NEW DEVELOPMENTS IN QUANTITATIVE TRADING AND INVESTMENT

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ARTIFICIAL INTELLIGENCE IN FINANCIAL MARKETS

Cutting-Edge Applications for Risk Management, Portfolio Optimization and Economics

New Developments in Quantitative Trading and Investment

Christian L. Dunis • Peter W. Middleton • Konstantinos Theofilatos
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Editors

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Preface

The aim of this book is to focus on Artificial Intelligence (AI) and to provide broad examples of its application to the field of finance. Due to the popularity and rapid emergence of AI in the area of finance this book is the first volume in a series called 'New Developments in Quantitative Trading and Investment' to be published by Palgrave Macmillan. Moreover, this particular volume targets a wide audience including both academic and professional financial analysts. The content of this textbook targets a wide audience who are interested in forecasting, modelling, trading, risk management, economics, credit risk and portfolio management. We offer a mixture of empirical applications to different fields of finance and expect this book to be beneficial to both academics and practitioners who are looking to apply the most up to date and novel AI techniques. The objective of this text is to offer a wide variety of applications to different markets and assets classes. Furthermore, from an extensive literature review it is apparent that there are no recent textbooks that apply AI to different areas of finance or to a wide range of markets and products.

Each Part is comprised of specialist contributions from experts in the field of AI. Contributions offer the reader original and unpublished content that is recent and original. Furthermore, as the cohort of authors includes various international lecturers and professors we have no doubt that the research will add value to many MA, MSc, and MBA graduate programmes. Furthermore, for the professional financial forecaster this book is without parallel a comprehensive, practical and up-to-date insight into AI. Excerpts of programming code are also provided throughout in order to give readers the opportunity to apply these techniques on their own.

Authors of this book extend beyond the existing literature in at least three ways. The first contribution is that we have included empirical applications of AI in four different areas of finance: time-series modelling, economics, credit and portfolio management. Secondly, the techniques and methodologies applied here are extremely broad and cover all areas of AI. Thirdly, each chapter investigates different datasets from a variety of markets and asset classes. Different frequencies of data are also investigated to include daily, monthly, macroeconomic variables and even text data from different sources. We believe that the Parts presented here are extremely informative and practical while also challenging existing traditional models and techniques many of which are still used today in financial institutional and even in other areas of business. The latter is extremely important to highlight since all of the applications here clearly identify a benefit of utilizing AI to model time-series, enhance decision making at a government level, assess credit ratings, stock selection and portfolio optimization.

Contents

Part I

Following the introduction, the first part focuses on numerous time-series, which will include commodity spreads, equities, and exchange traded funds. For this part the objective is to focus on the application of AI methodologies to model, forecast and trade a wide range of financial instruments. AI methodologies include, Artificial Neural Networks (ANN), Heuristic Optimization Algorithms and hybrid techniques. All of the submissions provide recent developments in the area of financial time-series analysis for forecasting and trading. A review of publications reveals that existing methodologies are either dated or are limited in scope as they only focus on one particular asset class at a time. It is found that the majority of the literature focuses on forecasting foreign exchange and equities. For instance, Wang et al. [14] focus their research and analysis on forecasting the Shanghai Composite index using a Wavelet-Denoising-based back propagation Neural Network (NN). The performance of this NN is benchmarked against a traditional back propagation NN. Other research is now considered redundant as the field of AI is evolving at a rapid rate. For instance, Zirilli [19] offers a practical application of neural networks to the prediction of financial markets however, the techniques that were used are no longer effective when predicting financial variables. Furthermore, data has become more readily available so input datasets can now be enriched to enable methodologies to capture the relationships between input datasets and target variables more accurately. As a result, more recent research and technological innovations have rendered such methodologies obsolete.

While numerous journal publications apply AI to various assets our search did not uncover recent textbooks that focus on AI and in particular empirical applications to financial instruments and markets. For this reason we believe that an entire section dedicated to time-series modelling, forecasting and trading is justified.

Part II

The second part focuses on economics as a wider subject that encompasses the prediction of economic variables and behavioural economics. Both macro- and micro-economic analysis is provided here. The aim of this part is to provide a strong case for the application of AI in the area of economic modelling and as a methodology to enhance decision making in corporations and also at a government level. Various existing work focuses on agent-based simulations such as Leitner and Wall [16] who investigate economic and social systems using agent-based simulations. Teglio et al. [17] also focus on social and economic modelling relying on computer simulations in order to model and study the complexity of economic and social phenomena. Another recent publication by Osinga et al. [13] also utilizes agent-based modelling to capture the complex relationship between economic variables. Although this part only provides one empirical application we believe that it goes a long way to proving the benefits of AI and in particular 'Business Intelligence'.

