Neural Comput & Applic (1997)6:193–200

Neural Computing & Applications

The Impact of Neural Networks in Finance

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The financial industry is becoming more and more dependent on advanced computer technologies in order to maintain competitiveness in a global economy. Neural networks represent an exciting technology with a wide scope for potential applications, ranging from routine credit assessment operations to driving of large scale portfolio management strategies. Some of these applications have already resulted in dramatic increases in productivity. This paper brings together, from diverse sources, a collection of current research issues on neural networks in the financial domain. It examines a range of neural network systems related to financial applications from different levels of maturity to fielded products. It discusses the success rate of the neural network systems, and their performance in resolving particular financial problems.

Keywords: Economic modelling; Finance; Neural networks

1. Introduction

The financial industry has been a prime application area of Artificial Intelligence (AI) techniques, with the latest advances rapidly ingested in the drive to maintain a competitive edge. Expert System (ES) approaches have been explored in many areas of finance [1]. An analysis of market prices, with a view to forecasting future behaviour, presumes that such an approach is meaningful, whether its methodology is technical analysis (which assumes historical price studies alone are sufficient for prediction) or fundamental analysis (which studies general economic variables, company performance statistics, prevailing supply and demand, and many more) [2]. More and more areas are being investigated in finance that are now beyond the scope of ES technology. Also, there are a number of drawbacks to traditional ES approaches which include: the difficulty of programming and maintaining the system; the enormous time and effort required to extract the knowledge base from human experts; and the time to translate this knowledge into rules upon which the system is based. There is also the inability of many expert systems to use inductive learning and inference to adapt the rule base to changing situations. These problems are found to be particularly troublesome in financial analysis and management environments. Among the technologies widely in use in the financial economics community today are fuzzy logic, genetic algorithms and object-oriented programming, but it is Neural Networks (NN), modelled on the human brain, that have caused the most excitement.

Systems developed using a NN approach is a field of research which has enjoyed a rapid expansion and great popularity in both the academic and industrial research communities. NNs are essentially statistical devices for performing inductive inference. From the statistician's point of view they are analogous to non-parametric, non-linear regression models. The novelty about the NNs lies in their ability to model non-linear processes with few (if any) *a priori* assumptions about the nature of the generating process. This is particularly useful in investment management and other financial areas where much is assumed, and little is known, about the nature of the processes determining asset prices.

Neural networks are being applied to a number of 'live' systems in financial engineering and have shown promising results [3]. One of the first applications of neural networks in forecasting was

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performed by Lapedes and Farber [4]. They designed networks for forecasting chaotic time series generated by the logistic map and the MacKay and Glass equation [5]. They also introduced sinusoidal transfer functions for neurons. However, early applications of neural networks forecasting to the stock markets were reported as unsuccessful [6,7]. Only recent research has been increasingly positive in assessing the potential for successful financial forecasting.

The potential of neural networks can be measured by the great amount of success achieved by researchers and practitioners, as well as the level of international government investment in the research. In the US, for example, the Department of Defence Advanced Research Projects Agency (DARPA), carried out a $300 million programme in the last two years. In 1992 Japan began a $400 million, 10 year neurocomputing research programme. Financial organisations are second only to defence as sponsors of research in neural network applications.

In the UK, two programmes were sponsored by the Department of Trade & Industry (DTI) that focused on the financial sector [8]. The Neuroforecasting Club, a technology transfer programme run by the London Business School (LBS) with the University College London (UCL) and the Neural Networks for Financial Services project run by TSB Bank Technology with the Henley Centre for Forecasting and, again, UCL. Meanwhile, Chemical Bank, Citibank, JP Morgan, Barclays de Zoete Wedd, Societe Generale and the World Bank are among the many institutions investigating or using the technology.

