANNS was 98.5%, while ANN resulted accuracy of 95.0%.

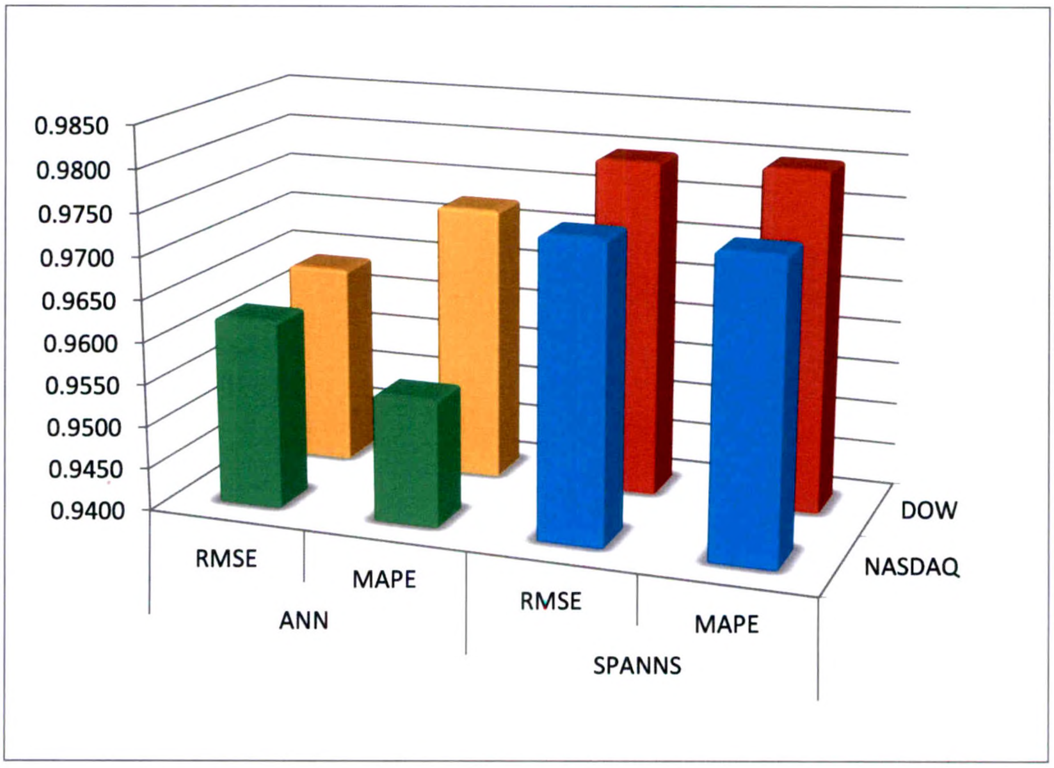


Figure 7.16: Comparison of ANN and SPANNS.

7.2.4 Prediction using Various Daily Prices

This section presents experiments conducted on various daily prices of selected data (low, high, open and close). The main objective of this experiment is to verify that the system is reliable for tracking price movements and predicting future prices using DOW30 and NASDAQ100 data. Table 7.3 summarizes the results of the four daily different prices of indices to demonstrate the system's prediction accuracy. The prediction accuracy for the next day close price is almost the same regardless of using low, high, open or close price of the day (Figure 7.17).

Table 7.3

Prediction Accuracy of Various Daily Prices

No.	Price	Accuracy for Next Day Close ((%)	
		NASDAQ100	**DOW30**
1	Low	0.976	0.979
2	High	0.973	0.979
3	Open	0.978	0.981
4	Close	0.975	0.979

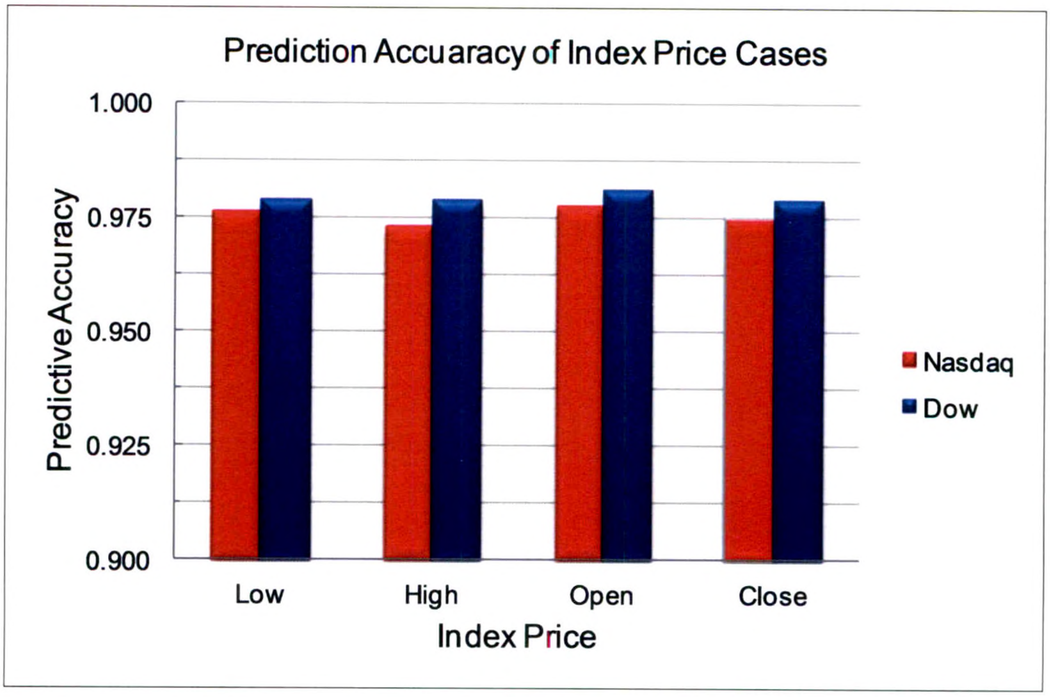


Figure 7.17: Prediction Accuracy of Index Prices: Open Close, Low and High.

7.2.5 Comparison of RMSE and MAPE

Additionally, the study has considered several error measures for evaluating the prediction capabilities of the system including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). Among the aforementioned measures, there are two popular ones: MAPE and RMSE. The study investigated the performance of the system to providing an insight on how to analysis the impact of these measures. Table 7.4 tabulates a matrix of the different experimental results of both RMSE and MAPE. Furthermore, these results are plotted in Figure 7.18. The results reveal that the RMSE for all experiments was 2.98%, while the MAPE for all experiments was 2.94%. This means that, MAPE performance was about 0.04% better than RMSE, which is not significantly different.

Table 7.4 Comparison of RMSE and MAPE				
INDEX	ANN		SPANNS	
	RMSE	MAPE	RMSE	MAPE
NASDAQ	0.038	0.045	0.025	0.025
DOW	0.036	0.027	0.020	0.020

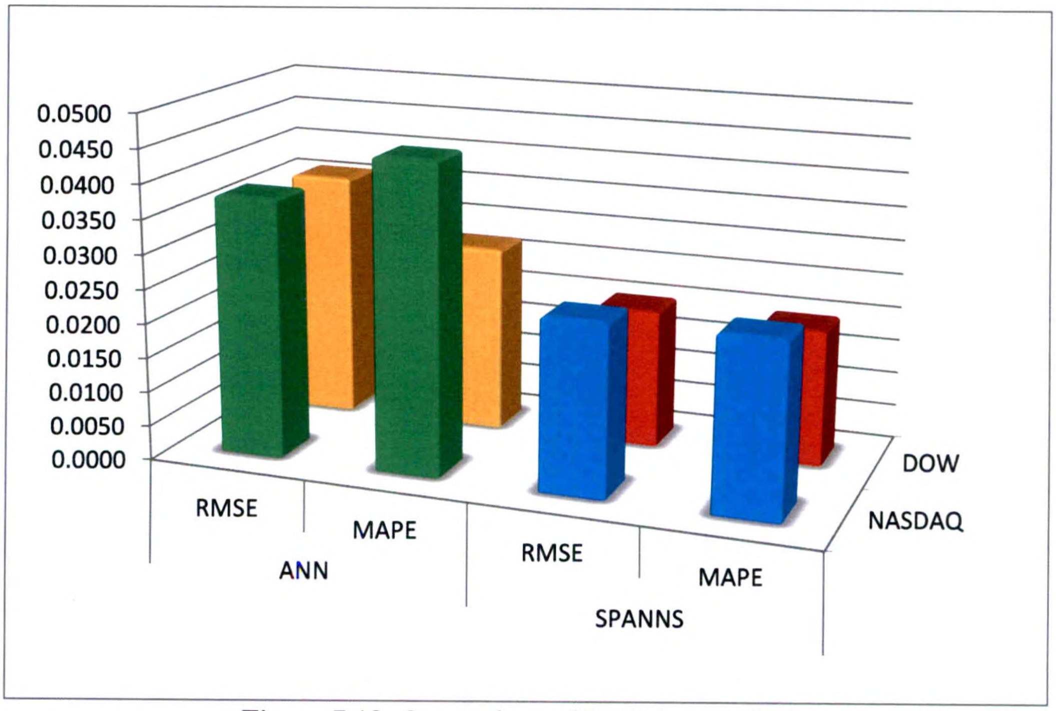


Figure 7.18: Comparison of RMSE and MAPE.