With extensive research being carried out in the area of economic modelling it is clear that a whole section should also be devoted to this particular area. In fact we expect this section to draw a lot of attention given its recent popularity.

Part III

The third part focuses on analyzing credit and the modelling of corporate structures. This offers the reader an insight into AI for evaluating fundamental data and financial statements when making investment decisions. From a preliminary search our results do not uncover any existing textbooks that exclusively focus on credit analysis and corporate finance analyzed by AI methodologies. However, the search uncovered a few journal publications that provide an insight into credit analysis in the area of bankruptcy prediction. For instance, Loukeris and Matsatsinis [9] research corporate finance by attempting to predict bankruptcy using AI models. From results produced by these journal publications we believe that corporate finance could benefit from more recent empirical results published in this part.

Earlier research in the area of credit analysis is carried out by Altman et al. [1] who examine the use of layer networks and how their use has led to an improvement in the reclassifying rate for existing bankruptcy forecasting models. In this case, it was found that AI helped to identify a relationship between capital structure and corporate performance.

The most recent literature reviewed in the area of corporate finance applies AI methodologies to various credit case studies. We suspect that this was inspired by the recent global credit crisis in 2008 as is the case with most credit-based research published after the 2008 'credit crunch'. For instance, Hajek [6] models municipal credit ratings using NN classification and genetic programs to determine his input dataset. In particular, his model is designed to classify US municipalities (located in the State of Connecticut) into rating classes based on their levels of risk. The model includes data pre-processing, the selection process of input variables and the design of various neural networks' structures for classification. Each of the explanatory variables is extracted from financial statements and statistical reports. These variables represent the inputs of NNs, while the rating classes from Moody's rating agency are the outputs. Experimental results reveal that the rating classes assigned by the NN classification to bond issuers are highly accurate even when a limited sub-set of input variables is used. Further research carried out by Hajek [7] presents an analysis of credit rating using fuzzy rule-based systems. A fuzzy rule-based system adapted by a feed-forward neural network is designed to classify US companies (divided into finance, manufacturing, mining, retail trade, services, and transportation industries) and municipalities into the credit rating classes obtained from rating agencies. A genetic algorithm is used again as a search method and a filter rule is also applied. Empirical results corroborate much of the existing research with the classification of credit ratings assigned to bond issuers being highly accurate. The comparison of selected fuzzy rule-based classifiers indicates that it is possible to increase classification performance by using different classifiers for individual industries.

León-Soriano and Muñoz-Torres [8] use three layers feed-forward neural networks to model two of the main agencies' sovereign credit ratings. Their results are found to be highly accurate even when using a reduced set of publicly available economic data. In a more thorough application Zhong et al. [20] model corporate credit ratings analyzing the effectiveness of four different learning algorithms. Namely, back propagation, extreme learning machines, incremental extreme learning machines and support vector machines over a data set consisting of real financial data for corporate credit ratings. The results reveal that the SVM is more accurate than its peers.

With extensive research being carried out in the area of bankruptcy prediction and corporate/sovereign credit ratings it is clear that the reader would benefit from a whole section being devoted to credit and corporate finance. In fact the first chapter provides an interesting application of AI to discover which areas of credit are most popular. AI is emerging in the research of credit analysis and corporate finance to challenge existing methodologies that were found to be inadequate and were ultimately unable to limit the damage caused by the 2008 ‘credit crisis’.

Part IV

The final section of the book focuses on portfolio theory by providing examples of security selection, portfolio construction and the optimization of asset allocation. This will be of great interest to portfolio managers as they seek optimal returns from their portfolios of assets. Portfolio optimization and security selection is a heavily researched area in terms of AI applications. However, our search uncovered only a few existing journal publications and textbooks that focus on this particular area of finance. Furthermore, research in this area is quickly made redundant as AI methodologies are constantly being updated and improved.

Existing journal publications challenge the Markowitz two-objective mean-variance approach to portfolio design. For instance, Subbu et al. [15] introduce a powerful hybrid multi-objective optimization approach that combines evolutionary computation with linear programming to simultaneously maximize return, minimize risk and identify the efficient frontier of portfolios that satisfy all constraints. They conclude that their Pareto Sorting Evolutionary Algorithm (PSEA) is able to robustly identify the Pareto front of optimal portfolios defined over a space of returns and risks. Furthermore they believe that this algorithm is more efficient than the 2-dimensional and widely accepted Markowitz approach.

