1999 Third International Conference on Knowledge-Based Intelligent Information Engineeing Systems, 31st Aug-1st Sept 1999, Adelaide, Australia

A Neuro Fuzzy Time Series Prediction Application in Telephone Banking

A C La Pensee & N Mort

Department of Automatic Control & Systems Engineering
The University of Sheffield, Sheffield, UK

Introduction

The prediction of financial time series is big business and large financial institutions are keen to utilise any prediction method that may give them an advantage in the market place. In recent years researchers have investigated the nature of non-linear dependence in time series arising from the stock market. [1] contains a comprehensive analysis of typical patterns to be found in financial data. Also, modelling techniques originating within engineering disciplines, for example, neural networks, fuzzy logic and genetic algorithms, are increasingly being used in economics. Many examples of this are included in [2-4]. These are data driven models and so are well suited to financial applications as they require no *a priori* knowledge of the systems being predicted, and there is always a rapid flow of data readily available with which they can be trained.

In this paper , we consider the application of neuro-fuzzy prediction to an application in the financial sector but the object here is not to estimate financial indices such as exchange rates or stock market movements. Instead, we address the rather intriguing issue of the impact of television advertising on customer response for a telephone banking organisation.

The Telephone Banking Application

First Direct is a telephone banking company operating as part of the HSBC group. The prediction that First Direct was seeking was the impact of any one television advertisement on the number of telephone calls subsequently received. The data was supplied as two separate sets. The first set contained the number of telephone calls received in each hour of the day between the dates of Tuesday 5th January 1999 and Wednesday 10th March 1999. This data set included both the number of calls received and the number of calls handled. From this information it is possible to develop an estimate of the number of new customers calling in each hour. It was necessary to distinguish between the number of new customers and the number of calls received. This is because it is assumed that a certain number of the customers not handled will call back (some in the present hour, and some in the next hour). The empirical relationship used by First Direct is based on the following. From all the calls not handled then 20% will call back in the next hour and 50% will call back in the same hour. The second set of data contained information involving the audience when the advertisement was broadcast with the following information:

- *Channel on which advert broadcast*
- *Date, day and time of transmission*
- *Duration of advert*
- *Programme name on which advert broadcast*
- *Size of Audience viewing advert*

Development of a Neuro-Fuzzy system in the FuzzyTECH Environment

FuzzyTECH™ is a software package that has been developed to develop fuzzy and neuro fuzzy systems with ease and convenience. A description of the operation of FuzzyTECH. Is contained in (Von Altrock [5]. Figure 1 shows the complete structure of the fuzzy system produced for this application including input interfaces, rule blocks and output interfaces. The connecting lines symbolize the data flow from left to right. It is not possible to describe in full the internal elements of the neuro-fuzzy predictor due to space limitations – a comprehensive description is contained in [6]. The neuro-fuzzy structure adopted extends the traditional fuzzy rule base concept by incorporating a neural network architecture which can be trained using historical data. This augments the rule base

0-7803-5578-4/99/$10.00©1999 IEEE

by attaching a weighting to each rule. In this study, the weighting is determined using the well-known back-propagation training algorithm.
Some insight into the problem can be obtained by noting the linguistic variables used – these are listed in Table 1 below:

Variable	Definition	Poss. Values
Day_no	Day advert broadcast	Mon., Tues., etc
Impact	# of viewers	Low, Med., High
Prog_no	Type of Programme	Game,Docum. News, Movie, etc
Region	Broadcast Area	Nat., Lond. N, S, Mid
Station	Channel	A,B,C,D
Time	Time	am, pm, even.
Peak	Impact	+, -, 0
Audience	Type	Types 1,2,3
Content	Type	Types 1,2,3

Table 1 Linguistic Variables used

Results

The system represented in Figure 1 was developed to be able to predict peaks and troughs in the number of calls received. For this reason it was necessary to develop a base value from which the peak or trough could be predicted. This was achieved by taking an average of the number of new callers for each hour of each day which formed a basis from which predictions were made. The system developed for First Direct gave a best prediction accuracy of around 75%-80%. This figure was obtained after trials using different sizes of training and testing set data. In selecting the size of data sets, it was considered important to ensure that there is enough data in the training set to give a good spread of possible inputs to the system. At the same time it was necessary to ensure that there is sufficient data in the validation data set to give a representative set against which the system can be tested. Figure 2 and Table 2, show that a training set of around 74% gives the lowest percentage error.