2. Neural Network Applications in Finance

Prior to the use of neural networks and other AI techniques, acceptance of the market has always been governed by purely random forces. This gave rise to the use of econometric modelling techniques such as, the Efficient Market Hypothesis, statistical analysis, Portfolio Management Theory (CAPM and APT), and Financial Ratios. These methods suffered from certain weaknesses and they were subject to some major criticisms.

Neural networks can be used to replace, or supplement, these traditional modelling techniques in different areas of finance such as forecasting of stock performance, financial time series forecasting, bankruptcy prediction, bond rating improvement, loan risk analysis and investment management. Many of the financial applications of NNs have been successful, and this has prompted financial and economic researchers to undertake further studies into other areas. These applications can be grouped into a number of specific areas.

2.1. Analysis of Financial Conditions

Accounting reports are an important source of information for all users of a company's financial statements, especially for corporate managers, investors and financial analysts. Statistical techniques have often been used to extract information from financial statements, but have often proved inefficient.

The Chase Manhattan Bank, one of the largest banks in the United States, has a statistical-based hybrid NN system which has proven most successful. This system addresses a critical success factor in the Bank's strategic plan such as, reducing losses on loans made to public and private corporations. The ability to improve on loan assessment (forecasting the creditworthiness of corporate loan candidates) and to seek out new business opportunities, prompted the Bank to develop a financial NN system. The bank's focus was on a Public Company Loan Model (PCLM), and thus developed the Creditview system [9]. This was a hybrid system consisting of an Expert System, NN and the ADAM model, and was used to perform a three year forecast which succeeded in producing the likelihood of companies that would be either good or bad credit risks to the Bank.

A similar experiment on analysing financial conditions was undertaken by Barker [10]. This was another hybrid system using an expert system shell, a NN toolkit and a database package. This was used to analyse small firms in performing two main tasks: (1) interpreting the ratios of a company; and (2) estimating the likelihood that a firm will be able to acquire additional capital through borrowing. The author believed that both the heuristics and the facts necessary for performing the first task were unambiguous and reliable, thus making it an ideal choice for an expert system solution. The neural network approach had the best chance of producing plausible results for the second task, where clearly defined rules and precise data were absent. The reported results indicated a high level of success and this, in turn, demonstrated the power of combining both expert systems and NNs as complementary reason mechanisms.

Other means of extracting meaningful information from accounting reports was developed by Berry and Trigueiros [11], using the information on companies quoted on the London Stock Exchange. Companies were classified into different industry groups and a combination of traditional discriminant analysis and multi-layer perceptron networks (using a back-propagation algorithm) were used for a comparison of the company's reports. The results of the study indicated that the performance of NNs is capable of building structures similar to financial ratio, and such an approach removes the need for an analyst to search for appropriate ratios before model building can begin. Also, the NN approach proved able to outperform the classification performance of the traditional discriminant analysis approach. Although the results were successful, these were not without the problems associated with the topology of the net and the time taken to train the network.

Klemic [12] developed a NN system that helped to overcome the problems faced by the Inland Revenue Service in identifying the debtors who would be most likely to become delinquent. The author indicated that the more traditional forms of AI involving the use of rules, drawn from the knowledge of the domain expert, could take several weeks to months in attempting to identify and analyse these rules. Thus, the author highlighted the advantages of neural-computing over the traditional AI methods and proposed that there was a good possibility that neural-computing could be used to resolve the IRS problem, as the benefits greatly outweigh the costs.

2.2. Business Failure Prediction

Auditors verify financial statements of companies to see if they have been prepared according to generally accepted accounting principles, and present fairly the financial picture of the company. Interpretation and prediction are left to the user of the statements. However, there is a belief that the auditor's responsibilities go beyond mere verification of the statement. The auditor has a responsibility to evaluate whether there is substantial doubt about the entity's ability to continue as a going concern for a reasonable period of time (not to exceed one year beyond the date of the financial statement). The auditor's work in this respect is made difficult by uncertainty and fuzziness in the financial statement information, laws, and guidelines. This necessitates a good decision support system that the auditor can use to make confident predictions about the future status of a company, for example, to reach a valid conclusion whether the company will go bankrupt or remain a going concern.