The study further supported the effectiveness of the proposed system on the basis of the comparison of with ANN using RMSE and MAPE for testing data for DOW30 and NASDAQ100.

7.3 RESULTS BASED ON GANNS

The proposed system GANNS and ANN were tested on the same data sets that were used previously for the Signal Processing based Artificial Neural Network System

(SPANNS). The study was conducted on the three different cases. These cases were (1) DOW30 and NASDAQ100 data sets, (2) comparison of ANN and GANNS, and (3) N days future prediction.

The study investigated the effectiveness of the GANNS in comparison to Back Propagation Artificial Neural Network (BPANN) using all four partitions of both the data sets. The system training took place using each partition with the help of GA to optimize the weights and independently to ANN. After the training using each partition, predictions were made for the next day close prices.

7.3.1 DOW30 and NASDAQ Data Sets

The study investigated the robustness of the GANNS for which the data set was partitions into four parts. The system training took place using each partition with the help of GA to optimize the input (open, high, low, close) weights. After the training using each partition, predictions were made for the next day close prices. The partition 3 of DOW 30 resulted into the precise prediction for the next day close prices; hence, partition 3 was selected to make predictions for the time horizon from one day to thirty days. Similar experiment took place for the NASDAQ100 data sets and partition 1 yielded the best prediction for the next day close price in comparison to other partitions. Therefore, partition 1 was selected to make predictions for the time horizon from one day to thirty days.

Figures (7.19 - 7.22) show a comparative graph of actual and predicted prices for DOW30 data set and Figures (7.23 - 7.26) show a comparative graph for NASDAQ100 data set, which was used for training and testing. The analysis of trends exhibited from the figures that the predicted values were very close to the actual values using GANNS.

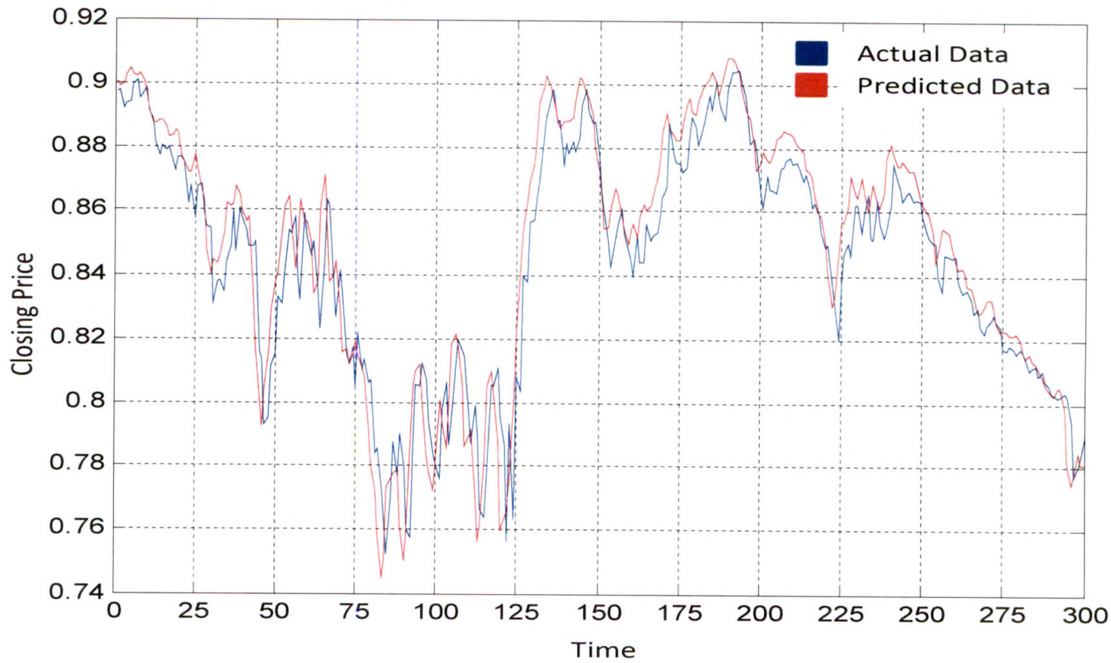


Figure 7.19: DOW30 Prediction Performance for 40% Data Set.

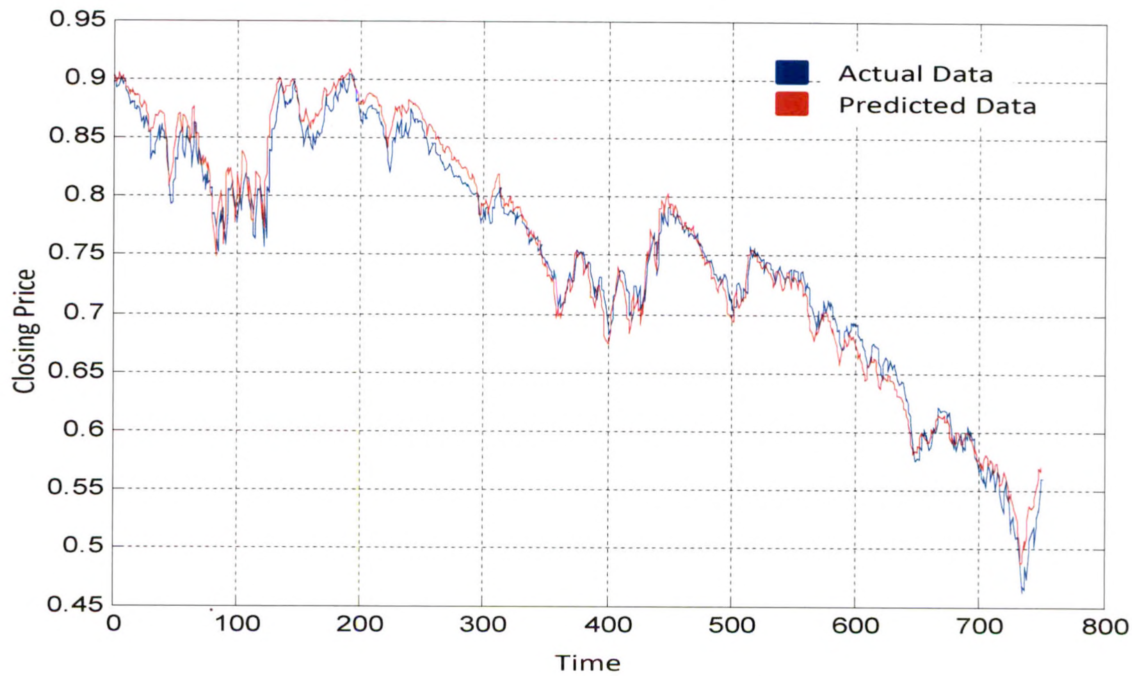


Figure 7.20: DOW30 Prediction Performance for 25% Data Set.

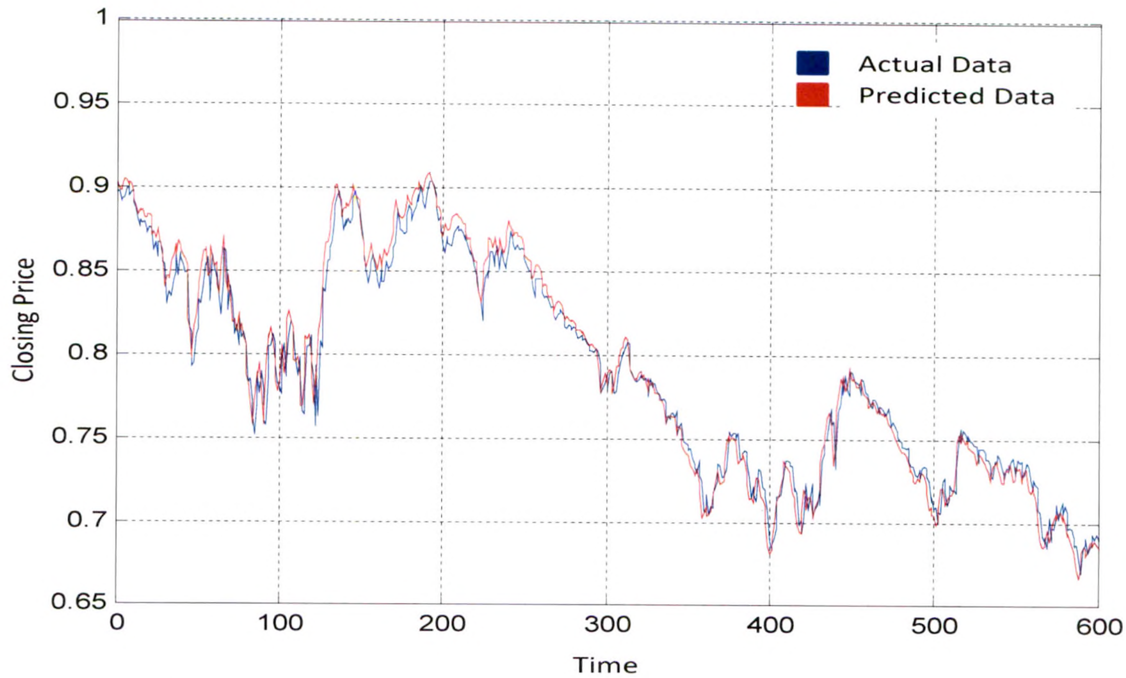


Figure 7.21: DOW30 Prediction Performance for 20% Data Set.

