Artificial Neural Network (ANN) Approach to Financial Engineering

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Abstract— **Artificial Neural Networks (ANNs) are one such process, that is, it maps some type of input stream of information to an output stream of data. In general ANN is a valuable forecasting tool in Financial Engineering due to the learning, generalization and nonlinear behavior properties. This paper reviews the application of ANNs in Financial Engineering. Financial Engineering is a multidisciplinary field involving financial theory, the methods of engineering, the tools of mathematics and the practice of programming. The objective of this paper is to discuss the potential of ANNs in solving Financial Engineering related problems. The paper will provide some guidelines and references for the research and implementation. The first section of this paper reviews the basic foundation of ANNs to provide a common basis for further elaboration. Subsequently the paper focuses on the reviews of ANN's implications and applicability to the Financial Engineering field based on previous researches.**

Keywords—ANN; financial engineering; forecasting; stock market; credit risk; bankruptcy, exchange rate.

I. INTRODUCTION

There can be little doubt that the greatest challenge facing managers and researchers in the field of finance is the presence of uncertainty. Indeed risk, which arises from uncertainty, is fundamental to modern finance theory and, since its emergence as a separate discipline, much of the intellectual resources of the field have been devoted to risk analysis. The presence of risk, however, not only complicates financial decision making, but also it creates opportunities for reward for those who can analyze and manage risk effectively [1].

Dealing with uncertainty in finance primarily involves recognition of patterns in data and using these patterns to predict future events. Accurate prediction of economic events, such as interest rate changes and currency movements currently ranks as one of the most difficult exercises in finance; it also ranks as one of the most critical for financial survival.

ANNs are one of the most innovative analytical tools to surface in the financial arena. The availability of vast amounts of historical data in recent years, coupled with the enormous processing power of computers, has enabled the use of ANNs to assist in complex decision making environments. However, ANNs are not transparent, thus making them difficult to interpret. Their lack of explanation for the models that they create is the major weakness of ANN. Even though ANNs are easy to construct, finding a good ANN structure, as well as the pre-processing and post processing of the data, is a very time consuming processes [2].

This paper reviews the application of ANNs in Financial Engineering. Financial Engineering is a multidisciplinary field involving financial theory, the methods of engineering, the tools of mathematics and the practice of programming. The objective of this paper is to discuss the potential of ANNs in solving Financial Engineering related problems. The paper will provide some guidelines and references for the research and implementation. The first section of this paper reviews the basic foundation of ANNs to provide a common basis for further elaboration. Subsequently the paper focuses on the reviews of ANN's implications and applicability to the Financial Engineering field based on previous researches.

II. ARTIFICIAL NEURAL NETWORKS

ANNs have seen an explosion of interest over the last few years and are being successfully applied across an extraordinary range of problem domains, in areas as diverse as finance, medicine, engineering, geology, physics and biology. The excitement stems from the fact that these networks are attempts to model the capabilities of the human brain. The human brain is a very complex part of the human body, due mainly to the interactions and connectivity with other parts of our body and the way it controls and defines every aspect of our being. The brain has continued to be a mystery to many scientists, but its role and capacity to process information is mimicked in many aspects of academia. Neural networks are one such process, that is, it maps some type of input stream of information to an output stream of data. It consists of ways to connect data/information to produce output that is consistent with the processes. It may seem simple, but as the analysis will highlight, this process is far from trivial. From a statistical perspective neural networks are interesting because of their potential use in prediction and classification problems.

Artificial neural network models employ artificial intelligence techniques and are data driven; they learn and memorize a data structure and subsequently simulate the structure. They are able to learn key information patterns within a multidimensional information domain [3]. In a way, artificial neural network mimic the learning process of a human brain and therefore do not need characteristic information about the system; instead, they learn the relationship between input parameters and the output variables by studying previously recorded data. This makes artificial neural network ideal for modeling non-linear, dynamic, noisy data and complex systems [4]. Further, artificial neural networks are good for tasks involving incomplete data sets [5]. Fig. 1 shows a typical neural network, which consists of an input layer, a hidden layer and an output layer. An input x_j is transmitted through a connection, which multiplies its strength by a weight w_{ij} to give a product $x_j w_{ij}$. This product is an argument to a transfer function *f*, which yields an output y_i represented as:

$$y_i = f\left(\sum_{j=1}^{n} x_j w_{ij}\right)$$

Where *i* is an index of neurons in the hidden layer and *j* is an index of an input to the neural network.