Research by Raghupathi et al. [13] on bankruptcy prediction, indicated that NNs can be accurate to the extent that the data used can reflect the actual financial condition of the firm. Similar experiments by Rahimian et al. [14] used three paradigms, namely, multi-layer nets, single-layer nets, both using back propagation, and Athena. Athena is a NN for pattern classification based on an entropy measure [15,16]. The results of the analysis indicated that the formulated bankruptcy problem is potentially linearly separable. The best performance was achieved by the Athena, while the accuracy of prediction was the same with other models.

Classification error of bankruptcy risk was analysed by Ballarin et al. [17] using a multilayer, full-connected feed-forward network with a sigmoid activation function. This system was capable of classifying a firm into two groups: good and no good (i.e. not-bankrupt, bankrupt). Balance sheet items, that were considered necessary to judge the economic-financial status of every firm in the sample, were selected as data. The NN architecture was compared against the Z-score model [18] and Zeta-analysis [19]. The authors regarded the performance of the connectionist model as the best, with fewer errors. Classification errors in the generalisation set were, at worst, 13% for the connectionist model whereas for the Z-score they were 25–30%.

The predictive ability of an NN was compared with multivariate discriminant analysis (MDA) by Odom and Sharda [20], who found that the MDA had a correct predictive rate of 59.26% whilst the neural network had a correct predictive rate of 77.78%. Thus, a NN is more robust, as it performed better than the MDA model. It also appeared to be more consistent [21]. NNs can also have a positive impact on the rising problems of institutional, company, and individual bankruptcies. Coleman et al. [22] suggested that a combination of a NN and expert system could be used to great effect in quelling the problem of bankruptcies, by not only predicting the occurrence of bankruptcy but also recommending courses of action that can be taken against such a situation.

Tam and Kiang [23] applied a NN approach to the binary classification problem and compared it with the discriminant analysis method. The data set consists of 118 banks (59 failed and 59 non-failed). The result obtained showed that the NN offers better predictive accuracy power than discriminant analysis and other existing bankruptcy prediction models. However, they found that the NN results were rather more difficult to interpret than those of the traditional methods.

Salchenberger et al. [24], reported the effectiveness of backpropagation in predicting thrift failure. They tested five financial ratios, and found that NN models can be a promising tool for classification problems. The authors also revealed some limitations that may restrict the use of these models for prediction. In effect, inability of a NN to provide explanations of how and why conclusions may be a major restriction to their use in modelling techniques. Furthermore, there is no formal theory for determining optimal network topology. Therefore, decisions such as the appropriate number of layers and middle layer nodes must be determined using experimentation. The development and interpretation of NNs require expertise and experience, and the training of the network can be computationally intensive. It was suggested, however, that many of these limitations can be overcome by developing a hybrid system.

2.3. Debt Risk Assessment

The ability to assess risk in the financial market, is an area of paramount importance in the real world of finance. This area is lacking a well defined model or theory, thus it can be difficult to apply either conventional mathematical techniques or standard AI approaches (e.g. rule-based system). A NN can be a useful tool for the domain of risk assessment as it does not require a prior specification or a functional domain model.

Dutta and Shekhar [25] carried out a research on bonds rating (in a recognition and generalisation problem) using both a multilayer network consisting of simple processing elements, and regression models. The authors were able to compare the performance of neural-nets and regression model by applying the same data set and variables. They found that the NNs consistently outperformed the regression models in predicting bond ratings from the given set of financial ratios. Both in training and learning samples, the total squared errors for regression analysis were about an order of magnitude higher than those of a NN. Furthermore, the success rates of prediction for NNs were considerably higher than for regression analysis. The success rate of neural-nets was 88.3%, as compared to 64.7% for the regression model. In a similar study, Surkan and Singleton [26] compared the performance of NNs and discriminant classification techniques. The authors stated that a NN may be a more powerful classification technique if the mappings of layers are carried out in the appropriate manner. However, they believe that both methods can be applied fairly, and to their best advantage, in order to obtain accurate results.