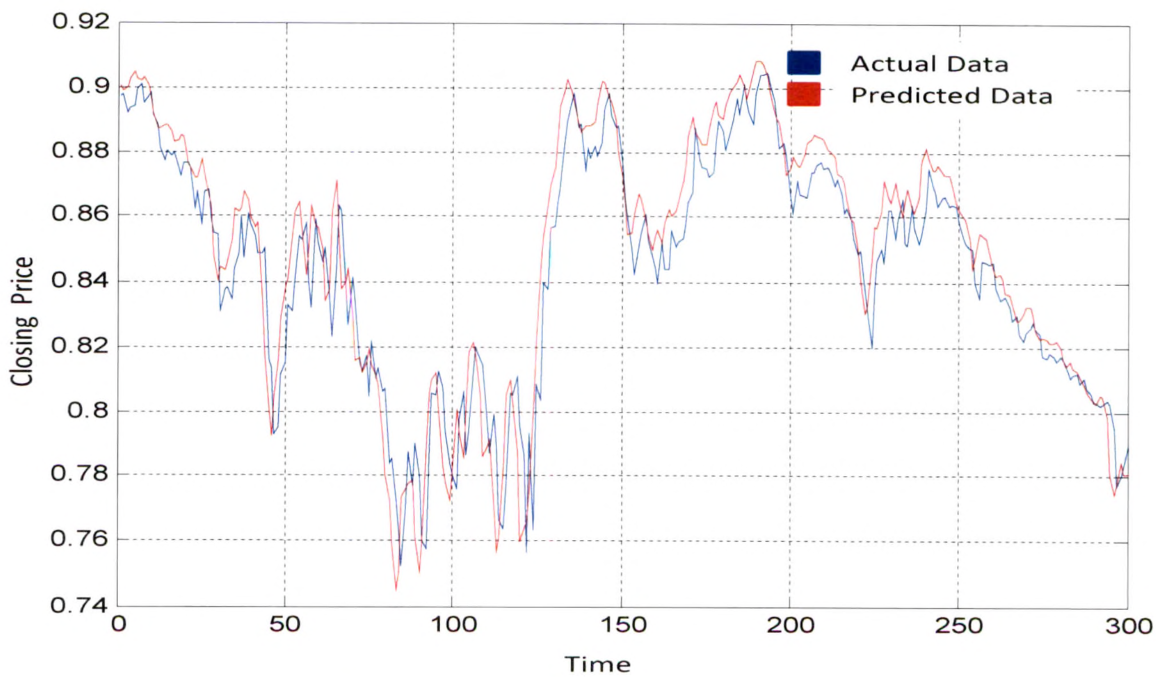


Figure 7.22: DOW30 Prediction Performance for 10% Data Set.

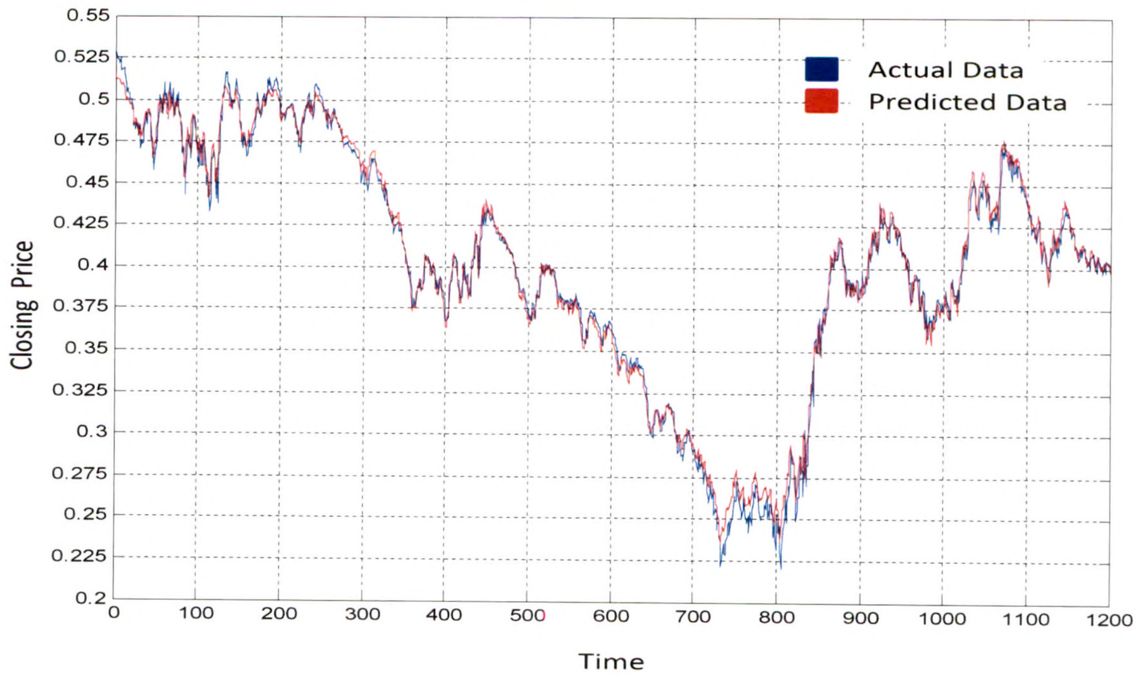


Figure 7.23: NASDAQ100 Prediction Performance for 40% Data Set,

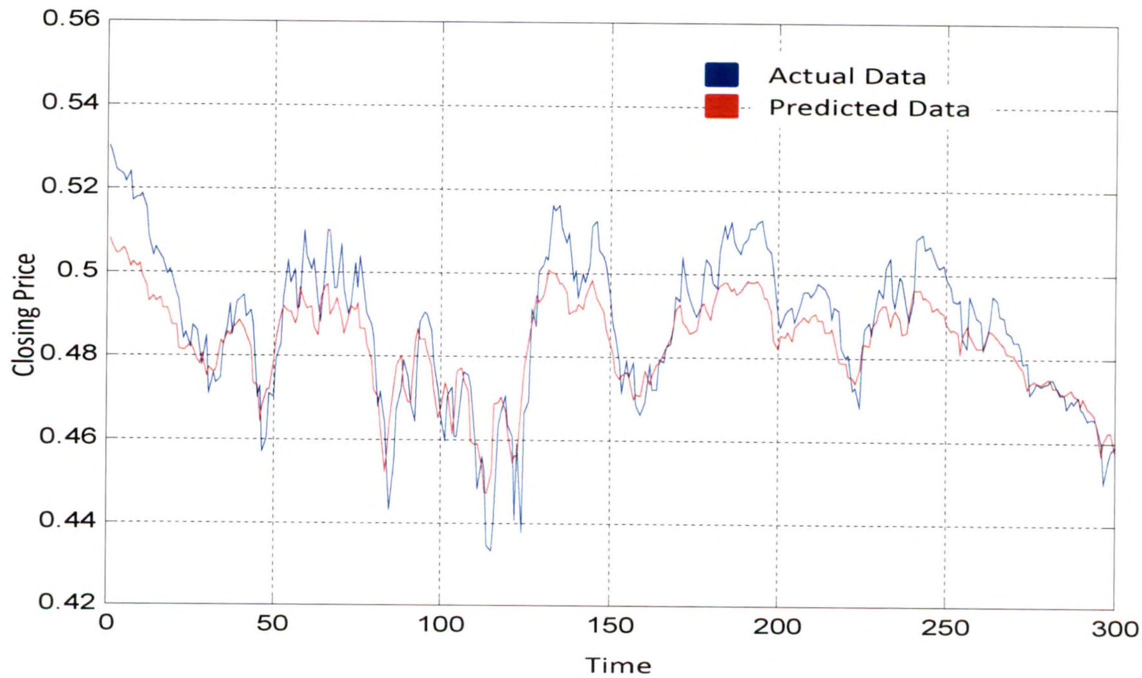


Figure 7.24: NASDAQ100 Prediction Performance for 25% Data Set.

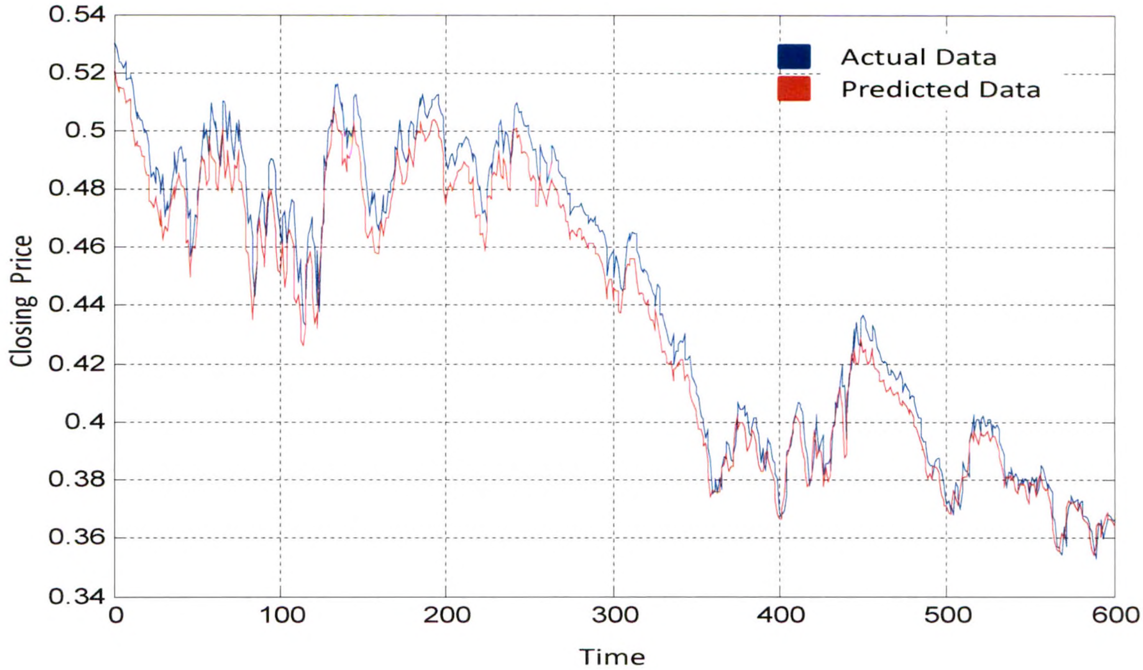


Figure 7.25: NASDAQ100 Prediction Performance for 20% Data Set.