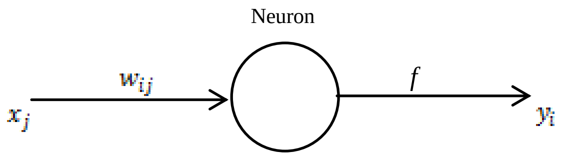

Figure 1. Typical neuron in a neural network system.

Followings are the characteristics of ANNs [6]:

- The ANNs exhibit mapping capabilities, that is, they can map input patterns to their associated output patterns.
- The ANNs learn by examples. Thus, ANN architectures can be ‘trained’ with known examples of a problem before they are tested for their ‘inference’ capability on unknown instances of the problem. They can, therefore, identify new objects previously untrained.
- The ANNs possess the capability to generalize. Thus, they can predict new outcomes from past trends.
- The ANNs are robust systems and are fault tolerant. They can, therefore, recall full patterns from incomplete, partial or noisy patterns.
- The ANNs can process information in parallel, at high speed and in a distributed manner.

There are three steps in solving an ANN problem which are 1) training, 2) generalization and 3) implementation. Training is a process that network learns to recognize present pattern from input data set. We present the network with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units. For this reason each ANN uses a set of training rules that define training method. Generalization or testing evaluates network ability in order to extract a feasible solution when the inputs are unknown to network and are not trained to network. We determine how closely the actual output of the network matches the desired output in new situations. In the learning process the values of interconnection weights are adjusted so that the network produces a better approximation of the desired output. ANNs learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself and its operation can be unpredictable.

III. ANNs in Financial Engineeting

Financial Engineering has numerous areas with potential applications for ANNs. Given this potential of ANN, during the last two decades, a number of studies have focused on the applications of ANN in Financial Engineering fields. After reviewing several papers, the following areas are found that involve ANN in solving Financial Engineering problems:

- Credit Scoring and Predicting Bankruptcy
- Forecasting Exchange Rates
- Predicting Stock Values
- Portfolio Management
- Inflation and Cash Forecasting

The following section is devoted to each of the Financial Engineering areas that involve ANN. Each section begins with a brief introduction and then the application of ANN in that particular area are reviewed. The studies are drawn from a broad cross-section of the literature and are intended to show where ANN has made inroads into the Financial Engineering areas.

A. Credit Scoring and Predicting Bankruptcy

To predict business failure accurately is a very important issue in financial decision making. Wrong decision making in financial institutions can cause serious consequences, e.g. financial crises or distress. Two well-known issues in financial decision-making are bankruptcy prediction and credit scoring. The objective of the credit scoring models is to evaluate the risk profile of the companies and then to assign different credit scores to companies with different probability of default. Therefore credit scoring problems are basically in the scope of the more general and widely discussed discrimination and classification problems.

M. A. Doori and B. Beyrouti, in the paper titled “Credit Scoring Model Based on Back Propagation Neural Network Using Various Activation and Error Function”, attempted to assess and compare the results using a combination of activation and error functions applied differently on the hidden and output layers of the network. Sigmoid, Hyperbolic Tangent and Gaussian are the activation functions under study. Furthermore, error functions such as the Mean Squared Error, Huber and the Complex Sine-Hyperbolic have been considered [7].

V. Pacelli and A. Michele, in the paper "An Artificial Neural Network Approach for Credit Risk Management", analyzed the ability of the artificial neural network model developed to forecast the credit risk of a panel of Italian manufacturing companies. In a theoretical point of view, this paper introduced a literature review on the application of artificial intelligence systems for credit risk management. In an empirical point of view, this research compares the architecture of the artificial neural network model developed in this research to another one, built for a research conducted in 2004 with a similar panel of companies, showing the differences between the two neural network models [8].