Asset allocation is a critical decision in fund management and is having a profound effect in many industries. Developing a dynamic system to model such a task can be very labour intensive and time consuming. Diamond et al. [27] presented a neural network system for tactical asset allocation in seven major bonds markets. For each market, they found that a NN captures the underlying relationships in the data, and thus provides the best portfolio. The authors proposed that the neural-portfolio outperforms the benchmark by a factor of 2.9. They also noted that small changes in the network design, learning times, and initial conditions may produce large changes in the network behaviour.

Mortgage insurance risk assessment using multiple neural-net learning systems (MNNLS) was carried out in a study by Collins et al. [28], who reported that such systems are more consistent in their decisions than the human underwriters. The system offered an economic benefit by reduced processing costs and risk, and offered an economic gain by improved consistency in underwriting judgements. A different aspect of the problem arises for the network, not in automating the human decision-making process, but rather from the use of the network to improve on the quality of the decisions through its ability to learn to estimate some measure of the risk of a loan applicant's defaulting on his or her mortgage payments. Reilly et al. [29] showed that for a certain percentage of the applications (10%), it is possible to predict, with 95% accuracy, the loans which, if granted, would go delinquent in payment.

Burgress [30] investigated the use of neural-nets for loan risk analysis. The objective was to identify and quantify the business benefits which accrue from using the powerful modelling capability of NNs, as opposed to the more established linear regression methodology which underlies most current 'scorecard' systems. He found that the NN exploits non-linearities and interaction efforts within the data to outperform consistently, an equivalent linear regression 'scorecard' by identifying customers whose applications would normally be rejected as being 'out of policy' but, who nevertheless, represent an acceptable level of risk. Moreover, the NN allows a 76% increase in the amount of business that can be accepted for a fixed level of risk.

2.4. Security Market Applications

The use of NNs to detect the mysteries of price movements in the stock market attracts a strong interest of many researchers. The traditional approaches have limits in their ability to predict price movements. NN approaches in this area have shown considerable improvements.

Kimoto et al. [31] devised a prediction system for when to buy and sell stocks. The prediction system made an excellent profit in a simulation exercise. The authors concluded that the NN approach is more effective than the traditional multiple regression. This, along with pattern recognition, has achieved some interesting insights in financial market research. Bosarge [32] detected a new class of inefficiencies in the liquid capital markets by using pattern recognition technology. He reported that the technology had the ability to predict price movements associated with these inefficiencies. Bergerson and Wunsch [33] point out that rule-based approaches are lacking in the flexibility to easily deal with the recognition of these poorly defined patterns, and unaided neural networks are better at pattern recognition (in a theoretical sense). They are good at doing things that are naturally well handled by rules, such as risk management. It was possible to make a theoretically excellent market prediction system using neural networks alone, but it is the combination of this capability, together with a rule-based system, that makes a useful real-world investment system. Kamijo and Tanigawa [34] applied recurrent neural-nets to recognition of stock price patterns. Sixteen experiments were accomplished, and they confirmed that the test pattern was accurately recognised in 15 out of the 16 experiments.

Refenes and Azema-Barac [35] studied bond returns prediction on a month-on-month basis. The application performed quantitative asset allocation between bond markets and USA cash (dollars), and achieved returns significantly higher than any industry benchmark. Assets were allocated in seven markets (USA, Japan, UK, Germany, Canada, France and Australia) which were chosen on the basis of capitalisation. Each market was modelled on an individual basis using local (e.g. interest rates) and global parameters (e.g. oil prices, the ratio of precious to non-precious metals). The system was divided into two stages: in the first stage each local market was modelled with the aim of producing a local portfolio (i.e. local market plus USA cash). This outperformed a local bench mark (50% market and 50% cash). In the second stage the results for the individual markets were integrated in the global portfolio. The result of the study indicated that the *neural-portfolio* clearly outperformed the benchmark by a factor of 3·6.