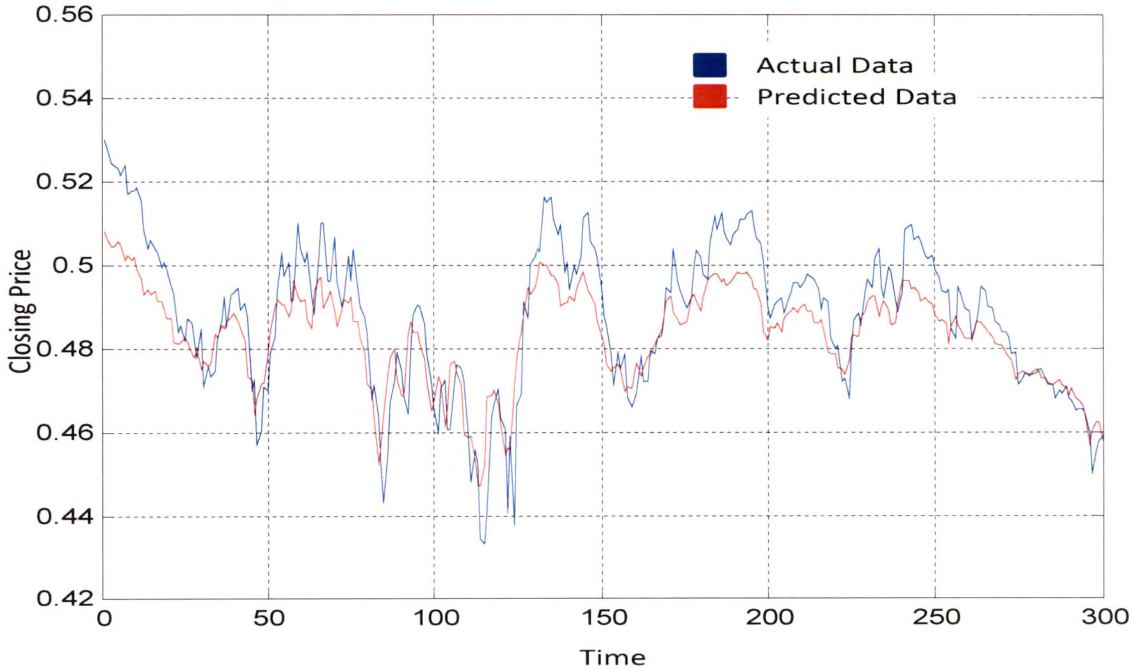


Figure 7.26: NASDAQ100 Prediction Performance for 10% Data Set.

7.3.2 Comparison of ANN and GANNS

Tables 7.5 and 7.6 show the result of the simulations using ANN and GANNS respectively. The values of MAPE by both systems were not consistent for all partitions. The results varied for Partition 1 in both training and testing cases and for partition 4 in case of training only. ANN performed well while in other partitions (Partitions 2 and 3 and in case of testing using partition 4) GANNS performs better.

Table 7.5

MAPE of two models for DOW30 Data Set

Data Partition	ANN		GANNS	
	Training	Testing	Training	Testing
Partition 1	1.23	1.69	1.07	1.56
Partition 2	1.42	1.72	1.36	1.65
Partition 3	1.21	1.10	1.11	1.00
Partition 4	1.34	1.24	1.64	1.20

Table 7.6

MAPE of two models for NASDAQ100 Data Set

Data Partition	ANN		GANNS	
	Training	Testing	Training	Testing
Partition 1	1.41	1.63	1.37	1.55
Partition 2	1.60	2.10	1.58	2.07
Partition 3	1.95	1.99	1.90	1.80
Partition 4	1.78	1.82	2.01	1.60

We have run ANN and GANNS many times with different data partitions and found the highest accuracy in the case of partition 3 (Table 7.5). Testing accuracy is higher than training accuracy for data partition 3, which may be due to proper sampling of training and testing set. It also has been observed that the sampling of data to be used for training and testing may play a very crucial role in terms of accuracy. The same trend can be seen in the case of the NASDAQ100 (Table 7.6) data set. The range of MAPE in the case of the NASDAQ100 data set is larger than that of DOW30. This may be due to highly nonlinear trends in the time series data. A comparative result based on testing data set for both the indices is depicted in Figure 7.27 for DOW30 and in Figure 7.28 for NASDAQ100, which clearly show the performance of GANNS for stock index forecasting. Although the range of error in case of GANNS is very close to that of ANN, but it is smaller for all the partitions and for both the indices, which confirms that GANNS can produce a better result compare to conventional ANN.

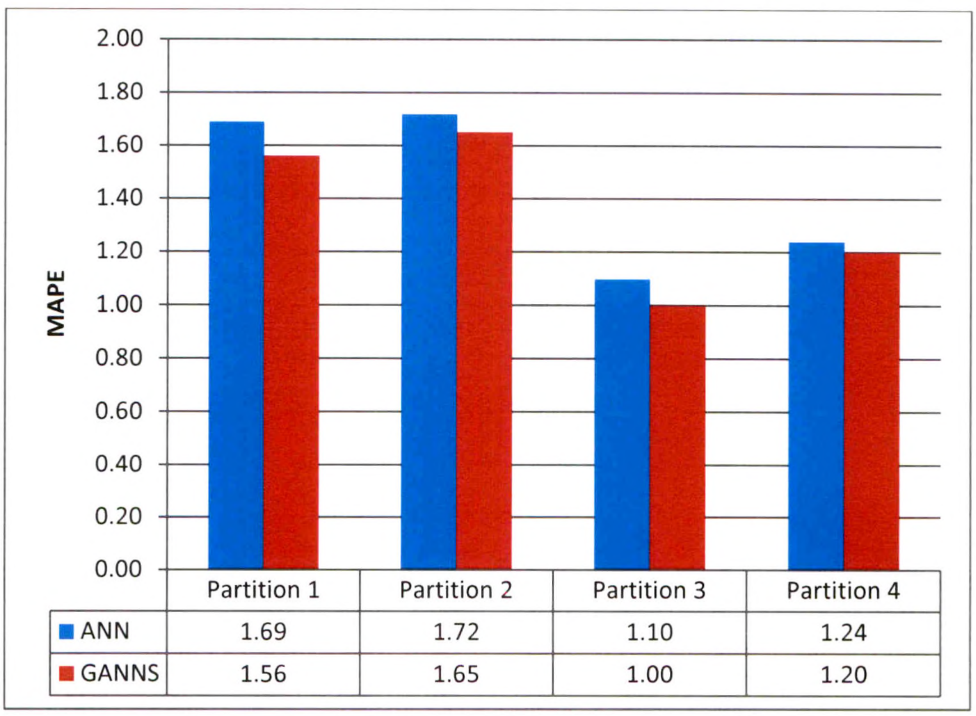


Figure 7.27: Comparison of ANN and GANNS based on MAPE of testing data for DOW30.

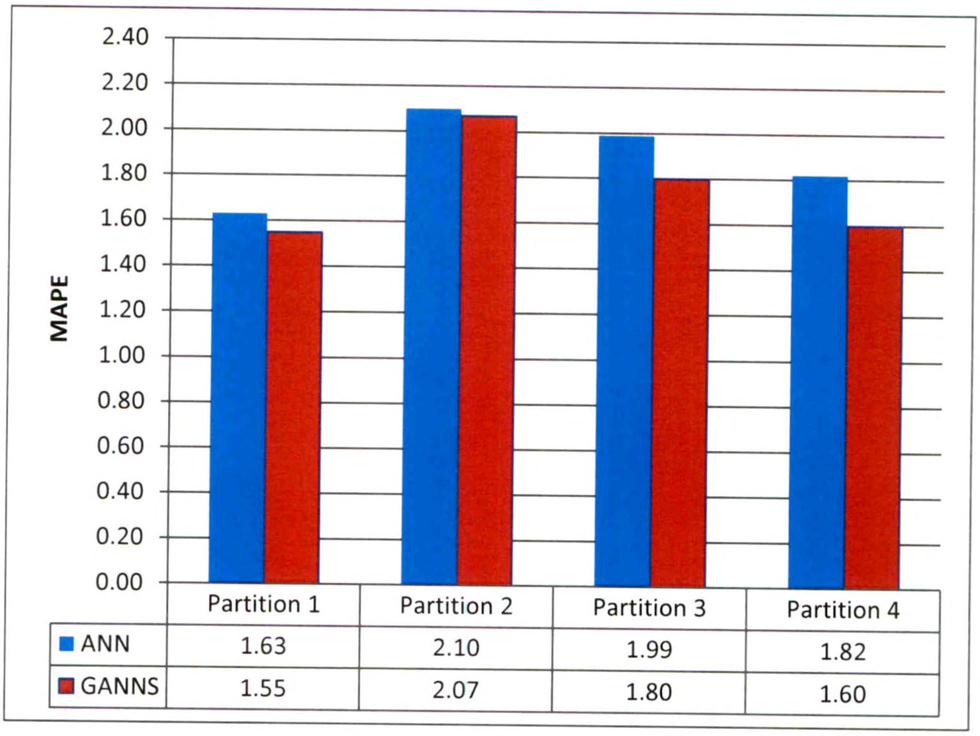


Figure 7.28: Comparison of ANN and GANNS based on MAPE of testing data for NASDAQ100.