An older textbook, which was co-authored by Trippi and Lee (1995), focuses on asset allocation, timing decisions, pattern recognition and risk assessment. They examine the Markowitz theory of portfolio optimization and adapt it by incorporating it into a knowledge-based system. Overall this is an interesting text however it is now almost 20 years old and updated applications/methodologies could be of great benefit to portfolio managers and institutional investors.

The Editors

All four editors offer a mixture of academic and professional experience in the area of AI. The leading editor, Professor Christian Dunis has a wealth of experience spanning more than 35 years and 75 publications, both in academia and quantitative investments. Professor Dunis has the highest expertise in modelling and analyzing financial markets and in particular an extensive experience with neural networks as well as advanced statistical analyses. Dr Peter Middleton has recently completed his PhD in Financial Modelling and Trading of Commodity Spreads at the University of Liverpool. To date he has produced five publications and he is also a member of the CFA institute and is working towards the CFA designation having already passed Level I. He is also working in the finance industry in the area of Asset Management. Dr Konstantinos possesses an expertise in technical and computational aspects with backgrounds in evolutionary programming, neural networks, as well as expert systems and AI. He has published numerous articles in the area of computer science as well being an editor for *Computational Intelligence for Trading and Investment*. Dr Andreas Karathanasopoulos is currently an Associate Professor at the American University of Beirut and has worked in academia for six years. He too has numerous publications in international journals for his contribution to the area of financial forecasting using neural networks, support vector machines and genetic programming. More recently he has also been an editor for *Computational Intelligence for Trading and Investment*.

Acknowledgements

We would like to thank the authors of who have contributed original and novel research to this book, the editors who were instrumental in its preparation and finally the publishers who have ultimately helped provide a showcase for it to be read by the public.

Final Words

We hope that the publication of this book will enhance the spread of AI throughout the world of finance. The models and methods developed here have yet to reach their largest possible audience, partly because the results are scattered in various journals and proceedings volumes. We hope that this book will help a new generation of quantitative analysts and researchers to solve complicated problems with greater understanding and accuracy.

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Part I

Introduction to Artificial Intelligence

1

A Review of Artificially Intelligent Applications in the Financial Domain

Swapnaja Gadre-Patwardhan, Vivek V. Katdare, and Manish R. Joshi

1 Introduction

Undoubtedly, the toughest challenge faced by many researchers and managers in the field of finance is uncertainty. Consequently, such uncertainty introduces an unavoidable risk factor that is an integral part of financial theory. The manifestation of risk not only complicates financial decision making but also creates profitable opportunities for investors who can manage and analyze risk efficiently and effectively. In order to handle the complex nature of the problem an interdisciplinary approach is advocated.

Computational finance is a division of applied computer science that deals with practical problems in finance. It can also be defined as the study of data and algorithms used in finance. This is an interdisciplinary field that combines

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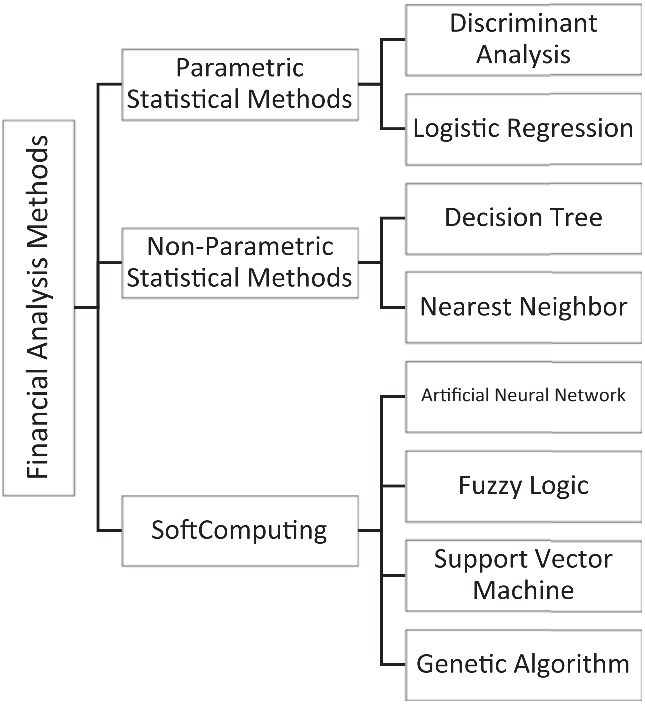

Fig. 1.1 Techniques for analysis of financial applications

numerical methods and mathematical finance. Computational finance uses mathematical proofs that can be applied to economic analyses thus aiding the development of finance models and systems. These models are employed in portfolio management, stock prediction and risk management and play an important role in finance management.