T. S. Lee, C. C. Chiu, C. J. Lu and I. F. Chen, in the paper titled "Credit Scoring Using the Hybrid Neural Discriminant Technique", explored the performance of credit scoring by integrating the back propagation neural networks with traditional discriminant analysis approach. The results reveal, the proposed hybrid approach converges much faster than the conventional neural networks model. Moreover, the credit scoring accuracies increase in terms of the proposed methodology and outperform traditional discriminant analysis and logistic regression approaches [9].

E. Angelini, G. Tollo and A. Roli, in the paper titled "A Neural Network Approach for Credit Risk Evaluation" described the case of a successful application of neural networks to credit risk assessment. They developed two neural network systems, one with a standard feed forward network, while the other with a special purpose architecture. The application is tested on real-world data, related to Italian small businesses. They show that neural networks can be very successful in learning and estimating the default tendency of a borrower, provided that careful data analysis, data pre-processing and training are performed [10].

R. Pradhan, K. K. Pathak and V. P. Singh, in the paper titled "Application of Neural Network in Prediction Financial Viability", used Back Propagation Neural Networks (BPNN) to forecast the Z score for the firms. The research work first estimates the internal parameters of the Z score for a firm from 2001-2008 to the train the BPNN and uses the estimates of the year 2009 and 2010 values for the validation process. Finally it dwells to draw predictions for the period 2011-2015 and emphasizes the growing role of BPNN application based Z score computation of financial Bankruptcy [11].

Tsai, C. Fong and J. W. Wu, in the paper "Using Neural Network Ensembles for Bankruptcy Prediction and Credit Scoring", investigated the performance of a single classifier as the baseline classifier to compare with multiple classifiers and diversified multiple classifiers by using neural networks based on three datasets. By comparing with the single classifier as the benchmark in terms of average prediction accuracy, the multiple classifiers only perform better in one of the three datasets. They suggest that it is better to consider these three classifier architectures to make the optimal financial decision [12].

B. Forecasting Exchange Rates

The international activity of the largest banks and the increasing volatility of exchange rates emphasize the importance of exchange rate risk, whose active management by the banks require the use of effective forecasting models.

A. A. Philip, A. T. Akinwale and A. B. Akintomide, in the paper titled "Artificial Neural Network Model for Forecasting Foreign Exchange Rate", designed an artificial neural network foreign exchange rate forecasting model. The design was divided into two phases, namely: training and forecasting. In the training phase, back propagation algorithm was used to train the foreign exchange rates and learn how to approximate input. Feed forward Network was used to improve the efficiency of the back propagation. Multilayer Perceptron Network was designed for forecasting. The system was tested using mean square error and standard deviation with learning rate of 0.10, an input layer, 3 hidden layers and an output layer. This approach provided an improved technique for carrying out foreign exchange rate forecasting [13].

B. Oancea, Ş. T. C. Ciucu, in the paper titled "Time Series Forecasting Using Neural Networks", compared the performances of different feed forward and recurrent neural networks and training algorithms for predicting the exchange rate EUR/RON and USD/RON. They used data series with daily exchange rates starting from 2005 until 2013 [14].

V. Pacelli, B. Vitoantonio and A. Michele, in the paper titled "An Artificial Neural Network Model to Forecast Exchange Rates", predicts the trend of the exchange rate Euro/USD up to three days ahead of last data available. They concluded that by the analysis of the data the developed ANN model can largely predict the trend to three days of exchange rate Euro/USD [15].

C. Panda and V. Narasimhan, in the paper "Forecasting Daily Foreign Exchange Rate in India with Artificial Neural Network", used neural network to make one-step-ahead prediction of weekly Indian rupee/US dollar exchange rate. They also compared the forecasting accuracy of neural network with that of linear autoregressive and random walk models. Using six forecasting evaluation criteria, they found that neural network has superior in-sample forecast than linear autoregressive and random walk models. Neural network is also found to beat both linear autoregressive and random walk models in out-of-sample forecasting. This finding provides evidence against the efficient market hypothesis and suggests that there exists always a possibility of extracting information hidden in the exchange rate and predicting it into the future [16].

C. Predicting Stock Values

In the past two decades, a large body of research for predicting stock market returns has been developed. This body of knowledge contains many AI approaches, namely ANN, Fuzzy Logic and Genetic Algorithms [17-24].