Additionally, the study conducted experiment using Root Mean Squared Error (RMSE). However, the results obtained from RMSE were in the same line as discussed in section 7.2.5 for SPANNS. Therefore, the findings of this experiment were not further discussed here.

7.3.3 N Days Future Prediction

The study further investigated capabilities of GANNS, similar to SPANNS, to predict future prices ranging from one day to 30 days. To accomplish this task, the experiment was started from time distance of one-day and gradually incremented this time distance to thirty days, 5 days (a week) at a time. The accuracy for each experiment was tabulated and plotted for analysis. Figure 7.29 shows a consistent trend for both the indices. After analyzing the prediction accuracy and prediction horizon, it can be inferred that the prediction accuracy is inversely proportional to the time-distance. However, NASDAQ predictions were less precise with the increase of time horizon.

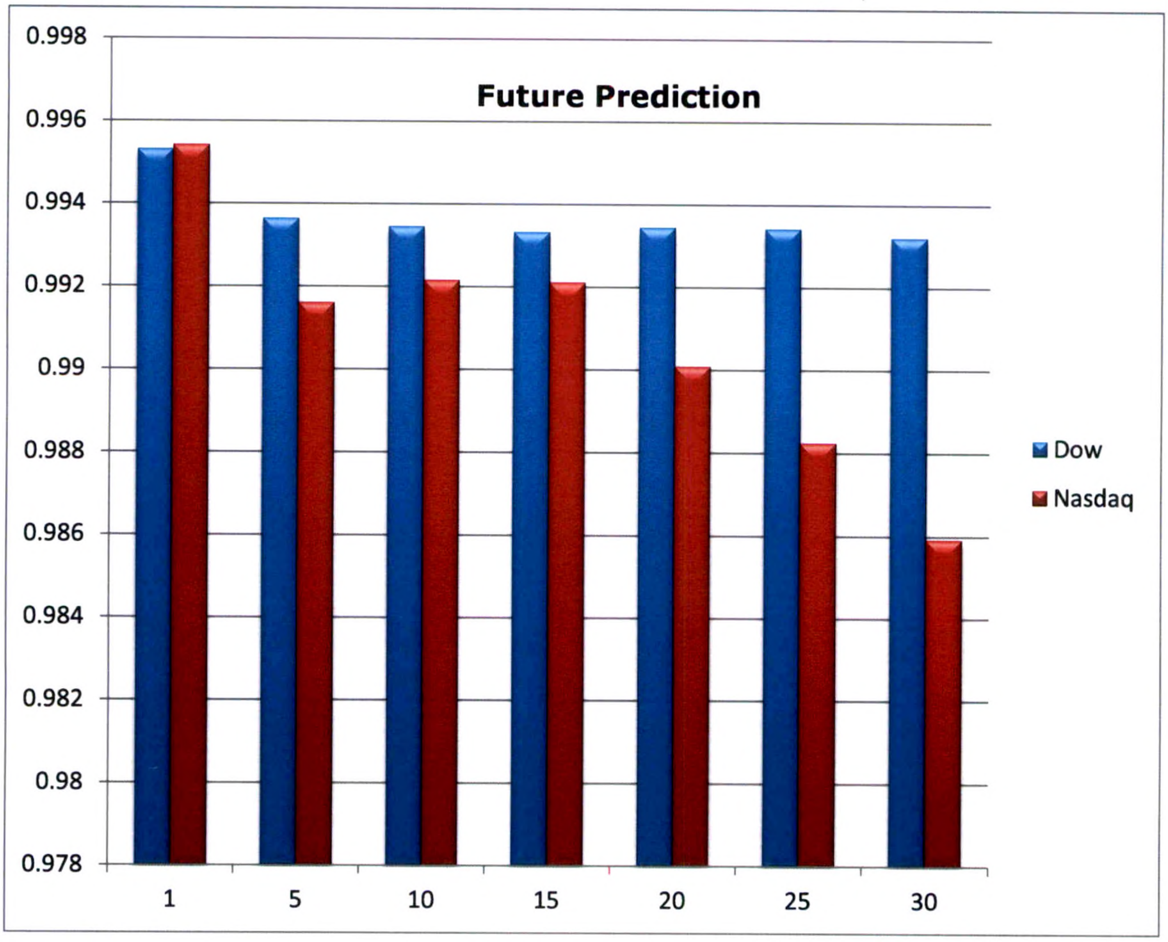


Figure 7.29: Testing N Days Future Prediction (Nasdaq and Dow).

7.4 WEB BASED FPMS RESULTS AND FINDINGS

From an investor's view point, it is very important to make a decision on the amount to be invested in certain stocks. Investing major proportion of money in a particular stock may be sometimes very risky. As a result, the fund diversification is a crucial issue.

The web based fuzzy portfolio management system (FPMS) was tested on DOW 30 data for short- and long-terms returns using one, three and five year investment horizon. The results and findings of this research are discussed below:

For the investigation purpose, two cases are considered. In the first case, it is assumed that an investor will not invest more than 5% of money in a particular stock, and in the second case, it is 10%. Two more cases are also investigated – goals with equal and different priorities.

7.4.1 Goals with equal priorities

In this case, the following data are set by the decision maker:

1 year return goal target = 0.529, and tolerance = 0.3, 3 years return goal target = 0.03, and tolerance = 0.003, 5 years return goal target = 0.087, and tolerance =0.008, risk goal target = 0.711, and tolerance = 0.2, dividend goal target = 1.644, and tolerance = 0.4.

Case Ia: 1 year return, 5% investment limit, the stocks selected and allocation percentages are given in Table 7.41:

Table 7.7: Equal priority case: 1 year return, 5% investment limit

X3	X5	X7	X8	X11	X13	X15	X17	X18	X19	X20
0.05	0.01603	0.03397	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

X21	X22	X23	X24	X25	X26	X27	X28	X29	X30
0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Membership grade of risk goal = 0.80370, dividend goal = 0.89581, return goal = 0.38088. This yields the following goals values: risk = 0.75026, dividend = 1.60232, return = 0.34326.

Case Ib: 1 year return, 10% investment limit, the stocks selected and allocation percentages are given in Table 7.8:

Table 7.8: Equal priority case: 1 year return, 10% investment limit

X3	X15	X17	X18	X19	X20	X21	X24	X26	X27	X29
0.1	0.1	0.1	0.1	0.02982	0.1	0.1	0.1	0.07707	0.1	0.09311

Membership grade of risk goal = 1.0, dividend goal = 1.0, return goal = 0.65896. This yields the following goals values: risk = 0.711, dividend = 1.644, return = 0.42669.

Case IIa: 3 years return, 5% investment limit, the stocks selected and allocation percentages are given in Table 7.9:

Table 7.9: Equal priority case: 3 years return, 5% investment limit

X5	X6	X7	X9	X11	X12	X13	X14	X15	X16	X17
0.05	0.05	0.02997	0.05	0.05	0.05	0.05	0.05	0.05	0.02003	0.05

X18	X19	X20	X22	X24	X26	X27	X28	X29	X30
0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Membership grade of risk goal = 0.48493, dividend goal = 0.27883, return goal = 0.86387. This yields the following goals values: risk = 0.81401, dividend = 1.35553, return = 0.35810.

Case IIb: 3 years return, 10% investment limit, the stocks selected and allocation percentages are given in Table 7.44:

Table 7.10: Equal priority case: 3 years return, 10% investment limit

X7	X13	X17	X18	X19	X20	X22
0.03379	0.08545	0.07803	0.1	0.1	0.1	0.1

X24	X25	X26	X28	X29	X30
0.1	0.1	0.1	0.1	0.1	0.00273

Membership grade of risk goal = 1.0, dividend goal = 1.0, return goal = 1.0. This yields the following goals values: risk = 0.64842, dividend = 1.644, return = 0.27390.

Case IIIa: 5 years return, 5% investment limit, the stocks selected and allocation percentages are given in Table 7.11:

Table 7.11: Equal priority case: 5 years return, 5% investment limit

X3	X5	X6	X7	X9	X12	X13	X15	X16	X17	X18
0.05	0.05	0.05	0.03216	0.05	0.05	0.05	0.05	0.05	0.01784	0.05

X19	X20	X21	X24	X25	X26	X27	X28	X29	X30
0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Membership grade of risk goal = 0.41357, dividend goal = 0.56294, return goal = 0.77817. This yields the following goals values: risk = 0.82829, dividend = 1.46917, return = 0.37534.