During past few years, researchers have aimed to assist the financial sector through trend prediction, identifying investor behaviour, portfolio management, fraud detection, risk management, bankruptcy, stock prediction, financial goal evaluation, finding regularities in security price movement and so forth. To achieve this, different methods like parametric statistical methods, non-parametric statistical methods and soft computing methods have been used as shown in Fig. 1.1. It is observed that many researchers are exploring and comparing soft computing techniques with parametric statistical techniques and non-parametric statistical techniques. Soft computing techniques, such as, Artificial Neural Network (ANN), Fuzzy Logic, Support Vector Machine (SVM), Genetic Algorithm, are widely applied and accepted techniques in the field of finance and hence are considered in this review.

(A) Parametric statistical methods: Parametric statistics is a division of statistics. It assumes that data is collected from various distributed systems and integrated in order to draw inferences about the parameters of the distribution. There are two types of parametric statistical methods namely discriminant analysis and logistic regression:

(I) Discriminant analysis: Discriminant analysis is a statistical analysis carried out with the help of a discriminant function to assign data to one of two or more naturally occurring groups. Discriminant analysis is used to determine the set of variables for the prediction of category membership. Discriminant function analysis is a type of classification that distributes items of data into classes or groups or categories of the same type.

(II) Logistic regression: Logistic regression is a method of prediction that models the relationship between dependent and independent variables. It the best-fit model to be found and also identifies the significance of relationships between dependent and independent variables. Logistic regression is used to estimate the probability of the occurrence of an event.

(B) Non-parametric statistical methods: These are the methods in which data is not required to fit a normal distribution. The non-parametric method provides a series of alternative statistical methods that require no, or limited, assumptions to be made about the data. The techniques of non-parametric statistical methods follow.

(I) Decision tree: A decision tree is a classifier that is a tree-like graph that supports the decision making process. It is a tool that is employed in multiple variable analyses. A decision tree consists of nodes that a branching-tree shape. All the nodes have only one input. Terminal nodes are referred to as leaves. A node with an outgoing edge is termed a test node or an internal node. In a decision tree, a test node splits the instance space into two or more sub-spaces according to the discrete function.

(II) Nearest neighbour: The nearest neighbour algorithm is a non-parametric method applied for regression and classification. Nearest neighbour can also be referred as a similar search, proximity search or closest-point search, which is used to find the nearest or closest points in the feature space. The K-nearest neighbour algorithm is a technique used for classification and regression.

(C) Soft computing: Soft computing is a set of methods that aims to handle uncertainty, partial truth, imprecision and approximation that are fundamentally are based on human neurology. Soft computing employs techniques like: ANN, fuzzy logic, SVM, genetic algorithm [1].

(I) Artificial neural network: A neuron is a fundamental element of ANN. These neurons are connected to form a graph-like structure, which are also referred to as networks. These neurons are like biological neurons. A neuron has small branches, that is, dendrites, which are used for receiving inputs. Axons carry the output and connect to another neuron. Every neuron carries a signal received from dendrites as shown in Fig. 1.2 [2]. When the strength

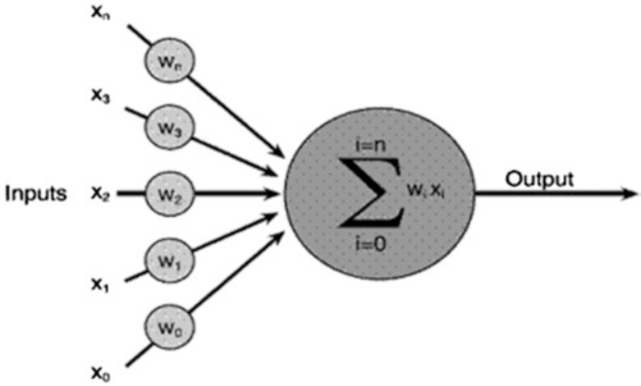

Fig. 1.2 Structure of Artificial Neurons

of a signal exceeds a particular threshold value, an impulse is generated as an output, this is known as the action signal.

