Neural Network Regression and Alternative Forecasting Techniques for Predicting Financial Variables

by
Christian L. Dunis* and Jamshidbek Jalilov**
(*Liverpool Business School and CIBEF**)**

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Abstract

In this paper, we examine the use of Neural Network Regression (NNR) and alternative forecasting techniques in financial *forecasting* models and financial *trading* models. In both types of applications, NNR models results are *benchmarked* against simpler alternative approaches to ensure that there is indeed added value in the use of these more complex models.
The idea to use a nonlinear nonparametric approach to predict financial variables is intuitively appealing. But whereas some applications need to be assessed on traditional forecasting accuracy criteria such as root mean squared errors, others that deal with trading financial markets need to be assessed on the basis of financial criteria such as risk adjusted return.
Accordingly, we develop two different types of appications. In the first one, using monthly data from April 1993 through June 1999 from a UK financial institution, we develop alternative *forecasting models* of cash flows and cheque values of four of its major customers. These models are then tested *out-of-sample* over the period July 1999-April 2000 in terms of *forecasting accuracy*.
In the second series of applications, we develop financial *trading models* for four major stock market indices (S&P500, FTSE100, EUROSTOXX50 and NIKKEI225) using daily data from 31 January 1994 through 4 May 1999 for in-sample estimation and leaving the period 5 May 1999 through 6 June 2000 for out-of-sample testing. In this case, the trading models developed are not assessed in terms of forecasting accuracy, but in terms of *trading efficiency* via the use of a simulated trading strategy.
In both types of applications, for the periods and time series concerned, we clearly show that NNR models do indeed add value in the forecasting process.

** Christian Dunis is Girobank Professor of Banking and Finance at Liverpool Business School and Director of CIBEF (E-mail: cdunis@totalise.co.uk). The opinions expressed herein are not those of Girobank.*
*** Jamshidbek Jalilov is an Associate Researcher with CIBEF and is currently working at the National Bank of Uzbekistan (E-mail: jjalilov@central.nbu.com).*
**** CIBEF – Centre for International Banking, Economics and Finance, JMU, John Foster Building, 98 Mount Pleasant, Liverpool L3 5UZ.*

1. INTRODUCTION

Over the last decade, academic research has highlighted the usefulness of Neural Network Regression (henceforth NNR) in many different fields of science, business and industry. Applications of NNR models have surged over that period and NNR models have now been recognised as a major forecasting technique in a forecaster's toolbox.

Yet the application of NNR models to financial data has lagged that to other fields, as demonstrated for instance by the relatively few such applications listed by Zhang *et al.* (1998) in their well-known survey on forecasting with NNR models. One of the reasons may be that traditional performance metrics such as root mean squared error (RMSE) are often inappropriate to assess financial performance: as mentioned by several authors (see, amongst others, Dacco and Satchell (1999) and Dunis (1996, 2001b)), the evaluation of the results in such applications often, although not always, requires more appropriate financial cost functions, such as risk-adjusted return measures.

Accordingly, we develop two different types of appications. In the first one, using monthly data from April 1993 through June 1999 from a UK financial institution, we develop alternative *forecasting models* of cash flows and cheque values of four of its major customers. These models are then tested *out-of-sample* over the period July 1999-April 2000 in terms of *forecasting accuracy*.

In the second series of applications, we develop financial *trading models* for four major stock market indices (S&P500, FTSE100, EUROSTOXX50 and NIKKEI225) using daily data from 31 January 1994 through 4 May 1999 for in-sample estimation and leaving the period 5 May 1999 through 6 June 2000 for out-of-sample testing. In this case, the trading models developed are not assessed in terms of forecasting accuracy, but in terms of *trading efficiency* via the use of a simulated trading strategy.

The motivation for this paper is to check whether NNR models add value in both types of applications, by benchmarking their results against those achieved with simpler modelling techniques. In the end, for the periods and time series concerned, we clearly show that NNR models do indeed add value in the forecasting process.

The paper is organised as follows. Section 2 presents a short survey of the existing literature on financial applications of NNR models. Section 3 briefly describes the data used in both applications. Section 4 presents the benchmark models and forecasts against which the NNR model forecasts are assessed later. Section 5 explains the procedures and methods used in applying the NNR modelling procedure to our financial time series. Section 6 describes the forecasting accuracy and trading results obtained using traditional statistical accuracy criteria and, where appropriate, a financial trading strategy. Finally, section 7 provides some concluding comments.

2. LITERATURE REVIEW

Financial applications of NNR models started in the late Eighties/early Nineties. It is beyond the scope of this short literature review to provide an exhaustive survey of all financial applications of NNR models, but it is fair to say that they have been mostly applied to three major areas of Finance: corporate distress and business failure prediction, debt assessment and bond rating forecasts and, finally, forecasting financial markets and the development of trading models.

Contributions in the field of business failure prediction include Odom and Sharda (1990), Coleman *et al.* (1991), Salchenberger *et al.* (1992), Tam and Kiang (1992), Fletcher and Goss (1993), Raghupathi *et al.* (1993), Rahimian *et al.* (1993), Wilson and Sharda (1994), Alici (1996), Tyree and Long (1996) and Yang (1999).

Several contributions have been made in the field of credit markets and debt assessment (see, amongst others, Collins *et al.* (1988) and Reilly *et al.* (1991)), and particularly in the sensitive area of bond ratings with, for instance, Dutta and Shekkar (1988), Surkan and Singleton (1990) and Albanis and Batchelor (1999).

Applications in the field of financial markets forecasting and the development of trading models have spanned many markets. Several papers concern applications to the stock markets, such as White (1988), Ahmadi (1990), Kimoto *et al.* (1990), Kamijo and Tanigawa (1990), Bosarge (1991), Yoda (1994), Yoon and Swales (1991), Baestens *et al.* (1996), Burgess *et al.* (1996), Kim (1998), Albanis and Batchelor (2000) and Leung *et al.* (2000), with some contributions concentrating more specifically on the particular problem of porfolio allocation (see, amongst others, Kryzanowski *et al.* (1993), Hall (1994) and Naï m *et al.* (2000)).

A few articles have concentrated on commodities markets (see, for instance, Bergerson and Wunsch (1991), Collard (1993), Kohzadi *et al.* (1996), Robles and Naylor (1996) and Ntungo and Boyd (1998)), interest rate markets (as Deboeck and Cader (1994) and Barucci and Landi (1996)), emerging markets (with, for instance, Jang and Lai (1994) and Siriopoulos *et al.* (1996)) and even, more recently, volatility (see Bartlmae and Rauscher (2000) and Dunis and Huang (2001b)).

Yet the majority of applications has probably been geared towards the foreign exchange markets, with contributions such as Weigend *et al.* (1992), Refenes (1993), Azoff (1994), Green and Pearson (1994), Kuan and Liu (1995), Wu (1995), Dunis (1996), Hann and Steurer (1996), Nabney *et al.* (1996), Tenti (1996), Bolland *et al.* (1998), Franses and Homelen (1998) and Nelson *et al.* (1999).

It seems therefore that there is a good reason to check whether, as an alternative technique to more traditional statistical forecasting methods or technical trading rules, NNR models can add value in the case of our specific applications with financial forecasting models and financial trading models.

3. THE BANK CUSTOMERS AND STOCK MARKET DATA

We present in turn the two databanks we have used for this study and the modifications to the original series we have made where appropriate.

3.1 – The Cash Flow and Cheque Value Data

For the first application, we used the cash flows and cheque values of selected customers of a UK bank. The series are monthly and span the period from April 1993 to April 2000, i.e. a total of 85 data points per time series. We decided to retain the period April 1993 to June 1999 as our in-sample period for model estimation and to hold out the period from July 1999 to April 2000, approximately 12% of our total data bank, for out-of-sample forecasting purposes.

These monthly cash flows and cheque values were sorted out by industry sector. In this data bank, we chose a total of 8 series of cash flows and cheque values coming from 4 companies from different sectors. The selection of the series was determined by the size of those cash flows and cheque values coming to the bank each month. Table 3.1 documents the companies and sectors retained for further analysis[1].