Prediction is a difficult task, especially when the relationship between input and output is nonlinear, stock price prediction is one such an item. Ramani, Prakash and P. D. Murarka, in the paper "Stock Market Prediction Using Artificial Neural Network", proposed a method for stock price prediction. The method makes use of ANN and back propagation algorithm. Historical stock prices are used for training the network [25].

K. Ryota and N. Tomoharu, in the paper titled “Stock Market Prediction Based on Interrelated Time Series Data”, proposed a method based on interrelated time series data for predicting stock market. Although there are many methods proposed for stock market price but only a few of them consider other time series data for the same. In the proposed method the interrelationship between the predicted stock and various time series data such as other stocks, world stock market indices, foreign exchanges and oil prices are derived. These interrelationships are used for predicting the daily up and down changes in the closing value. The experimental results proved to be good especially in the manufacturing industry [26].

Abhishek, Kumar, A. Khairwa, T. Pratap and S. Prakash, in the paper “A Stock Market Prediction Model Using Artificial Neural Network”, predicted the market share price using Neural Networks with the given input parameters of the share market. Artificial Neural Network can remember data of any number of years, which can be used for training the network and thus predicting the future based on the past data. The proposed method makes use of feed forward architecture for prediction. The network was trained for one year data [27].

In the paper titled “Stock Market Prediction Using Artificial Neural Networks”, B. Egeli, proposed a method for predicting the Istanbul Stock Exchange (ISE) market index value using the Artificial Neural Network. The inputs to the system includes previous days index value, previous days TL/US exchange rate, previous day’s overnight interest rate and 5 dummy variables each representing the working day of the week. The Network Architecture includes Multi-Layer Perceptron and Generalized Feed forward Networks. Training and Testing is performed with these two Network Architectures. Results are compared to moving averages where ANN prove to be better in performance [28].

M. Thenmozhi, in his paper “Forecasting Stock Index Returns Using Neural Networks”, applied neural network models to predict the daily returns of the BSE (Bombay Stock Exchange) Sensex. Multilayer perceptron network is used to build the daily return’s model and the network is trained using Back Propagation algorithm. It is found that the predictive power of the network model is influenced by the previous day’s return than the first three-day’s inputs. The study shows that satisfactory results can be achieved when applying neural networks to predict the BSE Sensex [29].

K. Abhishek, in his paper “Stock Prediction using Artificial Neural Networks”, presented an Artificial Neural Network approach to predict stock market indices. He outlined the design of the Neural Network model with its salient features and customizable parameters. A number of activation functions are implemented along with options for cross validation sets. He finally tested his algorithm on the Nifty stock index dataset where he predicted the values on the basis of values from the past n days. He achieved a best case accuracy of 96% on the dataset [30].

D. *Portfolio Management*

Portfolio management is the centralized management of one or more portfolios, which includes identifying, prioritizing, authorizing, managing and controlling projects, programs and other related work to achieve specific strategic business objectives [31]. Investor managing a portfolio is always faced with the problem of best assets allocation. Which assets should be exposed more and which less from the others? Often this decision is made based on the analysis of reports produced by analysts. These reports are the results of work which often tries to predict future behavior of analyzed time series. By doing so, they base their predictions on personal experience and expertise, economic indicators or market factors. This is with no doubt, very difficult task. Therefore, ANN is a good option to automate the process of portfolio optimization.

Marcin Radlak, in the paper titled “Artificial Intelligence with Modern Portfolio Theory”, designed a novel adaptive algorithm to produce assets allocation weights in a portfolio of assets for any desired moment in time. Using combination of Artificial Neural Networks, Evolutionary Programming and Modern Portfolio Theory, it is aimed to beat simple historical method for Optimal Risky Portfolio estimation and provide an investor with an edge in continuously changing financial environment [32].

Abdelazim, Y. Hazem and K. Wahba, in the paper “Application of Artificial Intelligence Approach to Portfolio Selection and Management”, used neural network technique to provide a better estimate for expected returns than the conventional historical average. It was found that, even in bearish market periods, the optimally selected portfolio, which was weekly managed using ANNs, was able to generate positive returns utilizing the Markowitz Efficient Frontier. The research result has demonstrated the usefulness of applying the proposed ANN in active portfolio and management [33].