Training data set size	**25%**	**44%**	**63%**	**74%**
Average incorrect predictions	42.4%	32.7%	33.2%	27.3%

Table 2 – Average incorrect prediction for each training set size

In Figure 3, we see an example of the neuro-fuzzy prediction applied to a real data set. The average number of call taken in a time period is shown as a dotted line. The aim of the predictor is to identify deviations from this effective base line. When the deviation from the average is greater than 25 calls, either greater than (peak) or less than (trough), this is predicted by the solid line . Also shown in heavy dotted with a small triangle at interval are the actual callers during the period. It can be seen that the predictor has a high success rate in following the peaks/troughs in actual calls. It must be understood that the function of the predictor is to estimate whether a peak/trough will occur - not the intensity of the deviation. This is seen as a much more difficult issue and will be the subject of future research.

Conclusions

This paper has briefly described a successful venture into an application area in which fuzzy logic and neural networks have rarely been applied.. There is potential for improving the present system, but only with access to further concentrated expert knowledge and further, related industrial data. There are many other time series to which predictive models can be applied: from weather patterns to the flow of mail through a sorting office. The success gained in this work is an incentive to explore other interesting applications.

References

[1] Hsieh, D A "Chaos and non-linear dynamics: Applications to financial markets," *Journal of Finance,* Vol. 44, pp 1839-1877. 1991.
[2] Deboeck, G (Ed.) "Trading on the edge: Neural, genetic, and fuzzy systems for chaotic financial markets," John Wiley & Sons, Inc. 1994.
[3] Refenes, A P (Ed.) "Neural networks in the capital markets," John Wiley & Sons, Inc. 1995.
[4] Robinson, C and Mort N "Evolutionary heirarchical model for predicting values from real world time series" in Applications of Soft Computing, Bruno Bosacchi, James C Bezdek and

David B Fogel, Editors, Proceedings of SPIE, Vol 3165, pp135-143, 1997

[5] Von Altrock, C Fuzzy Logic & NeuroFuzzy Applications in Business and Finance, Prentice-Hall, 1997

[6] La Pensee, A C A Neuro-Fuzzy approach to Time Series Prediction, Dissertation, Department of Automatic Control & Systems Engineering, University of Sheffield, 1999