Table 3.1 - *Selected Companies and Sectors*

No	Companies	Sectors
1	Customer 1	Financial Institutions
2	Customer 2	Food & Drink Services
3	Customer 3	Non Food Retail
4	Customer 4	Food Retail

We also created combined so-called industry averages by adding up the values of all of the bank's customers in every industrial sector, and got 8 other series, namely cash flows and cheque values for all four industries: Financial Institutions, Food & Drink Services, Non Food Retail and Food Retail. This amalgamation is useful from two points of view: first, it helps us to include specific information for each industry into our models; and, at the same time, it increases the data points available for the study, which is essential in preventing the NNR models from overfitting.

As mentioned below in section 4.1, to account for their non-stationarity[2], all variables were first-differenced.

3.2 – The Stock Market Data

[1] Actual customer names have been omitted for obvious confidentiality reasons.
[2] Despite some contrary opinions, e.g. Balkin (1999), stationarity remains important if NNR models are to be assessed on the basis of the level of explained variance.

For the second application, the financial data we used were all extracted from a historical database provided by Datastream. The 4 stock markets retained for this study are representative of the 4 major world stock markets, i.e. the S&P500 for the USA, the FTSE100 for the UK, the Dow Jones EUROSTOXX50 for the EU and the NIKKEI225 for Japan.

To model these 4 stock markets, we used a range of related financial markets variables, which we thought may have a potential explanatory power: these included the USD 3-month interest rate, the GBP 3-month interest rate, the EUR and DEM 3-month interest rate[3], the 3-month JPY interest rate, the 10-year benchmark bond yields for the USA, the UK, Germany and Japan, the GBP/USD , USD/JPY, USD/DEM and EUR/USD exchange rates, the price of Brent Crude oil, the price of gold and the price of commodities as represented by the CRB index.

As mentioned above, the data were obtained from Datastream and Table 3.2 documents the mnemonics of the different time series retained.

Table 3.2 - *Datastream Codes for the Data*

No	Variable	Mnemonics
1	***FTSE 100*** *- PRICE INDEX*	FTSE100
2	***S&P 500*** *COMPOSITE - PRICE INDEX*	S&PCOMP
3	***NIKKEI 225*** *STOCK AVERAGE - PRICE INDEX*	JAPDOWA
4	***DJ EURO STOXX 50*** *- PRICE INDEX*	DJES50I
5	***US EURO-$ 3 MONTH*** *(LDN:FT) - MIDDLE RATE*	ECUS$3M
6	***JAPAN EURO-$ 3 MONTH*** *(LDN:FT) - MIDDLE RATE*	ECJAP3M
7	***EURO EURO-CURRENCY 3 MTH*** *(LDN:FT) - MIDDLE RATE*	ECEUR3M
8	***GERMANY EURO-MARK 3 MTH*** *(LDN:FT) - MIDDLE RATE*	ECWGM3M
9	***UK EURO-£ 3 MONTH*** *(LDN:FT) - MIDDLE RATE*	ECUK£3M
10	***JAPAN BENCHMARK BOND*** *-RYLD.10 YR (DS) - RED. YIELD*	JPBRYLD
11	***GERMANY BENCHMARK BOND*** *10 YR (DS) - RED. YIELD*	BDBRYLD
12	***UK BENCHMARK BOND 10*** *YR (DS) - RED. YIELD*	UKMBRYD
13	***US TREAS.BENCHMARK BOND*** *10 YR (DS) - RED. YIELD*	USBD10Y
14	***GERMAN MARK TO US $*** *(WMR) - EXCHANGE RATE*	DMARKE$
15	**US $ TO EURO** (WMR) - EXCHANGE RATE	USEURSP
16	***JAPANESE YEN TO US $*** *(WMR) - EXCHANGE RATE*	JAPAYE$
17	***US $ TO UK £*** *(WMR) - EXCHANGE RATE*	USDOLLR
18	***Brent Crude-Current Month****, FOB U$/BBL*	OILBREN
19	***GOLD BULLION*** *$/TROY OUNCE*	GOLDBLN
20	***Bridge/CRB Commodity Futures Index*** - PRICE INDEX	NYFECRB

All the series are daily and span the period from 31 January 1994 to 6 June 2000, i.e. a total of 1676 trading days. We decided to retain the period from 31 January 1994 to 4 May 1999 as our in-sample period for model estimation and to hold out the 284 trading day period from 5 May 1999 to 6 June 2000, approximately 17% of our total data bank, for out-of-sample forecasting purposes.

[3] For interest rates and exchange rates, we used DEM data until 31 December 1998 and EUR data from 4 January 1999.

To account for their non-stationarity, all variables were transformed into returns which were computed as:

$$R = (P_t / P_{t-1})-1 \quad (1)$$

where P_t is the price level or the index at time t.

Furthermore, in both applications, to cope with potential seasonality and calendar anomalies, we included appropriate variables such as day of the week, week of the month and month of the year.

4. BENCHMARK MODELS AND FORECASTS

As mentioned above, to ensure that more complex models such as NNR models do indeed add value in the forecasting process, it is neccessary to benchmark them against simpler, more widely used techniques.

4.1 – The Cash Flow and Cheque Value Benchmark ARIMA Models

For our first application, the UK bank itself was using a Box-Jenkins approach, so the choice of an ARIMA modelling procedure as the benchmark was quite obvious.

An ARIMA (p,d,q) process produces a dynamic forecast $\hat{y}_{t+n}$ using all available information of y_t at time t. The computation of the forecast $\hat{y}_{t+n}$ can be done recursively by using the estimated ARIMA (p,d,q) model. This involves first computing a forecast one period ahead, then using this forecast to compute a forecast two periods ahead, and continuing until the n-period forecast has been reached. Let us write the ARIMA (p,d,q) model as:

$$w_t = f_1 w_{t-1} + ... + f_p w_{t-p} + e_t - q_1 e_{t-1} - ... - q_q e_{t-q} + d \quad \text{(2-a)}$$

where $y_t = \sum^d w_t$ is the original time series and δ represents some deterministic trend if different from zero.

To compute the forecast $\hat{y}_{t+n}$, we begin by computing the one-period ahead forecast of w_T, $\hat{w}_{T+1}$. To do so, we rewrite equation (2-a) as:

$$w_{T+1} = f_1 w_T + ... + f_p w_{T-p+1} + e_{T+1} - q_1 e_T - ... - q_q e_{T-q+1} + d \quad \text{(2-b)}$$

We then compute our forecast $\hat{w}_{T+1}$ by taking the conditional expected value of w_{T+1} in equation (2-b):

$$\hat{w}_{T+1} = E(w_{T+1} \mid w_T, ...) = f_1 w_T + ... + f_p w_{T-p+1} - q_1 \hat{e}_T - ... - q_q \hat{e}_{T-q+1} + d \quad \text{(2-c)}$$

where $\hat{e}_T, \hat{e}_{T-1},$ etc. are the observed residuals.

Now, using the one-period ahead forecast $\hat{w}_{T+1}$, we can obtain a two-period ahead forecast, and so on until the n-period ahead forecast $\hat{w}_{T+n}$ is reached:

$$\hat{w}_{T+n} = f_1 \hat{w}_{T+n-1} + ... + f_n w_T + ... + f_p w_{T-p+n} - q_1 \hat{e}_T - ... - q_q \hat{e}_{T-q+1} + d \quad \text{(2-d)}$$

If n>p and n>q, the n-period ahead forecast will be:

$$\hat{w}_{T+n} = f_1 \hat{w}_{T+n-1} + ... + f_p \hat{w}_{T-p+n} \quad \text{(3)}$$

In practice, in order to define the ARIMA (p,d,q), we started to check for the stationarity of our data. Standard ADF tests (not reproduced here in order to conserve space) showed that our data were nonstationary in levels, but stationary in their first difference, meaning one of the necessary assumptions for using this modelling approach did hold[4].

We went on to find the values for p and q, building matrices of the Schwarz Bayesian Criterion (SBC) and the Akaike Information Criterion (AIC) for each series (see Appendix 1 for an example of this procedure). In case the AIC and SBC criteria differed, we ultimately selected our final model based on the SBC criterion.