Fernández, Alberto and S. Gómez, in the paper titled “Portfolio Selection Using Neural Networks”, applied a heuristic method based on artificial neural networks in order to trace out the efficient frontier associated to the portfolio selection problem. They considered a generalization of the standard Markowitz mean-variance model which includes cardinality and bounding constraints. These constraints ensure the investment in a given number of different assets and limit the amount of capital to be invested in each asset. They presented some experimental results obtained with the neural network heuristic and compared them to those obtained with three previous heuristic methods [34].

D. Freitas, D. Fabio and R. Ailson, in the paper “Portfolio Selection with Predicted Returns Using Neural Networks” presented a modified version of the Markowitz’s Model that uses time series prediction instead of first order statistical measurements. They have used a neural network predictor for providing an estimate of future returns, which were used as expected returns on the Markowitz’s Model. The resulting new model was named prediction-quadratic deviation model. They carried out investment simulations using real data with the Markowitz’s model and their model. These simulations shown that the prediction-quadratic deviation model can achieve a return 12.39% higher than the mean-variance model [35].

E. *Inflation and Cash Forecasting*

Inflation forecast is used as guide in the formulation of the monetary policy by the monetary authorities in the world. Monetary policy decisions are based on inflation forecast extracted from the information from different models and other information suggested by relevant economic indicators of the economy.

E. Nakamura, in her paper "Inflation Forecasting using a Neural Network" evaluated the usefulness of neural networks for inflation forecasting. It was found that a simple specification of the neural network model and specialized estimation procedures from the neural networks literature appear to play significant roles in the success of the neural network model [36].

P. D. McNelis and P. McAdam, in the paper titled "Forecasting Inflation with Thick Models and Neural Networks", applied linear and neural network-based "thick" models for forecasting inflation based on Phillips–curve formulations in the USA, Japan and the euro area. Thick models represent "trimmed mean" forecasts from several neural network models. They outperform the best performing linear models for "real-time" and "bootstrap" forecasts for service indices for the euro area and do well, sometimes better, for the more general consumer and producer price indices across a variety of countries [37].

S. Moshiri and N. Cameron, in the paper titled "Neural Network Versus Econometric Models in Forecasting Inflation", compared the performance of Back- Propagation Artificial Neural Network (BPN) models with the traditional econometric approaches to forecasting the inflation rate. They compare econometric model with a hybrid BPN model which uses the same set of variables. Dynamic forecasts are compared for three different horizons: one, three and twelve months ahead. Root mean squared errors and mean absolute errors are used to compare quality of forecasts. The results show that the hybrid BPN models are able to forecast with better accuracy than traditional econometric methods [38].

A. Haider and M. N. Hanif, in the paper "Inflation Forecasting in Pakistan Using Artificial Neural Networks", attempted to forecast monthly year to year inflation for Pakistan by using ANN for financial year 2008 on the basis of monthly data of July 1993 to June 2007. They also compared the forecast performance of the ANN model with conventional time series forecasting models such as AR(1) and ARIMA based models and observed that RMSE of ANN based forecasts is much less than the RMSE of forecasts based on AR(1) and ARIMA models [39].

The ability to predict the future demand estimate of currency within a reasonable accuracy is called cash forecasting. Cash forecasting is integral to the effective operation of an ATM/branch network. The primary objective of cash forecasting is to ensure that cash is used efficiently and effectively throughout the branch network.

P. Kumar and W. Ekta, in the paper titled "Cash Forecasting: An Application of Artificial Neural Networks in Finance", presented two neural network models for cash forecasting for a bank branch. One is daily model, taking the parameter values for a day as input to forecast cash requirement for the next day and the other is weekly model, which takes the withdrawal affecting input patterns of a week to predict cash requirement for the next week. The system performs better than other cash forecasting systems. This system can be scaled for all branches of a bank in an area by incorporating historical data from these branches [40].

CONCLUSION

The purpose of this article has been to provide the reader with an overview of where ANNs have been implemented in the field of Financial Engineering. Based on these studies, there is ample evidence that ANNs have made inroads into many facets of the Financial Engineering field. As we improve our understanding of the strengths and weaknesses of the ANNs and improve the manner by which we leverage their best features, it seems inevitable that ANNs will become one of our important tools in the field of Financial Engineering.

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