Case IIIb: 5 years return, 10% investment limit, the stocks selected and allocation percentages are given in Table 7.12:

Table 7.12: Equal priority case: 5 years return, 10% investment limit

X5	X15	X17	X18	X19	X21	X23
0.07496	0.01002	0.01048	0.1	0.1	0.1	0.00454

X24	X25	X26	X27	X29	X30
0.1	0.1	0.1	0.1	0.1	0.1

Membership grade of Risk goal = 1.0, Dividend goal = 1.0, Return goal = 1.0. This yields the following goals values: risk = 0.711, dividend = 1.64399, return = 0.33339.

7.4.2 Goals with different priorities

Define the following priority structure - the return goal is more important than the risk goal, and the risk goal is more important than the dividend goal.

Case IVa: 1 year return, 5% investment limit, the stocks selected and allocation percentages are given in Table 7.13:

Table 7.13: Different priority case: 1 year return, 5% investment limit

X3	X5	X7	X8	X9	X11	X12	X13	X15	X17	X18
0.05	0.05	0.03249	0.00918	0.05	0.05	0.04175	0.05	0.05	0.05	0.05

X19	X20	X21	X22	X23	X24	X26	X27	X28	X29	X30
0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.01659	0.05	0.05

Membership grade of risk goal = dividend goal = return goal = 0.56947. This yields the following goals values: risk = 0.79711, dividend = 1.47179, return = 0.39984.

Case IVb: 1 year return, 10% investment limit, the stocks selected and allocation percentages are given in Table 7.14:

Table 7.14: Different priority case: 1 year return, 10% investment limit

X3	X9	X15	X17	X18	X20	X21	X24	X26	X27	X29
0.1	0.06456	0.07744	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.05801

Membership grade of risk goal = dividend goal = return goal = 0.75139. This yields the following goals values: risk = 0.76072, dividend = 1.54475, return = 0.45442.

Case Va: 3 years return, 5% investment limit, the stocks selected and allocation percentages are same as the case of equal priority case (Case IIa).

Case Vb: 3 years return, 10% investment limit, the stocks selected and allocation percentages are same as the case of equal priority case (Case IIb).

Case VIa: 5 years return, 5% investment limit, the stocks selected and allocation percentages are given in Table 7.15:

Table 7.15: Different priority case: 5 years return, 5% investment limit

X3	X5	X6	X7	X9	X12	X13	X15	X16	X17	X18
0.01797	0.05	0.05	0.03284	0.05	0.05	0.05	0.05	0.05	0.04919	0.05

X19	X20	X21	X24	X25	X26	X27	X28	X29	X30
0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Membership grade of risk goal = 0.52395, dividend goal = 0.52395, return goal = 0.61744. This yields the following goals values: risk = 0.80621, dividend = 1.45358, return = 0.3583.

Case VIb: 5 years return, 10% investment limit, the stocks selected and allocation percentages are same as the case of equal priority case (Case IIIb).

From the obtained results, we can find out relationships among various factors. The most important finding is the return from the investment. In the short term (1 year) investment, investment of maximum of 10% in a particular equity can provide superior results with respect to all the considered three goals. The same trend has been obtained in both equal and different priority cases. In 3 years investment scenario, 10% investment limit yields slightly better return with a greater risk than 5% investment limit in the equal priority case. The same conclusion holds for the different priority case. The 5 year investment scenario is same as that of the 3 years case. Some of the cases are depicted in the figures below:

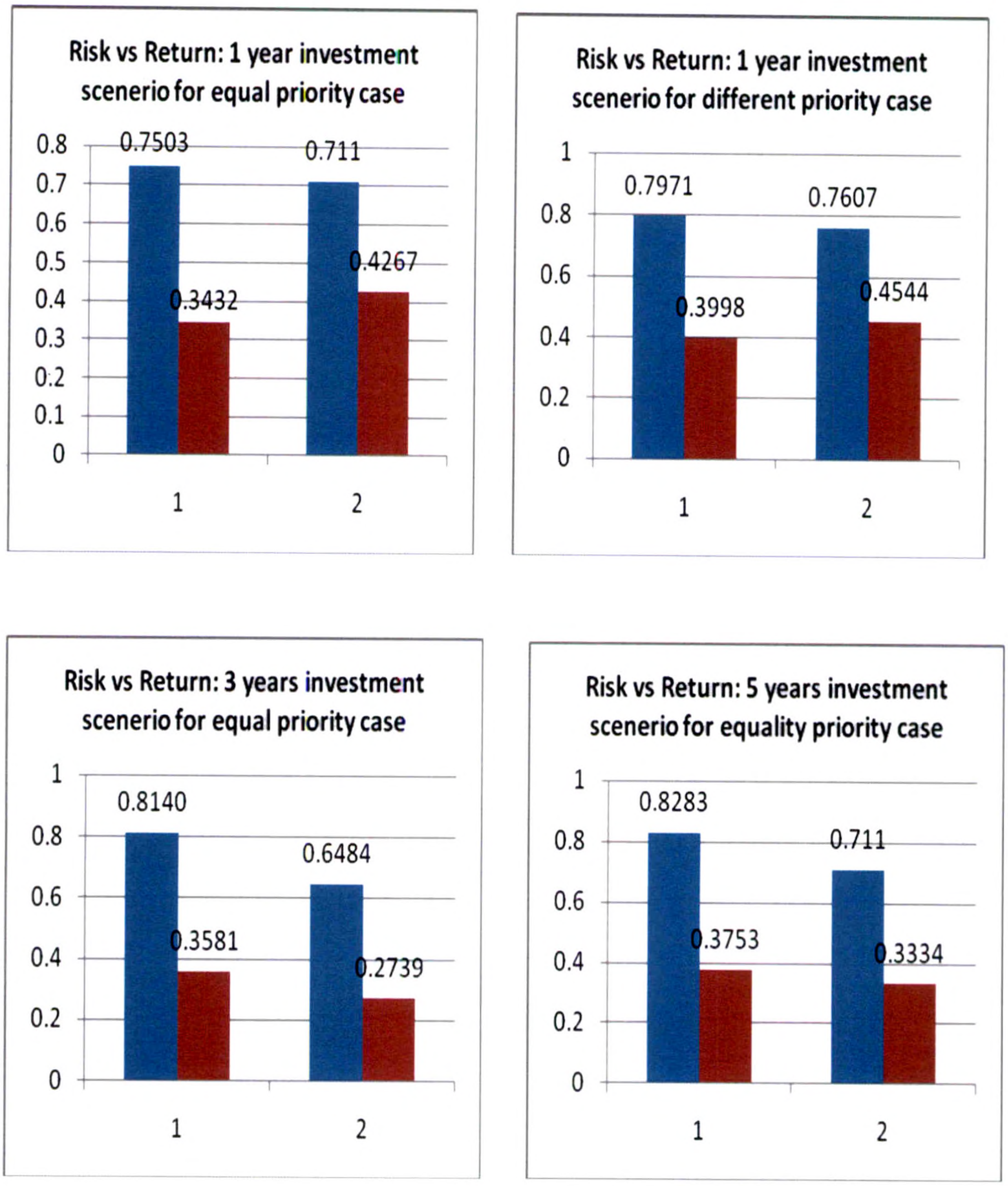


Figure 7.30: Risk vs. Return Scenarios.

The empirical results of proposed web based FPMS showed that the investment returns can significantly outperform the benchmark. Therefore, this hybrid FPMS methodology may advance the research in computational finance and will provide a promising solution to portfolio construction and management in practice.

7.5 SUMMARY

The study summarized results and findings in this chapter for all three systems. The SPANNS and GANNS were tested using historical data of DJIA and NASDAQ indices. The performance of RMSE and MAPE were compared to assess the precision of the results and performance evaluation. The data were partitioned to check the robustness of the SPANNS and GANNS. The performance of FPMS was tested using the DJIA short- and long-terms returns using one, three and five year investment horizon.

CHAPTER 8

CONCLUSIONS, CONTRIBUTIONS AND IMPLICATIONS

8.1 CONCLUSIONS

This research was an attempt to design and develop hybrid systems that provide robust performance in comparison to a single technique based system. The study proposed three new systems of which two of them were for stock market forecasting and the third was for managing active portfolios. The study evaluated and implemented the robustness of the systems for tracking of stock price movements, and actively making buying, selling and rebalancing an active portfolio on a continuous basis. The objectives of this research were to examine, analyze and propose two hybrid systems for stock market forecasting and one hybrid system for active portfolio management. The hybrid systems designed and developed were (1) Signal Processing based Artificial Neural Network System (SPANNS), (2) Genetic Algorithm based Artificial Neural Network System (GANNS), and (3) Web-based Fuzzy Portfolio Management System (FPMS). The objectives of the study envisioned and realized were as follows:

- Reviewed literature on existing tools and techniques for stock market forecasting and portfolio management decisions;
- Designed and developed SPANNS & GANNS for stock market forecasting;
- Evaluated the performance of SPANNS & GANNS by using root mean square error and mean absolute percentage error;

- Compared the trends predicted by ANN & SPANNS and ANN & GANNS.
- Designed and developed FPMS to incorporate impreciseness in the portfolio management; and
- Suggestions for future development of hybrid systems.