4.2 – The Stock Market Benchmark Trading Strategies

As mentioned earlier, for many financial applications, standard statistical measures of forecasting accuracy are often inappropriate: in such cases, the evaluation of the results requires more appropriate financial cost functions, such as risk-adjusted return measures.

In the same way, for an application geared to the stock markets like our second application to the S&P500, FTSE100, EUROSTOXX50 and NIKKEI225 stock indices, it seemed that the simple 'buy and hold' strategy, a naïve adaptive expectations strategy and a basket of moving averages (BMA) provided 3 sensible benchmark strategies to our NNR-based trading models.

4.2.1 – The 'Buy and Hold' Trading Strategy

The efficient market hypothesis holds that stock prices fluctuate randomly about their intrinsic value, and that the best investment strategy to follow is simply to 'buy and hold' the market as opposed to any attempt to 'beat the market'.

Following this rule we constructed a 'buy and hold' strategy, whose daily results simply mirror those of the market itself. Accordingly, daily returns obtained from this strategy are just the market returns as computed in equation (1).

4.2.2 – The Naï ve Adaptive Expectations Trading Strategy

[4] Exceptions were Customer 2 cash flows and Customer 4 cash flows and cheque values series, for which further differencing did not help. These series were found to be nonhomogeneous nonstationary (see Pyndick and Rubinfeld (1998)), which means that no matter how many times they are differenced, their autocorrelation function will not dampen down to zero.

One of the simplest trading models is a model based on adaptive expectations, we call it the 'naïve strategy'. According to this strategy, we go long if the stock market index went up the previous day and *vice versa*. The idea is that expectations of price movements adapt following the most recent price movement. This strategy does not use all information available at the time of decision-making.

Based on this naïve strategy, the algorithm for computing the daily returns $\hat{R}_t$ of this trading model is depicted in Figure 4.1 below.

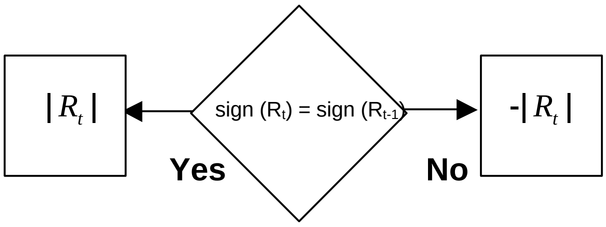


FIGURE 4.1: DAILY RETURNS OF THE NAIVE STRATEGY

4.2.2 – The Basket of Moving Averages Trading Strategy

Another strategy that we retained as a benchmark is quite a popular one among technical traders and fund managers (see Kaufman (1998)). Accordingly, we built three moving average (MA_t^n) models of orders 5, 10 and 20 trading days (i.e. 1, 2 and 3 trading weeks) for the actual stock price indices (P). The underlying idea is to track short-term market trends and to react accordingly.

$$MA_t^n = \frac{1}{n}\sum_{t-n}^{t} P \qquad (4)$$

Each moving average model gives buy/sell signals: the usual technical trading rules apply, i.e. if $P_t \geq MA_t^n$ buy the index, otherwise sell it. The signals coming from all three MA models are combined into one basket. Each signal in the basket was given an equal weight and a majority voting scheme was applied as in Albanis and Batchelor (2001), so that, in the end, the final signal is to buy (sell) the market if at least two of the models produce a buy (sell) signal.

The returns ($\hat{R}_t$) of this basket are computed according to the accuracy of the signal. If the signal at time *t* correctly predicted the price movement at time *t+1*, then $\hat{R}_{t+1} = |R_{t+1}|$, otherwise $\hat{R}_{t+1} = -|R_{t+1}|$.

5. NNR-BASED FORECASTS AND TRADING STRATEGIES

5.1 – The NNR Modelling Procedure

Over the past few years, it has been argued that new technologies and quantitative systems based on the fact that most financial time series contain nonlinearities have made traditional forecasting methods only second best. Neural Network Regression (NNR) models, in particular, have been applied with increasing success to economic and financial forecasting and would constitute the state of the art in forecasting methods (see, for instance, Zhang *et al.* (1998)).

It is clearly beyond the scope of this paper to give a complete overview of artificial neural networks, their biological foundation and their many architectures and potential applications (for more details, see, amongst others, Simpson (1990) and Hassoun (1995))[5].

For our purpose, let it suffice to say that NNR models are a tool for determining the relative importance of an input (or a combination of inputs) for predicting a given outcome. They are a class of models made up of layers of elementary processing units, called neurons or nodes, which elaborate information by means of a nonlinear transfer function. Most of the computing takes place in these processing units.

The input signals come from an input vector A = ($x^{[1]}$, $x^{[2]}$, ..., $x^{[n]}$) where $x^{[i]}$ is the activity level of the i^{th} input. A series of weight vectors W_j = (w_{1j}, w_{2j}, ..., w_{nj}) is associated with the input vector so that the weight w_{ij} represents the strength of the connection between the input $x^{[i]}$ and the processing unit b_j. Each node may additionally have also a *bias input* θ_j modulated with the weight w_{0j} associated with the inputs. The total input of the node b_j is formally the dot product between the input vector A and the weight vector W_j, minus the weighted input bias. It is then passed through a nonlinear transfer function to produce the output value of the processing unit b_j:

$$b_j = f\left(\sum_{i=1}^{n} x^{[i]} w_{ij} - w_{0j} \; q_j \right) = f(X_j) \tag{5}$$

In this paper, we have used the sigmoid function as activation function [6]:

$$f(X_j) = \frac{1}{1 + e^{-X_j}} \tag{6}$$

Figure 5.1 allows one to visualise a single ouput NNR model with one hidden layer and two hidden nodes, i.e. a model similar to those we developed for the GBP/USD and the USD/JPY volatility forecasts. The NNR model inputs at time *t* are $x_t^{[i]}$ (*i* = 1, 2, …, 5). The hidden nodes outputs at time *t* are $h_t^{[j]}$ (*j* = 1, 2) and the NNR model output at at time *t* is $\tilde{y}_t$, whereas the actual output is y_t.

[5] In this paper, we use exclusively the multilayer perceptron, a multilayer feedforward network trained by error backpropagation.

[6] Other alternatives include the hyperbolic tangent, the bilogistic sigmoid, etc. A linear activation function is also a possibility, in which case the NNR model will be linear. Note that our choice of a sigmoid implies variations in the interval]0, +1[. Input data are thus normalised in the same range in order to present the learning algorithm with compatible values and avoid saturation problems.

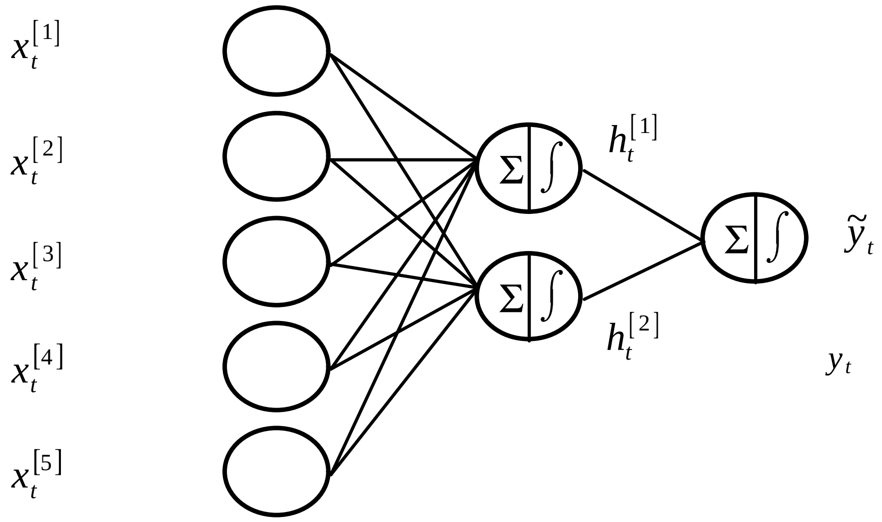


FIGURE 5.1: SINGLE OUTPUT NNR MODEL

At the beginning, the modelling process is initialised with random values for the weights. The output value of the processing unit b_j is then passed on to the single output node of the output layer. The NNR error, i.e. the difference between the NNR forecast and the actual value, is analysed through the *root mean squared error*. The latter is systematically minimised by adjusting the weights according to the level of its derivative with respect to these weights. The adjustment obviously takes place in the direction that reduces the error. As can be expected, NNR models with 2 hidden layers are more complex. In general, they are better suited for discontinuous functions; they tend to have better generalisation capabilities but are also much harder to train. In summary, NNR model results depend crucially on the choice of the number of hidden layers, the number of nodes and the type of nonlinear transfer function retained.