Like biological neurons, artificial neurons accept input and generate output but are not able to model automatically. In ANN information or data is distributed and stored throughout the network in the form of weighted interconnections. Simulation of a neuron is carried out with the help of non-linear function. Interconnections of artificial neurons are referred as weights. The diagram below shows the structure of an artificial neuron in which xi is the input to the neuron and wi is the weight of the neuron. The average input is calculated by the formula [2].

$$a = \sum_{i=0}^{n} xiwi \tag{1.1}$$

ANN has a minimum of three layers of artificial neurons: input, hidden and output as shown in Fig. 1.3 [3]. The input layer accepts the input and passes it to the hidden layer. The hidden layer is the most important layer from a computational point of view. All the complex functions reside in this layer.

(II) Fuzzy logic: Fuzzy logic is a type of many values logic that deals with approximate values instead of exact or fixed reasoning. Fuzzy logic is a method of computing based on the degree of truth rather than a crisp true or false value. Its truth value ranges in between 0 and 1.

(III) Support vector machine: SVM is a supervised learning model with related learning algorithms that is used for data analysis and pattern recognition in classification and regression. SVM uses the concept of a hyperplane,

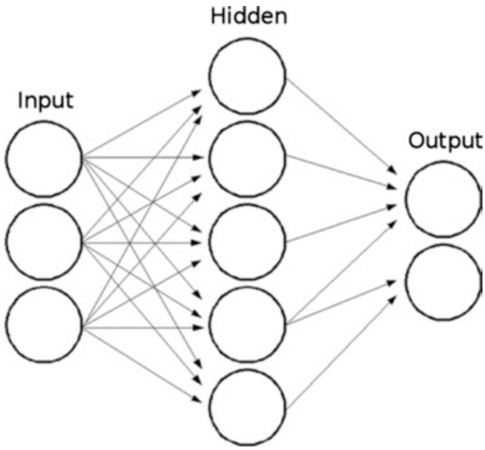

Fig. 1.3 Three layer architecture of ANN

which defines the boundaries of a decision. The decision plane separates the objects based on class membership and is able to handle categorical and continuous variables.

(IV) Genetic algorithm: A genetic algorithm is an artificial intelligence technique that mimics a natural selection process. This technique is mostly used for optimization and search problems using selection, crossover, mutation and inheritance operations.

This chapter emphasizes the application of soft computing techniques namely artificial neural network, expert system (ES) and hybrid intelligence system (HIS) in finance management.

In recent years, it has been observed that an array of computer technologies is being used in the field of finance; ANN is one of these. From the array of available AI techniques, financial uncertainties are handled in a more efficient manner by ANN. These uncertainties are handled by pattern recognition and future trend analysis. The most difficult aspects to incorporate in finance analysis are changes in the interest rates and currency movements. Large 'noisy' data can be handled well by ANN. ANN are characterized as numeric in nature. In statistical techniques, like discriminant analysis or regression analysis, data distribution assumptions are required for input data. However, ANN does not require any data distribution assumptions and hence could be applicable to a wider range of problems than other statistical techniques. Statistical techniques and symbolic manipulation techniques are batch oriented; old and new data are submitted in a single batch to the model and later new mining results are generated. In contrast, in ANN it is possible to add new data to a trained ANN so as to update the existing result. Since financial markets are dynamic in nature, ANN can accommodate new data without reprocessing old data and hence it is used in finance management [4].

An ES is knowledge-based system used to solve critical problems in a particular domain. These are rule-based systems with predefined sets of knowledge used for decision making. Generic ES contain two modules—the inference engine and the knowledge base. The inference engine combines and processes the facts associated with the specific problem using the chunk of the knowledge base relevant to it. The knowledge base is coded in the form of rules, semantic nets, predicates and objects in the system. ES are characterized as efficient, permanent, consistent, timely, complete decision-making systems and hence their use in finance management. ES are characterized as intelligent, capable of reasoning, able to draw conclusions from relationships, capable of dealing with uncertainties and so forth. ES are capable of reproducing efficient, consistent and timely information so as to facilitate decision making [5]. Furthermore Rich and Knight (1991) specified long ago that financial analysis is an expert's task.

HIS are software systems that combine methods and techniques of artificial intelligence, for example, fuzzy expert systems, neuro-fuzzy systems, genetic-fuzzy systems. The integration of various learning techniques is combined to overcome the limitation of an individual system. Because of its facility of combined techniques, it can be used effectively for finance management.

With reference to the financial market, we identified portfolio management, stock market prediction and risk management as the three most important AI application domains. As investment is an important aspect of finance management hence these three cases are considered. In this study, we consider the contribution of researchers in financial domains from the past 20 years in order to study and compare the applications of ANN, ES and HIS with traditional methods. The chapter is organized thus: the second, third and fourth sections deal with the application of ANN, ES and HIS respectively. In the fifth section conclusions are put forth. We enlist popularly used data mining tools as set out in Appendix 1 that includes some sample coding of NN techniques using MATLAB [6] in Finance Management. Code excerpts for implementing typical statistical functions including regression analysis, naïve Bayes classification, fuzzy c-means clustering extracted from different openly available authentic sources [7] are also presented in Appendix 1.