The first forecasting system, SPANNS, is integration of Signal Processing/Gaussian Zero-phase (GZ) filter and Artificial Neural Networks/Multi-Layered Perceptron (ANN-MLP) to develop a predictive model for tracking stock market movements and forecasting. The SPANNS models the input feature vectors to the MLP network as k-element vector of stock index close day entries. The classes of vectors were modeled as a last entry in each vector after mapping them to a suitable representation that meets MLP input output layer requirements, that is an integer class label. The GZ filter was extremely effective in de-noising the input signal, as well as, in retaining its phase. An archived data of DOW30 and NASDAQ100 indices for more than twelve years were used for training and testing the proposed system, and the results strongly supported the effectiveness of the proposed model with the overall average prediction accuracy of 98.7%.

Furthermore, the study applied to various decision making situations including stock index individual price, open, close, low and high signals, N day's future prediction. The effect of signal processing on the prediction reliability and the impact of the accuracy measure used to evaluate the performance. For each of the aforementioned case, the study conducted several experiments and summarized, plotted and analyzed the results to provide the conclusions and inferences, which would be helpful for decision making purposes.

The second system applied Artificial Neural Network (ANN) based Back Propagation Neural Network (BPNN) model and Genetic Algorithm (GA). The combined system called Genetic Algorithm based Artificial Neural Network System (GANNS). GANNS and ANN were tested on DOW30 and NASDAQ100 data sets. This system was integrated with the facility of graphical user interface (GUI) to work in a more interactive manner. Results obtained from both systems were compared in terms of RMSE and MAPE, and found that the performance of GANNS was better than ANN. The data set was partitioned into four different partitions to check the robustness of GANNS. Out of four data partitions, GANNS performed well for three partitions in training, while ANN performed well in one data partition only. BPANN often fails to optimize the weights of ANN due to the problem of local minima. Therefore, GANNS can be applied because GANNS can handle global optimizations. Also, GANNS can capture the nonlinearity situation of stock market in a more intelligent way.

The third study demonstrates the web based Fuzzy Portfolio Management System (FPMS) using a Goal Programming (GP) to formulate the mathematical model of the portfolio selection problem. The application of fuzzy set theory facilitates impreciseness in the model. This system accommodates investors' personal characteristics and preferences for constructing and managing an active investment portfolio. Additionally, the system provides flexibility for the decision-maker to refine the tolerance and targets of goals to find a feasible solution based on the current market conditions and forecasts of economic and financial variables. The robustness of proposed FPMS lies in managing risk and return effectively even in a volatile market situation. The strength of the FPMS reflects in the fact that it provides the decision-maker an easy to guide web based user-interface to construct an efficient portfolio of securities without knowing the complexity of the model. Thus, the FPMS can be used as a decision-making tool by both individual investors and financial advisors.

8.2 CONTRIBUTIONS

This research contributes to the existing literature related to financial forecasting and active portfolio management. The study strongly suggests the need of designing, developing and implementing hybrid systems by demonstrating their capabilities for stock market forecasting and active portfolio management. The first two systems designed in the study were SPANNS and GANNS for stock market prediction. A number of algorithms for modeling stock market predictions were proposed and compared in this study. Their influence on the overall system performance was also evaluated and verified. The proposed hybrid systems consisted of the signal processing combined with ANN and GA with ANN techniques. Additionally, the study proposed designing, developing and implementing a web based fuzzy portfolio management system (FPMS) for managing stock portfolios.

The study explored the use of signal processing techniques as a potential solution for stock market predictions with the expectation that this research would provide a strong foundation for system developers to design professional intelligent prediction systems. The system was evaluated on DOW30 and NASDAQ100 data set to authenticate the success of the proposed system. In fact, this study presented a unique investigation via exploring the potential of combining signal processing techniques with

ANN and their effectiveness in developing predictive models for stock market price movements.

The second system was designed to compare and contrast the effectiveness of a single technique based system, as well as, the first system proposed in the study on the same data set. The comparison of results supported the argument that GANNS yields the highest rated ranking of predictions, which implies that GANNS is more preferable over ANN and SPANNS.

The third contribution of this study was to design, develop and implement a web based FPMS for managing stock portfolios. The system incorporated several imprecise variables such as risk, return, and expense ratio as fuzzy goals. The proposed FPMS can serve as a useful tool for construction, and rebalancing of equity portfolios, because, the system is capable of enhancing the effectiveness of decision making of both individual and professional investors. The system can accommodate investors' personal characteristics and preferences for different types of decision-making needs via web. It provides flexibility for the decision-maker to refine the tolerance and targets of goals to find a feasible solution based on the current market conditions and forecasts of economic and financial variables. Thus, the study focused on identifying, analyzing, synthesizing, and addressing a number of issues associated with stock market predictions and active portfolio management. The contributions of the study reflect in designing and developing three hybrid systems (1) SPANNS, (2) GANNS, and FPMS. Details of the contributions are as follows:

(1) SPANNS

The SPANNS can provide precise stock market forecasting in comparison to that of existing intelligent systems. The contributions of the study can be exhibited in the following areas:

- Designed and developed the SPANNS that can be used in real stock market forecasting scenarios;
- Evaluated the performance of SPANNS by using root mean square error (RMSE) and mean absolute percentage error (MAPE) statistical techniques;
- Compared the performance of SPANNS with that of ANN;
- Implemented SPANNS using DOW30 and NASDAQ100 for stock market forecasting.

(2) GANNS

The GANNS can provide better solutions in global optimization, because it captures the nonlinearity situation of stock market in comparison to that of existing systems with no integration of GA. The contributions of the study can be exhibited in the following areas:

- Designed and developed the GANNS which can be utilized in actual stock market forecasting scenarios;
- Evaluated the performance of GANNS by using root mean square error (RMSE) and mean absolute percentage error (MAPE);
- Compared the performance of GANNS with that of ANN; and
- Implemented the GANNS on DOW30 and NASDAQ100 data for stock market forecasting.

(3) FPMS

- Designed and developed FPMS to incorporate impreciseness in the portfolio management; and
- Implemented the FPMS on DOW30 index for active portfolio management.

8.3 IMPLICATIONS

The implication of this research is multi–dimensional. Since existing systems with single technique have some inherent weaknesses such as ANN are suitable for learning ability and forecasting, but lack the explanatory capability. Whereas, GA do not rely on training data sets yet deciding suitable fitness function is a tedious task. Although, single technique based systems are easier in solving problems, yet the degree of precision of results from these systems is not meeting the expectations. On the other hand, a hybrid intelligent system utilizes merit of both techniques and enhances predictions and decision making capabilities. Therefore, this study provided a better alternative for forecasting stock market in general and specifically for active portfolio management of securities by proposing hybrid systems. The design of these systems is easy enough for individual investors and investment professionals with little or no knowledge of quantitative or algorithms aspects. Forecasting aspects of the study will provide academicians improved techniques and systems for future academic researches, as well as, active portfolio management tool for investors due to its precise predication capabilities and integration of multiple goals and objectives.

8.4 FUTURE WORK

The study anticipate that the future studies of SPANNS will utilize advanced signal processing techniques such as fast Fourier transform (FFT) and discrete wavelet transform (DWT) to further explore the effectiveness of these techniques for stock market predictions. Also, future research work related to GANNS can be carried out with some new hybrid techniques combining FFT, DWT and the Adaptive Neuro Fuzzy Inference techniques into GANNS. Furthermore, various tuning parameters like learning rates and momentum can also be incorporated in GANNS to improve the accuracy of results. The study further envisioned that portfolio management system can be enhanced with the integration of Genetic Algorithms.