In fact, the use of NNR models further enlarges the forecaster's toolbox of available techniques by adding models where no specific functional form is *a priori* assumed[7].

Following Cybenko (1989) and Hornik *et al.* (1989), it can be demonstrated that specific NNR models, if their hidden layer is sufficiently large, can approximate any continuous function[8]. Furthermore, it can be shown that NNR models are equivalent to *nonlinear nonparametric models*, i.e. models where no decisive assumption about the generating process must be made in advance (see Cheng and Titterington (1994)).

Kouam *et al.* (1992) have shown that most forecasting models (ARMA models, bilinear models, autoregressive models with thresholds, non-parametric models with kernel regression, etc.) are embedded in NNR

[7] Strictly speaking, the use of a NNR model implies assuming a functional form, namely that of the *transfer function*.

[8] This very feature also explains why it is so difficult to use NNR models, as one may in fact end up fitting the noise in the data rather than the underlying statistical process.

models. They show that each modelling procedure can in fact be written in the form of a network of neurons.

Theoretically, the advantage of NNR models over other forecasting methods can therefore be summarised as follows: as, in practice, the ‘best’ model for a given problem cannot be determined, it is best to resort to a modelling strategy which is a generalisation of a large number of models, rather than to impose *a priori* a given model specification.

This has triggered an ever increasing interest for applications to financial markets (see, amongst others, Trippi and Turban (1993), Deboeck (1994), Rehkugler and Zimmermann (1994), Refenes (1995) and Dunis (1996, 2001b)).

5.2 – The NNR Models Developed

In practice, as explained above (see footnote 5), all variables were normalised according to our choice of the sigmoid activation function.

Starting from a traditional linear correlation analysis and using the ‘windowing’ technique suggested by Refenes (1993)[9], variable selection was achieved via a backward stepwise neural regression procedure: starting with lagged historical values of the dependent variable and of all other potential input variables, we progressively reduced the number of inputs, keeping the network architecture constant. If omitting a variable did not deteriorate the level of explained variance over the previous ‘best’ model, the pool of explanatory variables was updated by getting rid of this input. If there was a failure to improve over the previous ‘best’ model after several attempts, variables in that model were alternated to check whether no better parcimonious solution could be achieved. The model chosen finally was then kept for further tests and improvements.

Finally, conforming with standard heuristics, we partitioned our total data set into three subsets, using roughly 2/3 of the data for training the model, 1/6 for testing and the remaining 1/6 for validation. This partition in training, test and validation sets is made in order to control the error and reduce the risk of overfitting. Both the training and the following test period are used in the model tuning process: the training set is used to develop the model; the test set measures how well the model interpolates over the training set and makes it possible to check during the adjustment whether the model remains valid for the future. As the fine tuned system is not independent from the test set, the use of a third validation set which was not involved in the model's tuning is necessary. The validation set is thus used to estimate the actual performance of the model in a deployed environment.

[9] The basic idea behind ‘windowing’ is to identify empirical regularities within a data set contaminated by noise and to find recurrent relationships between time series over different time windows: in our two applications, we used windows of 1 year for the monthly series and of 20 trading days for the daily time series.

The topology of a typical NNR model developed for our first application on cash flows and cheque values data is given in table 5.1 below. The out-of-sample statistical performance of these models is further analysed in section 6.3 below.

Table 5.1 – *NNR Model Specification for Customer 2 Cheque Values*

Layers	Number of Elements	Transfer Function
Input	19	Identity
Hidden	2	Sigmoid
Output	1	Linear

No	Explanatory Series	Lags
1	*1st Difference of Customer 2 Cheque Values*	*1*
2	*1st Difference of Customer 2 Cheque Values*	*12*
3	*1st Difference of Customer 3 Cash Flows*	*12*
4	*1st Difference of Customer 3 Cheque Values*	*12*
5	*1st Difference of Non-Food Retail Cash Flows*	*12*
6	*1st Difference of Non-Food Retail Cheque Values*	*12*
7	*1st Difference of Customer 4 Cash Flows*	*1*
8	*Month of the Year*	*0*
9	*Month of the Year*	*0*
10	*Month of the Year*	*0*
11	*Month of the Year*	*0*
12	*Month of the Year*	*0*
13	*Month of the Year*	*0*
14	*Month of the Year*	*0*
15	*Month of the Year*	*0*
16	*Month of the Year*	*0*
17	*Month of the Year*	*0*
18	*Month of the Year*	*0*
19	*Month of the Year*	*0*

In the same vein, table 5.2 shows the specification of a typical NNR model developed for our second application on stock market trading models, in this case the specification of the NNR model on the FTSE100 returns. Here again, the out-of-sample trading performance of these models is further documented in section 6.3 below.

Table 5.2 – *NNR Model Specification for FTSE100 Returns*

Layers	Number of Elements	Transfer Function
Input	23	Identity
Hidden	2	Sigmoid
Output	1	Linear

No	Explanatory Variables*	Lags
1	*Bridge/CRB Commodity Futures Index*	*19*
2	*DJ EUROSTOXX50 price index*	*1*
3	*DJ EUROSTOXX50 price index*	*2*
4	*DJ EUROSTOXX50 price index*	*3*
5	*DJ EUROSTOXX50 price index*	*4*
6	*DJ EUROSTOXX50 price index*	*5*

7	*FTSE 100 price index*	*3*
8	*FTSE 100 price index*	*4*
9	*FTSE 100 price index*	*5*
10	*FTSE 100 price index*	*6*
11	*FTSE 100 price index*	*7*
12	*Gold Bullion*	*8*
13	*EUR/USD exchange rate*	*3*
14	*EUR/USD exchange rate*	*4*
15	*EUR/USD exchange rate*	*5*
16	*NIKKEI 225 price index*	*1*
17	*S&P 500 price index*	*1*
18	*GBP Benchmark Bond 10 years*	*15*
19	*GBP 3 month middle rate*	*5*
20	*USD Benchmark Bond 10 years*	*11*
21	*GBP/USD exchange rate*	*4*
22	*GBP/USD exchange rate*	*5*
23	*GBP/USD exchange rate*	*6*

Note: * All variables except interest rates are in return form.

5.3 – The NNR Models Results Assessment

The assessment of the NNR models in terms of their capability to accurately forecast the cash flows and cheque values of selected bank customers is reasonably straightforward[10]: using standard statistical measures of forecasting accuracy, we just compare the NNR-based forecasts with those produced by the benchmark ARIMA models.

Concerning our application of NNR models to the S&P500, FTSE100, EUROSTOXX50 and NIKKEI225 stock indices, we use the forecast values obtained for the stock market returns ($\hat{R}_t$) to construct trading models and use them in a simulated trading exercise.

The expectation is that, at time *t*, the NNR-based trading models provide a correct forecast for the directional change of R_t at time *t+1*. According to that forecast, we can hopefully react appropriately at time *t*, buying the stock market if $\hat{R}_{t+1} > 0$ and selling it if $\hat{R}_{t+1} < 0$.

The series of returns ($\hat{R}_t$) of the NNR-based trading models are computed according to the accuracy of the signal produced. If the signal at time *t* correctly predicted the price movement at time *t+1*, i.e. $sign\,(\hat{R}_{t+1}) = sign\,(R_{t+1})$, then $\hat{R}_{t+1} = |R_{t+1}|$, otherwise $\hat{R}_{t+1} = -|R_{t+1}|$.