Applications of ANN in Finance

ANN are computational tools and are used in various disciplines for modelling real-world complex problem [8]. ANN resemble biological neurons acting as a source inspiration for a variety of techniques covering a vast field of application [9]. In general, ANN are referred to as information processing systems that which use earning and generalization capabilities, which are adaptive in nature. Due to their adaptive nature, ANN can provide solutions to problems such as forecasting, decision making and information processing. In recent years, ANN have proved to be a powerful tool for handling dynamic financial market in terms of prediction [10], panning, forecasting [11] and decision making [12].

With reference to this various studies have been carried out in order to classify and review the application of ANN in the finance domain [13, 14]. Mixed results have been obtained concerning the ability of ANN in finance domain. It has been observed that financial classification like financial evaluation, portfolio management, credit evaluation and prediction are significantly improved with the application of ANN in the finance domain. We further consider the application of ANN in the finance domain in portfolio management, stock market prediction and risk management. The details of these applications are presented as described previously.

Portfolio Management

The determination of the optimal allocation of assets into broad categories, for example, mutual funds, bonds, stocks, which suits investment by financial institutions across a specific time with an acceptable risk tolerance is a crucial task. Nowadays investors prefer diversified portfolios that contain a variety of securities.

Motiwalla et al. [15] applied ANN and regression analysis to study the predictable variations in US stock returns and concluded that ANN models are better than regression. Yamamoto et al. [16] designed a multi-layer Back Propagation Neural Network (BPNN) for the prediction of the prepayment rate of a mortgage with the help of a correlation learning algorithm. Lowe et al. [17] developed an analogue Neural Network (NN) for the construction of portfolio under specified constraints. They also developed a feed forward NN for prediction of short-term equities in non-linear multi-channel time-series forecasting. Adedeji et al. [18] applied ANN for the analysis of risky economic projects. For the prediction of the potential returns on investment, an NN model could be used. On the basis of results obtained from the neural network, financial managers could select the financial project by comparing the results to those obtained from conventional models. The survey conducted in this paper for portfolio management concludes that ANN performs better in terms of accuracy. Without any time consuming and expensive simulation experiments, accuracy can be obtained by combining conventional simulation experiments with a neural network.

Research papers surveyed for portfolio management demonstrates that when compared to other traditional methods, ANN performs better particularly BPNN. Zimmermann et al. [19] demonstrated the application of the Back/Litterman portfolio optimization algorithm with the help of an error correction NN. Optimization of the portfolio includes (1) allocation that comply investors constraints and (2) controlled risk in the portfolio. The method was tested with internationally diversified portfolios across 21 financial markets from G7 countries. They stated that their approach surpassed conventional portfolio forecasts like Markowitz's mean-variance framework. Ellis et al. [20] performed a portfolio analysis by comparing BPNN with a randomly selected portfolio method and a general property method concluding that ANN performs better.

Stock Market Prediction

In recent years with the help of online trading, the stock market is one of the avenues where individual investors can earn sizeable profits. Hence there is a need to predict stock market behaviour accurately. With this prediction investors can take decisions about where and when to invest. Because of the volatility of financial market building a forecasting model is a challenging task.

ANN are a widely used soft computing method for stock market prediction and forecasting. White applied ANN on IBM daily stock returns and concluded that the NN outperformed other methods [21]. Kimoto et al. [22] reported the effectiveness of learning algorithms and prediction methods of Modular Neural Networks (MNN) for the Tokyo Stock Exchange price index prediction system. Kazuhiro et al. [23] investigated the application of prior knowledge and neural networks for the improvement of prediction ability. Prediction of daily stock prices was considered a real-world problem. They considered some non-numerical features such as political and international events, as well as a variety of prior knowledge that was difficult to incorporate into a network structure (the prior knowledge included stock prices and information about foreign and domestic events published in newspapers.) It was observed that event knowledge combined with an NN was more effective for prediction with a significance level of 5 %. Pai et al. [24] stated that ARIMA (autoregressive integrated moving average) along with SVM can be combined to deal with non-linear data. The unique strengths of ARIMA and SVM are used for more reliable stock-price forecasting. Thawornwong et al. [25] demonstrated that the NN model with feed-forward and probabilistic network for the prediction of stock generated high profits with low risk. Nakayama et al. [26] proposed a Fuzzy Neural Network (FNN) that contained a specific structure for realizing a fuzzy inference system. Every membership function consists of one or two sigmoid functions for inference rule. They concluded that their FNN performed better. Duke et al. [27] used Back Propagation Network (BPN) for the prediction of the performance of the German government's bonds