Yoon and Swales [36], in their study of predicting stock price performance, indicated that the NN technique together with the MDA can significantly improve the predictability of stock price performance. However, not all the NN researches gave positive outcomes. White [7], in his study of IBM Daily Stock Returns, used a standard single hidden-layer network. The author reported his disappointment in the failure of the simple network in finding evidence against the simple EMH. The author found that to obtain evidence against efficient markets with a simple network is not an easy task. Even simple networks are capable of misleadingly overfitting an asset price series.

2.5. Financial Forecasting

Forecasting is another area that has been identified as one of the most promising applications of artificial neural networks [37]. Similar approaches in financial forecasting have been applied by a number of other researchers.

Sharda and Patil [38] reported the results of an empirical test of neural networks. They showed that neural-nets can be used for time series forecasting, at least for a single period forecasting problem. The authors tested and compared a series data sample containing annual, quarterly, and monthly observations using NN models and traditional Box-Jenkins forecasting models. The simple neural network models tested on this data could forecast about as well as an automatic Box-Jenkins ARIMA modelling system. Tests were based on one particular set of learning parameters and one architecture. Sharda and Patil [37] expanded their research by investigating a forecasting competition between their neural-net model and Box-Jenkins forecasting. They found that NNs provided a robust forecasting in cases of irregular time series, and thus offer promising alternative approach to time series forecasting. Moreover, their ability to forecast in a fuzzy sense makes it more appropriate than other forecasting methods. However, these systems are not always successful as Refenes et al. [39] described a Discounted Least Squares (DLS – statistical technique) procedure for a backpropagation network, designed to deal with the problems of weak non-stationarity in financial data series. They evaluated the procedure in a controlled simulation experiment and in a real application. They confirmed that DLS is a more robust procedure for 'weakly' non-stationary data series.

The forecasting of inflation rate and exchange rate prediction is another area where NNs have been successfully applied. Zwol and Bots [40], experimented with neural-nets in forecasting the

German inflation rate. A data set with German economic variables were built into a feed-forward backpropagation network. The results were promising. However, they found that NNs are most sensitive to changes in the learning rate. A learning rate of 0.25 proved to be too small. Only one of nine networks that were trained with a learning rate of 0.25 managed to reach 90% 'good facts'. The network also appeared sensitive to changes in the initial weight range. Nevertheless, Refenes et al. [41] reported that a successful outcome can be obtained if multi-layer perceptron networks are used in a non-trivial application in the forecasting of currency exchange rates. In their experiment, the network delivered an accurate prediction, making at least 22% profit on the last 60 trading days of the year 1989.

Tang et al. [42], discussed the results of a test of the performance of neural-nets and conventional methods in forecasting time series. The authors experimented with three time series of differing complexity using different feed-forward, backpropagation models, and the Box-Jenkins model. Their experiments demonstrated that, for time series with long memory, both methods produced comparable results. However, for series with short memory, neural-nets outperform the Box-Jenkins model. Neural networks are robust, parsimonious in their data requirements, and provide good long term forecasting.

The experiments with neural-nets in forecasting are not all positive. Fishwick [43], reported that the forecasting ability of neural-nets was inferior to simple linear regression and surface response methods. Burgess et al. [44] also point out that, even for inherently non-linear problems, a linear model with error-feedback terms can out-perform a neural-net model without error-feedback. Thus, the performance of both linear and non-liner models can be considerably improved by the use of error-feedback terms in financial time series forecasting. Marquez et al. [45] carried out an experiment to evaluate the performance of neural network models in estimating simple functional forms as an alternative to regression analysis approach. The model was evaluated in terms of forecasting accuracy by using functional forms such as the linear model, the logarithmic model and the reciprocal model. The authors reported that neural-nets estimated the linear model best, and they were also successful with the logarithmic model but not with the reciprocal model. However, they concluded that one cannot build a neural-net and always expect it to perform best.