6. FORECASTING ACCURACY AND TRADING RESULTS

6.1 – Out-of- Sample Forecasting Accuracy

[10] For the exogenous variables, only the information available up to time *t* was used in the forecasting procedure of the NNR models.

As is standard in the economic literature, we compute the Mean Absolute Error (MAE), the Mean Absolute Percentage Error (MAPE), the Root Mean Squared Error (RMSE) and Theil U-statistic (Theil-U). These measures have already been presented in details by, amongst others, Makridakis *et al.* (1983), Pindyck and Rubinfeld (1998) and Theil (1966).

Calling y_t the actual data and $\tilde{y}_t$ the forecast data at time *t*, with a forecast period going from *t* = 1 to *t* = T, the forecast error statistics we analyse are given in table 6.1 below.

Table 6.1 – *Statistical Performance Measures*

Performance Measure	Description
Mean Absolute Error (MAE)	$MAE = \frac{1}{T}\sum_{t=1}^{T}\lvert\tilde{y}_t - y_t\rvert$
Mean Absolute Percentage Error (MAPE)	$MAPE = \frac{100}{T}\sum_{t=1}^{T}\left\lvert\frac{\tilde{y}_t - y_t}{y_t}\right\rvert$
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\tilde{y}_t - y_t)^2}$
Theil's Inequality Coefficient (Theil's U)	$U = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\tilde{y}_t - y_t)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\tilde{y}_t)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t)^2}}$

The MAE and the RMSE statistics are scale-dependent measures but give us a basis to compare our forecasts with the realised figures. As for the MAPE, the Theil-U statistics is independent of the scale of the variables; it is also constructed in such a way that it necessarily lies between zero and one, with zero indicating a perfect fit.

For all these four error statistics retained the lower the output, the better the forecasting accuracy of the model concerned.

6.2 – Out-of-Sample Trading Models Performance Metrics

As mentioned earlier, traditional performance metrics such as root mean squared error (RMSE) or, more generally, standard statistical measures of forecasting accuracy are often inappropriate to assess financial performance. Also, in some cases, different trading strategies cannot be compared with these standard measures for the simple reason that they are not based on forecasting the same output: in such cases, the evaluation of the results requires more appropriate financial cost functions, such as risk-adjusted return measures.

We present the different performance measures used to compare the different trading strategies retained in table 6.2 below. These are standard performance measures used in the fund management industry and more details can be found in Gehm (1983), Vince (1990) and Kaufman (1998).

Table 6.2 – *Trading Performance Measures*

Performance Measure	**Description**
Annualised Return	$R^A = 252 \times \frac{1}{N} \sum_{t=1}^{N} R_t$
Annualised Cumulative Return	$R^C = \sum_{t=1}^{N} \hat{R}_T$
Annualised Volatility	$s^A = \sqrt{252} \times \sqrt{\frac{1}{N-1} \times \sum_{t=1}^{N} (R_t - \overline{R})^2}$
Sharpe Ratio	$SR = \frac{R^A}{s^A}$
Maximum Daily Profit *Maximum Daily Loss*	*Maximum Value of* R_t *over the period* *Minimum Value of* R_t *over the period*
*Maximum Drawdown**	*Maximum Negative Value of* $S(\hat{R}_T)$ *over the period* $MD = \underset{i=1,\dots,t;\ t=1,\dots,N}{Min} (\sum_{j=i}^{t} X_j)$
Winning Trades (%)	*WT=100*(Number of* R_t *>0)/Total Number of Trades*
Losing Trades (%)	*LT=100*(Number of* R_t *<0)/Total Number of Trades*
Number of Up-Periods	*Nup=Number of* R_t *>0*
Number of Down-Periods	*Ndown=Number of* R_t *<0*
Total Trading Days	*Number of all* R_t *s*
Average Gain in Up-Periods	*AG=(Sum of all* R_t *>0)/ Nup*
Average Loss in Down-Periods	*AL=(Sum of all* R_t *<0)/Ndown*
Average Gain/Loss Ratio	*GL=AG/AL*
*Probability of 10% Loss***	$PoL = \left[\frac{(1-P)}{P}\right]^{\left(\frac{MaxRisk}{A}\right)}$ *with P=* $0.5 \times \left(1 + \left(\frac{\langle (WT \times AG) + (LT \times AL) \rangle}{\sqrt{[(WT \times AG^2) + (LT \times AL^2)]}}\right)\right)$, *MaxRisk is the risk level defined by the user, in our case 10%*
Profit T-Statistics	*T-statistics* $= \sqrt{N} \times \frac{R^A}{s^A}$

Notes: * This measure was preferred to alternative measures of downside risk, such as that proposed by Fishburn (1977), as it is the most commonly used downside risk measure in the fund management community; we also present the measure proposed by Gehm (1983);
** For a more detailed presentation, see Gehm (1983) and Kaufman (1998).

6.3 – Out-of-Sample Empirical Results

6.3.1 – The Cash Flows and Cheque Values Application

Appendix 2 offers a visual comparison of the NNR models forecast with the ARIMA benchmark forecast, the bank forecast and the actual first difference of the series. One can see that, more often than not, the NNR models forecasts follow the actual first-differenced series more closely than the other benchmark forecasts and do not suffer from the inertia which often affects the performance of the benchmarks.

Table 6.3 below compares, for each customer's cash flows and cheque values over the out-of-sample period, the NNR models forecasts with the two benchmark forecasts in terms of the statistical accuracy measures retained.

Table 6.3 – *Forecasting Accuracy Measures*

	RMSE			MAE		
	ANN	ARIMA	Bank Forecast	ANN	ARIMA	Bank Forecast
Customer 1 Cash Flows	14.89	17.82	16.90	12.16	15.79	12.36
Customer 1 Cheque Values	16.46	16.41	34.34	13.99	14.45	31.10
Customer 2 Cash Flows	2.96	2.76	14.65	2.50	2.20	12.40
Customer 2 Cheque Values	0.08	0.07	0.22	0.06	0.06	0.18
Customer 3 Cash Flows	8.34	12.37	11.56	6.17	9.91	10.43
Customer 3 Cheque Values	0.95	1.40	1.23	0.75	1.02	0.86
Customer 4 Cash Flows	13.87	17.54	21.69	12.44	15.84	17.36
Customer 4 Cheque Values	3.13	3.91	6.64	2.17	2.78	5.77

	MAPE			Theil's Inequality Coefficient		
	ANN	ARIMA	Bank Forecast	ANN	ARIMA	Bank Forecast
Customer 1 Cash Flows	0.10	0.13	0.11	0.06	0.07	0.06
Customer 1 Cheque Values	0.12	0.12	0.23	0.06	0.06	0.15
Customer 2 Cash Flows	0.10	0.09	0.54	0.06	0.05	0.28
Customer 2 Cheque Values	0.15	0.12	0.50	0.08	0.07	0.19
Customer 3 Cash Flows	0.08	0.10	0.12	0.04	0.06	0.06
Customer 3 Cheque Values	0.09	0.12	0.10	0.06	0.08	0.07
Customer 4 Cash Flows	0.04	0.05	0.06	0.02	0.03	0.04
Customer 4 Cheque Values	0.09	0.11	0.24	0.06	0.07	0.12

These results are most interesting: they show that, for the 32 statistical performance measures per model that we have[11], NNR models come first in terms of predictive accuracy in 24 cases or 75% of the time. Moreover, in the remaining 8 cases, they come as a very close second best.

6.3.2 – The Stock Market Trading Simulation Results

Let us first note that, as the 'buy and hold' strategy and the strategy based on a basket of moving averages (BMA) are not based on forecasting the next day's market return, a statistical accuracy comparison with the NNR models forecasts was irrelevant.

[11] That is: 2 series per customer times 4 customers times 4 statistical performance measures.

Tables 6.4 to 6.7 below therefore document the relative trading performance of our NNR trading models for the S&P500, FTSE100, EUROSTOXX50 and NIKKEI225 stock indices compared with that of our three benchmark strategies: the 'buy and hold', the naïve adaptive expectations and the BMA strategies.