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APPENDIX

Table A1
Artificial Neural Network applications in financial management

Problem domain	Studies
Bankruptcy Prediction	Odom et al. (1990), Dwyer et al. (1992), Salchenberger et al. (1992), Tam et al. (1992), Fletcher et al. (1993), Coats et al. (1993), Udo (1993), Altman et al (1994), Wilson et al. (1994), Boritz et al (1995), Boritz et al (1995), Chan et al (1995), Wilson et al. (1995), Chiang et al (1995), Austin et al. (1996), Serrano-Cinca (1997), Kim et al. (1997), Kiviluoto (1998), Aiken, (1998), Edelman et al. (1999), Koh et al. (1999), Zhang et al. (1999), Motiwalla et al. (2000), Motiwalla et al. (2000), Shah et al. (2000), Zapranis (2000), Atiya (2001), Hwarng (2001), ITC Access Somution Inc (2001), Nasir et al. (2001), Zhang et al. (2001), Chen et al (2003), Thevnin (2003), Casas(2004), Liao et al. (2004), Thawornwong et al. (2004), Wang (2004), Zhang et al.(2004), Enke et al. (2005), Grauer (2006), Panda et al. (2007), Santos et al. (2007), Kiani et al. (2008), Leu et al. (2008), Pao, (2008), Boyacioglu et al. (2009), Cao et al (2009), Faria et al. (2009), Ghazali et al. (2009), Marijana et al. (2009), Tsai (2009), Tsai et al. (2009).
Portfolio Management	Lowe (1994), Steiner (1997), Chapados et al (2001), Zimmermann et al. (2001), Zimmermann et al. (2002), Ellis et al. (2005), Zimmermann et al. (2005), Fernandez et al. (2007), Lowe (2009).
Stock Market Forecasting	Kaplan et al. (1979), Dutta et al. (1988), White (1988), Singleton et al. (1990), Trippi et al. (1992), Kryzanowski et al. (1993), Lin et al. (1993), Refenes et al. (1993), Refenes et al. (1994), Richeson et al. (1994), Dropsy et al. (1996), Glorfeld (1996), Torsun (1996), Arminger et al (1996), Wang et al. (1996), Desai et al. (1997), Kwon et al. (1997) Maher et al. (1997), Daniels et al. (1999), Lee et al. (1999), Jingtao et al. (2000), West (2000), Jingtao et al. (2000), West (2000), Refenes et al. (2001), Baesens et al (2002), Majhi et al. (2002), Malhorta et al. (2003), Chye et al.(2004), Hamid et al. (2004), Huang et al. (2004), Jiang et al. (2004), Lai et al. (2004), Bennell et al (2005), Cao et al. (2005), Ong et al. (2005), West et al. (2005), Constantinou et al. (2006), Sarlija et al. (2006), Abdou et al. (2007), Carvalhal et al. (2007),Kwon et al. (2007), Lee (2007), Tsang et al. (2007), Huang et al. (2008), Tsai et al. (2008), Zhu et al. (2008), Chang et al. (2009), Lee et al. (2009), Lin et al. (2009), Maher et al. (2009), Hadavandi et al. (2010), Mostafa et al. (2010), Cao et al. (2011), Chang (2011),Ebrahimpour et al. (2011), Enke et al. (2011), Guresen (2011),Hsieh et al. (2011), Jasemi et al. (2011), Jayne et al. (2011), Khansa et al. (2011), Lee et al. (2011), Lu et al. (2011), Lu et al. (2011), Malhorta et al. (2011), Manjula et al. (2011), Merh et al. (2011), Shen et al. (2011), Wang et al. (2011), Wang et al. (2011), Yeh et al. (2011), Chang et al. (2012), Chang et al. (2012), Lin et al. (2012), Liu et al. (2012), Wang et al. (2012).

Table A2 Expert System applications in financial management	
Problem domain	**Studies**
Bankruptcy Prediction	Elmer et al. (1988), Lecot(1988), Brown et al (1990), Murphy et al. (1992), Bharadwaj et al (1994), Doherty et al. (1995), Shiue et al. (2008), Petropoulos et al. (2008), Lecot (2009), Moynihan et al. (2009), Shue et al. (2009).
Portfolio Management	Shaw et al. (1988), Chan et al (1989), Apte et al (1989), Cohen et al. (1990), Bohanec et al (1995), Grudintski et al. (1995), Faghiri et al. (1996), Vranes (1996), Sycara et al. (1998), Casas (2001), Fan et al.(2001), Seo et al. (2004), Ellis et al. (2005), Mogharreban et al. (2005).Lai et al. (2006), Huang (2007), Ko et al. (2008), Freitas et al (2009).
Stock Market Forecasting	Zocco (1985), Ribar (1987), Klein (1989), Tamai et al. (1989), Kimet al. (1994), Stark(1996), Chaveesuk et al (1999), Bryant (2000), Bryant (2000), Walker et al. (2003), Griffiths et al. (2005).

Table A3 Fuzzy Logic applications in financial management	
Problem domain	**Studies**
Bankruptcy Prediction	Pau & Giannoti (1986), Lee & Stohr (1985), Shane et al. (1987), Lee et al. (1989), Suret et al. (1991), Syriopoulos et al. (1992), Tam et al. (1991), Liu & Lee (1997), Lee & Jo (1999).
Portfolio Management	Michaelsen (1984), Elliot & Kielich (1985), Hansen & Messier (1986), Steibart (1987), Brown & Wensley (1995), Lin et al. (2004), Wu et al. (2009).
Stock Market Forecasting	Elmer & Borowski (1988), Messier & Hansen (1988), Michalopoulos & Zopounidis (1993), Chen et al. (2007), Tiffany et al. (2008), Kuo et al. (2010), Na et al. (2011).

Table A4 Genetic Algorithm applications in financial management	
Problem domain	**Studies**
Bankruptcy Prediction	Pau & Giannoti (1986), Lee & Stohr (1985), Shane et al. (1987), Lee et al. (1989), Suret et al. (1991), Syriopoulos et al. (1992), Tam et al. (1991), Liu & Lee (1997), Lee & Jo (1999), Allen et al. (1988), Shapcott (1992), Tan (1994), Neely et al. (1997), Fernández et al. (2005), Lai et al. (2006), Chen et al. (2011), Kim et al. (2012).
Portfolio Management	Michaelsen (1984), Elliot & Kielich (1985), Hansen & Messier (1986), Steibart (1987), Brown & Wensley (1995), Lin et al. (2004), Zhou et al. (2006), Chen et al. (2011), Dastkhan et al. (2011), Bermúdez et al. (2012).
Stock Market Forecasting	Elmer & Borowski (1988), Messier & Hansen (1988), Michalopoulos & Zopounidis (1993), Gorgulho et al. (2011), Tsai et al. (2011).

Table A5 Support Vector Machines applications in financial management	
Problem domain	**Studies**
Bankruptcy Prediction	Pau & Giannoti (1986), Lee & Stohr (1985), Shane et al. (1987), Lee et al. (1989), Suret et al. (1991), Syriopoulos et al. (1992), Tam et al. (1991), Liu & Lee (1997), Lee & Jo (1999), Yu et al. (2010), Chaudhuri et al. (2011).
Portfolio Management	Michaelsen (1984), Elliot & Kielich (1985), Hansen & Messier (1986), Steibart (1987), Brown & Wensley (1995)
Stock Market Forecasting	Elmer & Borowski (1988), Messier & Hansen (1988), Michalopoulos & Zopounidis (1993), Chen (2006), Wen et al. (2011), Yang et al. (2011), Yuanbin et al. (2011).

Table A6 Hybrid System applications in financial management	
Problem domain	**Studies**
Bankruptcy Prediction	Pau & Giannoti (1986), Lee & Stohr (1985), Shane et al. (1987), Lee et al. (1989), Suret et al. (1991), Syriopoulos et al. (1992), Tam et al. (1991), Liu & Lee (1997), Markham et al. (1995), Back et al (1995), Ignizio et al (1996), Jo et al. (1996), Lee et al. (1996), Lee et al. (1996), Olmeda et al. (1997), Kuo et al. (1998), Luther (1998), Garliauskas (1999), Lee & Jo (1999), Beasley et al (2002), Lee et al. (2002), Chen et al (2003), Srinivasa et al. (2004), Tung et al. (2004), Armano et al (2005), Jeurissen et al. (2005), Chun et al. (2006), Kim (2006), Tsakonas et al. (2006), Chavarnakul et al (2007), Hassan et al. (2007), Hu (2007), Hua et al. (2007), Kimet et al. (2007), Taffese (2007), Ahn et al. (2008), Chiu et al. (2008), Fatima et al. (2008), Hu(2008), Huang et al. (2008), Lin et al. (2008), Ng et al. (2008), Nikolaos (2008), Ravi et al. (2008), Yu et al. (2008), Bildrici et al. (2009), Charbonneau et al. (2009), Chen et al (2009), Chena et al. (2009), Cho et al. (2009), Hassan (2009), Hsu et al. (2009), Hu (2009), Huang et al. (2009), Huang et al (2009), Kamo et al. (2009), Li et al. (2009), Li et al. (2009), Li et al. (2009), Li et al. (2009), Lu et al.(2009), Ni et al. (2009), O¨ g˘u¨t H et al. (2009), Sun et al. (2009), Tang (2009), Teoh et al. (2009), Tsai et al. (2009), Wang (2009), Wen et al. (2009), Tseng et al. (2009), Wen et al. (2009), Yudong et al. (2009), Bildirici et al (2010), Li et al (2010), Yeh et al. (2010).
Portfolio Management	Michaelsen (1984), Elliot & Kielich (1985), Hansen & Messier (1986), Steibart (1987), Brown & Wensley (1995), Stoppiglia et al. (1996), Casqueiro et al (2005), Yu et al. (2008), Chen et al. (2009), Li et al. (2010).
Stock Market Forecasting	Elmer & Borowski (1988), Messier & Hansen (1988), Michalopoulos & Zopounidis (1993), Piramuthu (1999), Shin et al. (1999), Thammano (1999), Yobas et al. (1999), Hoffmann et al. (2001), Armano et al (2002), Malhorta et al. (2003), Mues et al. (2004), Altay et al. (2005), Juma (2005), Lee et al. (2005), Gao et al. (2006), Gestel et al. (2006), Laha (2006), Dacha (2007), Hoffmann et al. (2007), Huang et al. (2007), Martens et al. (2007), Tsakonas et al. (2007), Angelini et al. (2009), Bahrammirzaee et al. (2009), Chang et al. (2009), Chen et al

	(2009), Chuang et al. (2009), Huang et al. (2009), Lin et al. (2009), S ˇ usˇtersˇicˇ et al. (2009), Ansari (2010), Hsieh et al. (2010), Lu et al. (2010), Ao (2011), Araújo (2011), Atsalakis (2011), Chen (2011), George et al. (2011), Hossain (2011), Hsieh et al. (2011), Hsu et al. (2011), Huang (2011), Kara et al. (2011), Wei et al. (2011), Dai er al. (2012), Hajizadeh et al. (2012), Khashei et al. (2012), Liu et al. (2012), Wang et al. (2012)