Risk Management

Financial risk management (FRM) is the process of managing economic value in a firm with the help of financial instruments to manage risk exposure especially market risk and credit risk. Financial Risk Management (FRM) is the process of identification of risk associated with the investments and possibly mitigating them. FRM can be qualitative or quantitative. FRM focuses on how and when hedging is to be done with the help of financial instruments to manage exposure to risk.

Treacy et al. [28] stated that the traditional approach of banks for credit risk assessment is to generate an internal rating that considers subjective as well as qualitative factors such as earning, leverage, reputation. Zhang et al. [29] compared Logistic Regression (LR), NN and five-fold cross validation procedures on the database of manufacturing firms. They employed Altman's five functional ratios along with the ratio current assets/current liabilities as an input to NN. They concluded that NN outperforms with accuracy 88.2 %. Tam et al. [30] introduced an NN approach to implement discriminant analysis in business research. Using bank data, linear classification is compared with a neural approach. Empirical results concluded that the neural model is more promising for the evaluation of bank condition in terms of adaptability, robustness and predictive accuracy. Huang et al. [31] introduced an SVM to build a model with a better explanatory ability. They used BPNN as a benchmark and obtained around 80 % prediction accuracy for both SVM and BPNN for Taiwan and United States markets.

Table 1.1 provides details of the literature that considers the application of ANN for portfolio management, stock market prediction and risk management.

2 Application of Expert Systems in Finance

An expert system is a computer system that is composed of a well-organized body of knowledge that emulates expert problem-solving abilities in a limited domain of expertise. Matsatsinis et al. [54] presented a methodology of acquisition of knowledge and representation of knowledge for the development of ES for financial analysis. Development of FINEVA (FINancial EVAluation), a multi-criterion knowledge base DSS (decision support software) for assessment of viability and corporate performance and the application of FINEVA was discussed. For a particular domain, a set of inference rules are provided by a human expert. The knowledge base is a collection of relevant facts, data, outcome and judgments [34]. Components of expert systems include the knowledge base, the user interface and the inference engine. Knowledge is represented through the techniques such as, predicate logic, frames and semantic nets but the most popular and widely used technique is the IF-THEN rule also referred as the production rule.

Liao et al. [55] carried out a review of the use of an ES in a variety of areas including finance during period 1995 to 2004. They observed that ES are flexible and provide a powerful method for solving a variety of problems, which can be used as and when required. Examples of the application of ES in finance domain follow.

Portfolio Management

It is a difficult and time-consuming task to explore and analyze a portfolio in relation to the requirements and objectives of the fund manager. Ellis et al. [34] examined the application of rule-based ES in the property market and portfolios randomly constructed from the market. They observed that rule-based outperform the random portfolio or market on risk adjusted return basis.

Bohanec et al. [56] developed a knowledge-based tool for portfolio analysis for evaluation of a project. This ES was developed for the Republic of Solvenia. The model is demonstrated with a tree structure supplemented by IF-THEN rules. Sanja Vraneš et al. [57] developed the Blackboard-based Expert Systems Toolkit (BEST) for combining knowledge from different sources, using different methodologies for knowledge acquisition. As far as investment decision making is concerned, information from proficient economist critical investment ranking might be combined with knowledge evolved from operational research methods. When decisions are made based on information combined from many sources, there is a probability of redundancy reduction and more promising results. Varnes et al. [58] suggested INVEX (investment advisory expert system) for investment management. This system assists investors and project analysts to select a project for investment. Mogharreban et al. [59] developed the PROSEL (PORtfolio SELection) system that uses a set of rules for stock selection. PROSEL consists of three parts (1) an information centre

Table 1.1 A Brief Review of ANNs Applied to Portfolio Management, Stock Market Prediction and Risk Management