Table 6.4 – *S&P500 Trading Performance Measures*

	Buy&Hold	Naïve Strategy	BMA	NNR Model
Annualised Return	10.75%	14.97%	-19.52%	60.15%
Cumulative Return	12.11%	16.87%	-21.92%	67.79%
Annualised Volatility	20.72%	20.71%	20.70%	20.38%
Sharpe Ratio	0.52	0.72	-0.94	2.95
Maximum Daily Profit	4.76%	5.83%	5.83%	5.83%
Maximum Daily Loss	-5.83%	-3.33%	-3.83%	-4.76%
Maximum Drawdown	-12.42%	-12.29%	-25.29%	-11.90%
% Winning trades	49.30%	47.89%	44.52%	57.75%
% Losing trades	50.70%	52.11%	55.48%	42.25%
Number of Up Periods	140	136	126	164
Number of Down Periods	136	140	149	112
Total Trading Days	284	284	283	284
Avg Gain in Up Periods	1.03%	1.08%	1.01%	1.05%
Avg Loss in Down Periods	-0.97%	-0.93%	-1.00%	-0.93%
Avg Gain/Loss Ratio	1.06	1.16	1.01	1.13
Probability of 10% Loss	73.76%	51.56%	100.00%	1.36%
Profits T-statistics	8.74	12.18	-15.89	49.74

Table 6.5 – *FTSE100 Trading Performance Measures*

	Buy&Hold	Naïve Strategy	BMA	NNR Model
Annualised Return	2.05%	-58.46%	1.94%	77.90%
Cumulative Return	2.31%	-65.89%	2.18%	87.80%
Annualised Volatility	19.36%	61.50%	4.87%	18.73%
Sharpe Ratio	0.11	-0.77	0.40	4.16
Maximum Daily Profit	2.73%	0.76%	0.76%	3.81%
Maximum Daily Loss	-3.81%	-0.82%	-0.82%	-2.85%
Maximum Drawdown	-13.97%	-7.14%	-3.95%	-5.63%
% Winning trades	50.00%	48.24%	48.41%	57.39%
% Losing trades	50.00%	51.76%	51.59%	42.61%
Number of Up Periods	142	137	137	163
Number of Down Periods	132	147	146	111
Total Trading Days	284	284	283	284
Avg Gain in Up Periods	0.97%	0.25%	0.27%	1.11%
Avg Loss in Down Periods	-1.03%	-0.69%	-0.23%	-0.83%
Avg Gain/Loss Ratio	0.95	0.37	1.13	1.33
Probability of 10% Loss	100.00%	100.00%	8.44%	0.32%
Profits T-statistics	1.79	-12.95	6.73	69.99

Table 6.6 – *EUROSTOXX50 Trading Performance Measures*

	Buy&Hold	Naïve Strategy	BMA	NNR Model
Annualised Return	33.69%	-60.18%	22.84%	123.67%
Cumulative Return	37.97%	-67.82%	25.64%	139.38%
Annualised Volatility	21.25%	76.78%	7.50%	19.87%
Sharpe Ratio	1.59	-0.78	3.05	6.22
Maximum Daily Profit	3.28%	1.16%	1.16%	3.95%
Maximum Daily Loss	-3.95%	-1.16%	-1.12%	-2.94%
Maximum Drawdown	-12.13%	-6.52%	-7.50%	-10.99%
% Winning trades	55.99%	54.23%	57.95%	65.14%
% Losing trades	44.01%	45.77%	42.05%	34.86%
Number of Up Periods	159	154	164	185
Number of Down Periods	120	130	119	94
Total Trading Days	284	284	283	284
Avg Gain in Up Periods	1.05%	0.40%	0.41%	1.18%
Avg Loss in Down Periods	-1.08%	-0.99%	-0.35%	-0.84%
Avg Gain/Loss Ratio	0.98	0.40	1.17	1.41
Probability of 10% Loss	13.08%	100.00%	1.92%	0.01%
Profits T-statistics	26.73	-13.19	51.33	104.69

Table 6.7 – *NIKKEI225 Trading Performance Measures*

	Buy&Hold	Naïve Strategy	BMA	NNR Model
Annualised Return	4.72%	-18.62%	-8.61%	104.16%
Cumulative Return	5.32%	-20.99%	-9.67%	117.39%
Annualised Volatility	20.46%	20.43%	20.49%	19.38%
Sharpe Ratio	0.23	-0.91	-0.42	5.38
Maximum Daily Profit	3.61%	6.98%	6.98%	6.98%
Maximum Daily Loss	-6.98%	-3.61%	-3.61%	-3.73%
Maximum Drawdown	-25.66%	-39.04%	-36.99%	-5.73%
% Winning trades	48.24%	43.31%	46.64%	61.62%
% Losing trades	51.76%	56.69%	53.36%	38.38%
Number of Up Periods	137	123	132	175
Number of Down Periods	131	145	136	93
Total Trading Days	284	284	283	284
Avg Gain in Up Periods	0.98%	0.99%	0.96%	1.09%
Avg Loss in Down Periods	-0.99%	-0.98%	-1.01%	-0.79%
Avg Gain/Loss Ratio	1.00	1.01	0.96	1.38
Probability of 10% Loss	100.00%	100.00%	100.00%	0.03%
Profits T-statistics	3.89	-15.34	-7.08	90.43

The results of the NNR trading models are quite impressive. Over the out-of-sample period from 5 May 1999 through 6 June 2000, they significantly outperform the benchmark strategies for each stock market index, not only in terms of overall profitability, with an annualised return ranging from 60.1% for the S&P500 to 123.7% for the EUROSTOXX50, but also in terms of risk-adjusted performance, as evidenced by the high Sharpe ratios achieved by these models (respectively 2.95 for the S&P500 and 6.22 for the EUROSTOXX50). Furthermore, the downside risk measures retained in our performance metrics, i.e. the maximum drawdown and the probability of a 10% loss, are much lower for the NNR trading models than for the other three trading strategies.

Admittedly, as noted by Dunis *et al.* (2001a), today most researchers would agree that individual forecasting models are misspecified in some dimensions and that the identity of the 'best' model changes over time. In this situation, it is likely that a combination of forecasts will perform better over time than forecasts generated by any individual model that is kept constant. But this important issue is beyond the scope of this paper.

In summary, with the limitation just mentioned and even if we do not take transaction costs into account when computing the trading performance measures[12], the results of the NNR trading models are highly significant and clearly superior to those achieved by the three benchmark strategies. Another conclusion from our results is that, for the period and stock indices considered, the markets concerned were inefficient as it was possible to extract excess returns from them.

7. CONCLUDING REMARKS

In this paper, we examined the use of Neural Network Regression (NNR) and alternative forecasting techniques in financial *forecasting* models and financial *trading* models. Our motivation was to check whether NNR models add value in both types of applications analysed, by benchmarking their results against those achieved with simpler and more conventional modelling techniques.

The first application implied developing alternative *forecasting models* of cash flows and cheque values of four major bank customers using monthly data from April 1993 through June 1999. These models were subsequently tested *out-of-sample* over the period July 1999-April 2000 in terms of *forecasting accuracy* and this exercise demonstrated a resounding superiority for the NNR models.

The second series of applications implied developing financial *trading models* for four major stock market indices (S&P500, FTSE100, EUROSTOXX50 and NIKKEI225) using daily data from 31 January 1994 through 4 May 1999 for in-sample estimation and leaving the period 5 May 1999 through 6 June 2000 for out-of-sample testing. In this case, the trading models developed were assessed not only in terms of *forecasting accuracy*, but also in terms of *trading efficiency* via the use of a simulated trading strategy. Again the NNR models demonstrated an overall superiority over the three benchmark strategies, not only in terms of maximising returns but also in terms of risk-adjusted profitability and in terms of minimising downside risk.

[12] These costs are quite moderate when trading a stock index on a futures market, in the order of 0.10 to 0.15 % for a roundtrip transaction (see Brooks *et al.* (2001)); they would therefore be dwarfed by the magnitude of the returns involved.

In the end, for the periods and time series concerned, the results of both applications clearly show that NNR models do indeed add value in the forecasting process. As such, it seems that NNR models can indeed offer a potentially rewarding alternative approach to more traditional modelling techniques. We strongly believe that nowadays these models should be part of any forecaster's toolbox and that a benchmarking exercise, as those carried out in this paper, should be the ultimate decision criterion on whether to apply them to a given problem or not.