3. Conclusions

Artificial neural networks represent a radically different form of computation from the more common algorithmic models. Neural computation is conceptually, massively parallel, typically employing from several thousand, to potentially many millions of individual simple processors. This NN technology can deliver performance that is similar to, or much better than, the conventional problem-solving approaches in a wide variety of areas. The unique learning capabilities of neural networks promise benefits in many areas of finance, and offers great potential for improvements in productivity and efficiency.

This study reveals that artificial neural networks can be successfully applied to different financial problem domains. Many of the authors who have used the technology reported that its use, in different financial areas, can provide positive outcomes. Neural networks are now well established in the field of academic research and commercial exploitation. They offer particular benefits to modelling tasks where little or no *a priori* knowledge is available. They provide a simple and effective means for constructing non-linear, non-parameteric models and have outperformed linear statistical approaches, econometric models, and other conventional methods in a large number of applications and financial problem domains. Unfortunately, not all the experiments carried out using NNs are always successful. Some authors [7,6,43–44] reported the inability of the NN technology to deliver in certain experiments. However, Marquez et al. [45] point out that one must not always expect the neural-net system to perform best. It is therefore important to recognise that neural network technology has its own drawbacks.

Neural networks can identify important decision-making factors that appear to be irrelevant, or even factors that conflict with traditional theories in the knowledge domain. Since the scope of training is always, to some extent, limited by economics and time, networks that contradict accepted theories run the risk of lacking generality, thus functioning well only on data with a structure similar to that of the training set. Furthermore, most neural networks lack explanatory capability. Thus, justifications for results are difficult to obtain because their connection weights do not usually have obvious interpretations. This is particularly true of pattern recognition where it is very difficult or even impossible to explain the logic behind specific decisions. Therefore, it is not possible to check intermediate computations or to debug a NN system in the traditional sense.

For most conceivable financial applications, ample training examples should be readily available, so that relatively little time or effort would be involved in data collection. Furthermore, the time and effort required to train a NN would be much less than that required to extract and translate an expert's knowledge base for an expert system. There are a number of factors that should also be considered when using NNs, in that most systems cannot guarantee an optimal solution to a problem or cannot guarantee a completely certain solution. Although, properly configured and trained, NNs can often make consistently good classifications, generalisations, or decisions, in a statistical sense. One of the major problems of the NN technology that is still an area of substantial research, is that of overfitting and generalisation.

Amongst the widely used neural network models, multilayer perceptrons with backpropagation neural network model seem to be the most successful when solving pattern recognition and classification problems. However, more research is required to determine if there are other types of problems that may be good candidates. The backpropagation algorithm suffers some drawbacks, but the recent cascade-correlation networks [46] tend to resolve most of these problems. Having said that, it is important to note that this study did not cover all the NN models that could have played vital roles in many other areas, such as Recurrent networks, Boltzmann machines, and Hopfield networks.

It is perhaps worth pointing out that most of the traditionally used techniques in finance were found problematic for one reason or another. The methods are statistical techniques, traditional ratio analysis, econometric models (i.e. efficient market hypothesis), Portfolio management theory (i.e. CAPM and APT) and other conventional AI techniques. These methods have been used for a number of decades, it would be rather unwise to discard them or replace them with recent technologies. Instead of using these methods in isolation however, their use in conjunction with neural network technology could provide a tremendous impact on financial applications. A similar idea was suggested by Barker [10], who pointed out that expert systems and neural networks are complimentary reasoning mechanisms that, because of their diverse nature, can be joined to form a versatile tool for tackling perplexing problems.

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