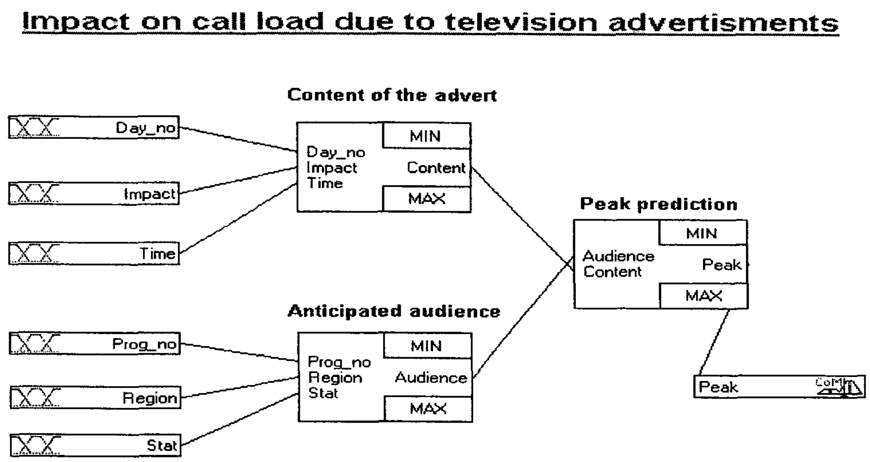

Figure 1 – Structure of the Fuzzy Logic System

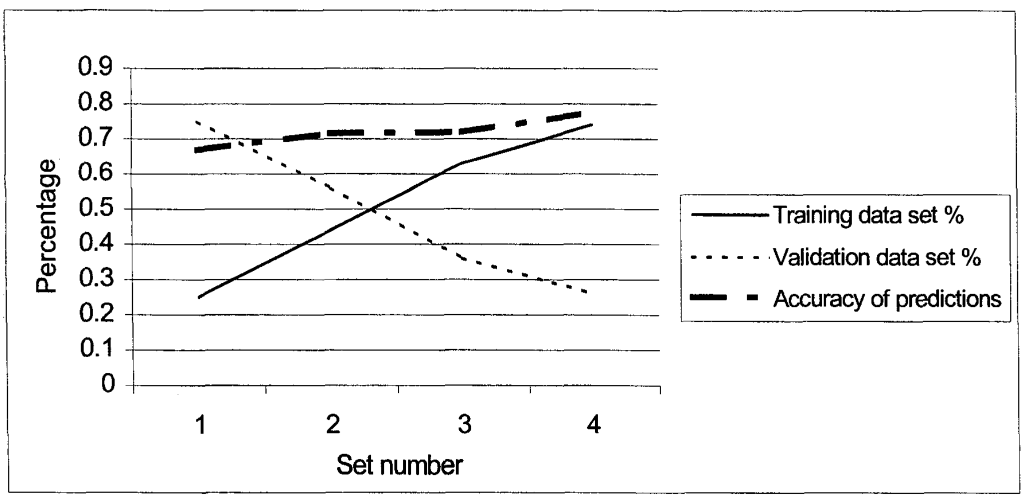

Figure 2 – Variation of prediction accuracy with training and validation data set size

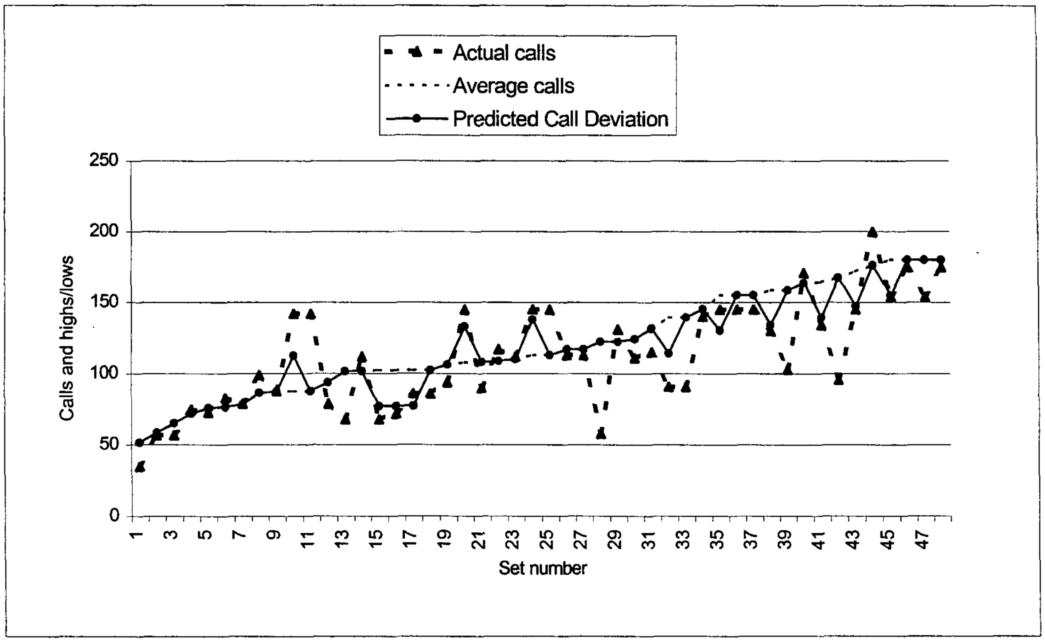

Figure 3 Example of Neuro-fuzzy prediction of telephone responses