APPENDIX 1

TABLE A1.1: SELECTION OF PARAMETERS FOR BENCHMARK ARIMA MODELS
(CUSTOMER 4)

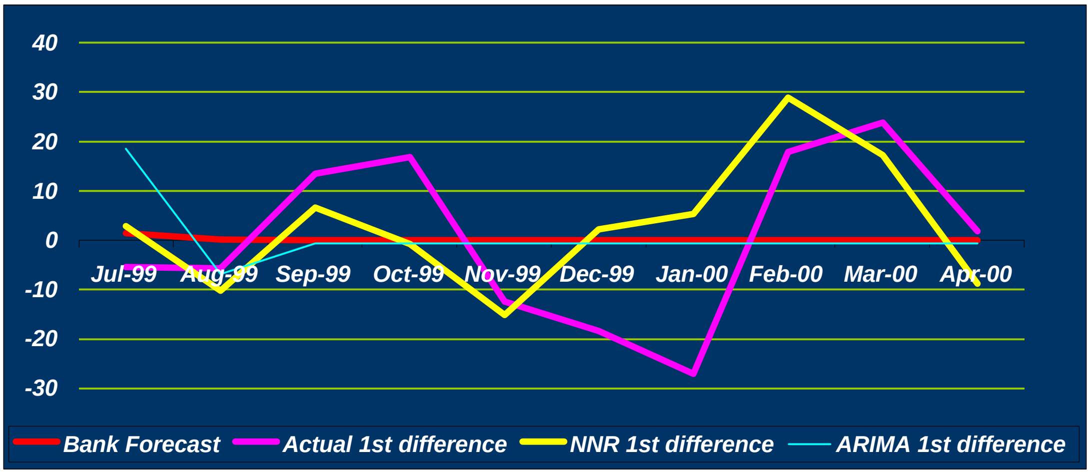
Customer 4 Cheque Values								
Shwarz-Bayesian Criterion					Akaike Information Criterion			
p/q	**0**	**1**	**2**		p/q	**0**	**1**	**2**
0	-237.1	***-236.4***	-238.6		**0**	-235.9	***-234.1***	-235.1
1	-236.6	-238.6	nc		**1**	-234.3	-235.1	nc
2	-238.5	-240.7	-242.8		**2**	-235.1	-236.1	237.1
Initial values for ARIMA								
	p,d,q	Value	*p,d,q*	Value	*p,d,q*	Value		
	0,1,0	0	**1,1,0**	0	**2,1,0**	0		
	0,1,1	-0.3	**1,1,1**	-0.3	**2,1,1**	-0.2		
	0,1,2	0	**1,1,2**	0	**2,1,2**	0		
Result		***ARIMA (0,1,1)***						

Customer 4 Cash Flows								
Shwarz-Bayesian Criterion					Akaike Information Criterion			
p/q	**0**	**1**	**2**		p/q	**0**	**1**	**2**
0	-366.2	***-365.2***	-367.4		**0**	-365.1	***-362.9***	-363.9
1	-365.6	-367.4	-369.5		**1**	-363.3	-363.9	-364.9
2	-367.2	-369.4	nc		**2**	-363.8	-364.8	nc
Initial values for ARIMA								
	p,d,q	Value	*p,d,q*	Value	*p,d,q*	Value		
	0,1,0	0	**1,1,0**	0	**2,1,0**	0		
	0,1,1	-0.4	**1,1,1**	-0.3	**2,1,1**	0.2		
	0,1,2	0	**1,1,2**	0	**2,1,2**	0		
Result		***ARIMA (0,1,1)***						

APPENDIX 2

TABLE A2.1: FORECASTS OF CUSTOMER 1 CASH FLOWS
AND CHEQUE VALUES

**Comparison of 1st differences of
Customer 1 Cash Flows**



**Comparison of 1st differences of
Customer 1 Cheque Values**

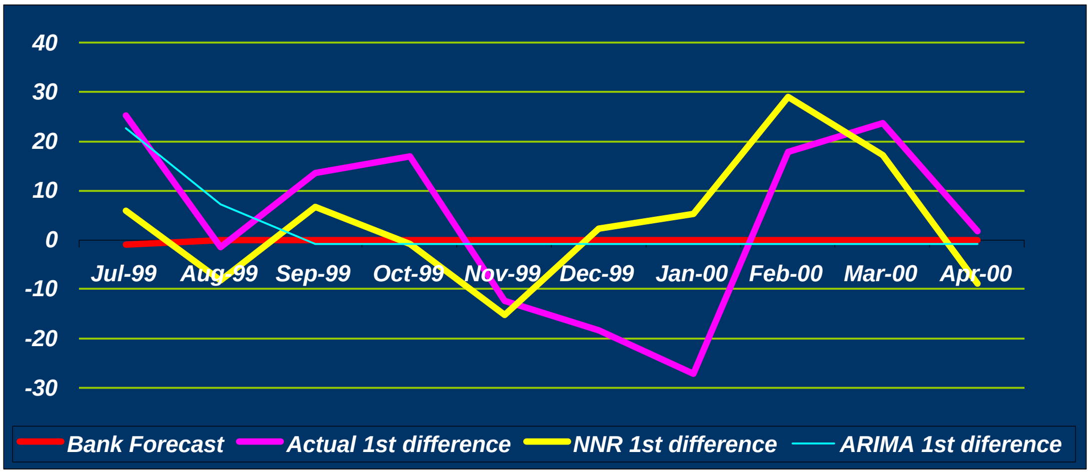
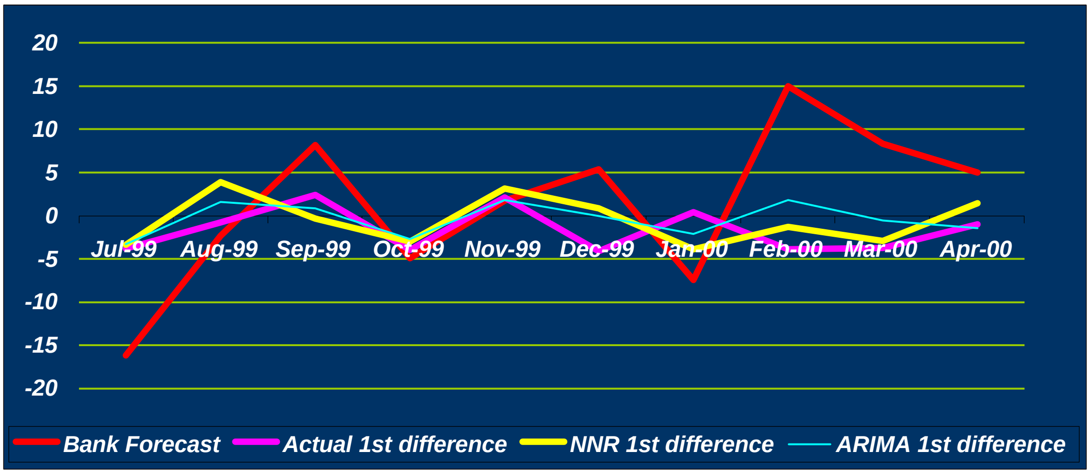