Author	Objective	Data Set	Preprocessing	Approach used	Compared with	Evaluation metrics
Stoppiglia H, Idan Y, Dreyfus G [32]	To develop a neural network -aided model for portfolio management	The database comprises 398 companies, with 172 A companies, 172 B companies,& 54 C companies	Fifteen financial ratios such as, working capital/ fixedassets, profit after taxes and interest/net worth, per year	ANN	Statistical Method	Classification
Hans Georg Zimmermann, Ralph Neuneier and Ralph Grothmann, Siemens AG [33]	Portfolio Optimization	Financial markets of the G7 countries	Monthly data extracted from all databases	ANN	Mean-variance theory	Forecasting
Ellis C, Willson P [34]	To select portfolios	Australian property sector stocks	Not mentioned	BPNN	Random selection portfolio	Performance measure
Fernandez A, Gomez S [35]	Portfolio selection and portfolio management	Hang Seng in Hong Kong, DAX 100 in Germany, FTSE 100 in UK, S&P 100 in USA and Nikkei 225 in Japan	Weekly prices from data sets are extracted	ANN, GA and SA	Heuristic methods	Portfolio selection and optimization
Freitas FD, De Souza AF, De Almeida AR [36]	Portfolio selection and Portfolio optimization	IBOVESPA	Selected a subset of 52 stocks with long enough time-series for training the neural networks	BPNN	Mean-variance model	Prediction

(*continued*)

Table 1.1 (continued)

Author	Objective	Data Set	Preprocessing	Approach used	Compared with	Evaluation metrics
Po-Chang Ko, Ping-Chen Lin [37]	Portfolio selection and portfolio optimization	Taiwan stock exchange	Not mentioned	ANN	Traditional ANN model	Portfolio optimization
Chiang W-C, Urban TL, Baldridge GW [38]	Asset forecasting	US mutual fund	15 economic variables are identified	BPNN	Regression model	NAV prediction
Chen A-S, Leung MT, Daouk H [39]	Stock index forecasting	Taiwan StockExchange	Data is extracted on the basis of length of investment horizon	PNN	Random walk model and the parametric GMM models	Return on investment
O'Connor N, Madden MG [40]	To predict stock market movement forecasting	New York Stock Exchange and NASDAQ	Daily opening and closing values of DJIA index	BPNN	Simple benchmark functions	Accuracy
De Faria EL, Marcelo P, Albuquerque J, Gonzalez L, Cavalcante JTP, Marcio Albuquerque P [41]	To predict stock market movement forecasting	Brazilian stock market	Not mentioned	BPNN	Adaptive exponential smoothing method	Accuracy
Liao A, Wang J [42]	Stock index forecasting	SP500, SAI, SBI, DJI, HIS and IXIC	Data normalization and adjusted to remove the noise	BP stochastic time effective NN	Brownian motion	Forecasting

Hyun-jung Kim, Kyung-shik Shin [43]	To detect patterns in stock market	Korea StockPrice Index 200	Daily stock data is extracted	ATNN	TDNN	Accuracy
Kuo RJ, Chen CH, Hwang YC [44]	Stock market forecasting	Taiwan stock market	Not mentioned	ANN, GFNN	Qualitative and quantitative factors of NN	Performance evaluation
Md. Rafiul Hassan, Baikunth Nath, Michael Kirley [45]	Stock market forecasting	www.finance.yahoo.com	Daily data is extracted	ANN, GA, HMM	ARIMA model	Forecasting
Chye KH, Tan WC, Goh GP [46]	Credit risk assessment	Australian and German credit data sets	For each applicant 24 variables are selected	SVM classifier	Neural networks, genetic programming, and decision tree classifiers	Accuracy
Eliana Angelini, Giacomo di Tollo, Andrea Roli [47]	Credit risk evaluation	Bankin Italy	Sample group is categorized into two groups i.e. boins and default	ANN	classical feed forward neural network and special purpose feed forward architecture	Classification
Fanning, Cogger Shrivastava [48]	To develop a model using neural network to find managerial fraud	Management database	Not mentioned	ANN	Generalized adaptive neural network architectures (GANNA) and the Adaptive Logic Network (ALN)	Accuracy

(*continued*)

Table 1.1 (continued)

Author	Objective	Data Set	Preprocessing	Approach used	Compared with	Evaluation metrics
Feroz EH, Taek MK, Pastena VS, and Park K [49]	To test the ability of selected red flags for prediction of the targets of the investigations.	AAER	Not mentioned	ANN	Investigated versus non-investigated forms	Prediction
Kurt Fanning, Kenneth Cogger O [50]	To develop a model for detection of management fraud	FFS.	Not mentioned	ANN	Statistical methods	Efficiency
Brause R, Langsdorf T, Hepp M	To detect credit card fraud	GZS	38 field per transaction are extracted	ANN	Traditional systems	Prediction
Koskivaara [51]	To investigate the impact of various preprocessing models on the forecast capability of neural network for financial auditing.	Manufacturing firm	Monthly balances	ANN	Traditional systems	Prediction