TABLE A2.2: FORECASTS OF CUSTOMER 2 CASH FLOWS AND CHEQUE VALUES

Comparison of 1st differences of Customer 2 Cash Flows



Comparison of 1st differences of Customer 2 Cheque Values

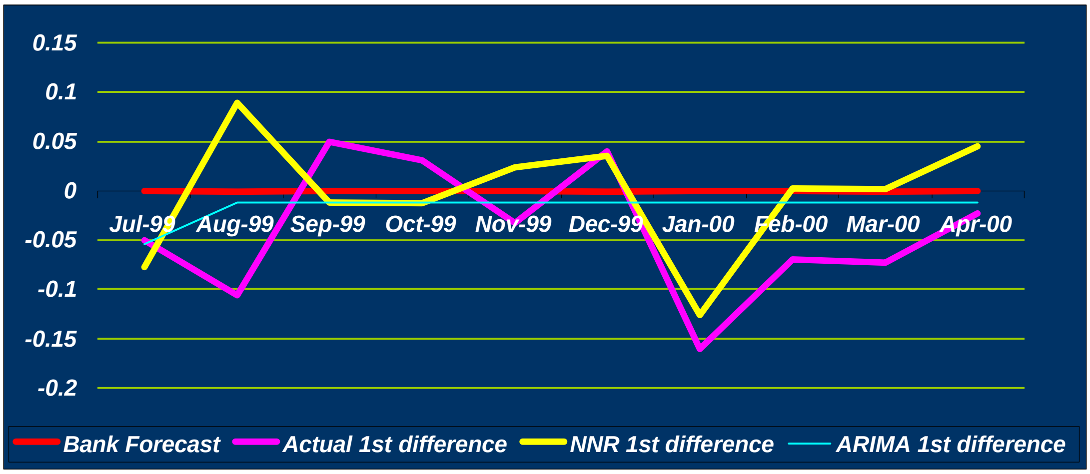
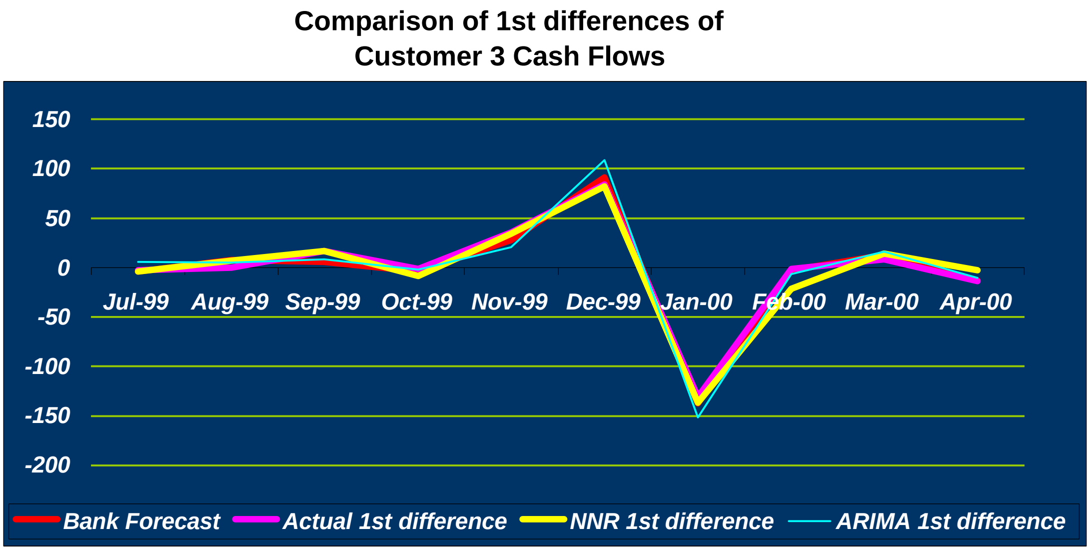


TABLE A2.3: FORECASTS OF CUSTOMER 3 CASH FLOWS
AND CHEQUE VALUES



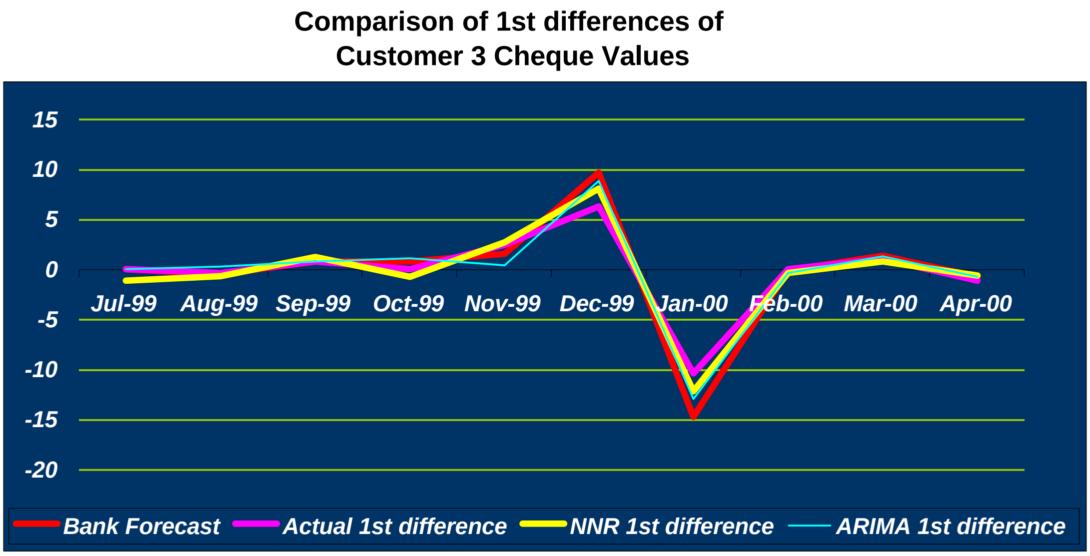
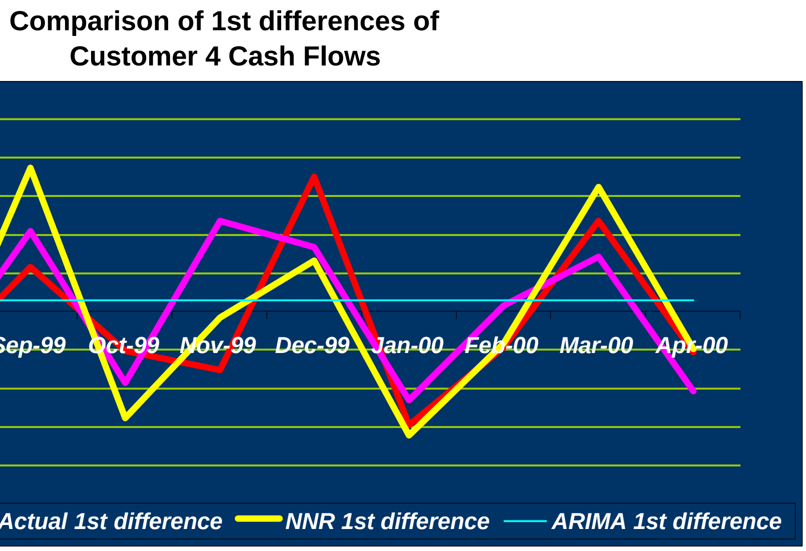
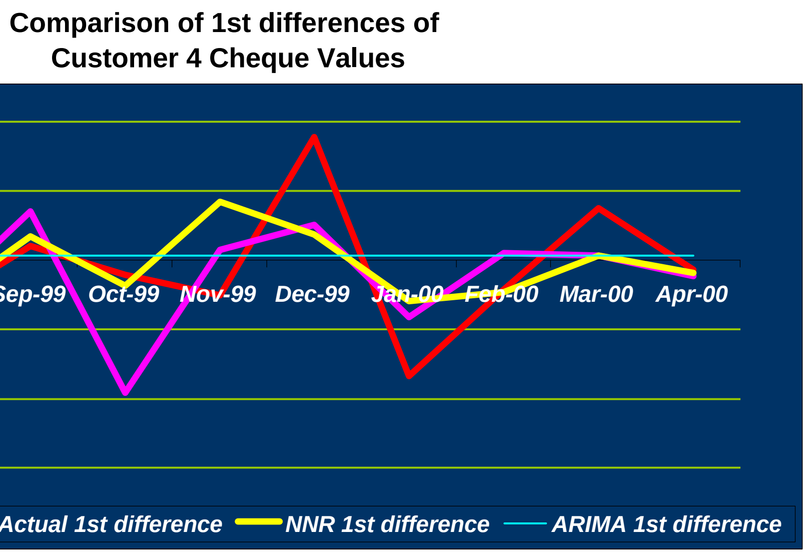


TABLE A2.4: FORECASTS OF CUSTOMER 4 CASH FLOWS
AND CHEQUE VALUES





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