USING ARTIFICIAL NEURAL NETWORKS TO FORECAST 
CHANGES IN NATIONAL AND REGIONAL PRICE INDICES FOR 
THE UK RESIDENTIAL PROPERTY MARKET 

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Certificate of Research

This is to certify that, except where specific reference is made, the work described in this thesis is the result of the candidate’s research. Neither this thesis, nor any part of it, has been presented, or is currently submitted, in candidature for any degree at any other University.

Signed ..............................................................................
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Director of Studies

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ABSTRACT

Using Artificial Neural Networks to Forecast Changes in National and Regional Price Indices for the UK Residential Property Market

Stuart David Paris

The residential property market accounts for a substantial proportion of UK economic activity. However, there is no reliable forecasting service to predict the periodic housing market crises or to produce estimates of long-term sustainable value. This research examined the use of artificial neural networks, trained using national economic, social and residential property transaction time-series data, to forecast trends within the housing market.

Artificial neural networks have previously been applied successfully to produce estimates of the open market value of a property over a limited time period within sub-markets. They have also been applied to the prediction of time-series data in a number of fields, including finance. This research sought to extend their application to time-series of house prices in order to forecast changes in the residential property market at national and regional levels.

Neural networks were demonstrated to be successful in producing time-series forecasts of changes in the housing market, particularly when combined in simple committees of networks. They successfully modelled the direction, timing and scale of annual changes in house prices, both for an extremely volatile and difficult period (1987 to 1991) and for the period 1999 to 2001. Poor initial forecasting results for the period 2002 onwards were linked to new conditions in the credit and housing markets, including changes in the loan to income ratio. Self-organising maps were used to identify the onset of new market conditions. Neural networks trained with a subset of post-1998 data added to the training set improved their forecasting performance, suggesting that they were able to incorporate the new conditions into the models.

Sensitivity analysis was used to identify and rank the network input variables under different market conditions. The measure of changes in the house price index itself was found to have the greatest effect on future changes in prices. Prediction surfaces were used to investigate the relationship between pairs of input variables.

The results show that artificial neural networks, trained using national economic, social and residential property transaction time-series data, can be used to forecasts trends within the housing market under various market conditions.
Chapter 1 - INTRODUCTION

This chapter sets out the background to the residential property market and explains its importance.

1.1 Background

The residential property market accounts for a substantial proportion of UK economic activity, and is significant at both the macroeconomic and personal level.

At a personal level, houses are often the most important component of the net worth of their owners (Miles, 1994). In Sweden, for example, housing wealth as a fraction of household net wealth fluctuated between 50 and 75% during the post-war period (Englund and Ioannides, 1997). In the UK at the end of 1992 almost 40% of total household net wealth was in the form of net equity in owner-occupied residential property (Miles, 1994). The Office for National Statistics concluded that, of total assets of over £7,000 billion in 2004, nearly 55 per cent of the wealth of the household sector was held in the form of non-financial assets, primarily housing, and that “even when account is taken of the loans outstanding on the purchase of housing, this form of wealth has shown strong growth between 1991 and 2004” (Office for National Statistics, 2006).

At the macroeconomic (national economy) level, houses are important commodities and what happens in the property market is of significance. In the UK and USA, investment in residential property since the second World War typically accounted for between 3% and 4% of GDP (Miles, 1994). The total value of the UK owner-occupied housing stock was £1,450 billion in 2000 (Jenkins, 2000). This had risen to £3.4 trillion by the end of 2005 (Halifax, 2006) and £4.0 trillion by the end of 2007 (Halifax, 2008b). Major changes in the housing market can have a significant impact on the economy as a whole. The large fall in house prices in the UK between 1989 and 1992 (when real house prices fell by about 25%) was a period during
which the savings rate almost doubled (from just over 6% to around 12%), GDP stagnated and business confidence slumped (Miles, 1994). Many individuals were left in a situation of negative equity, when they had paid (and were usually still paying) more for their homes than they could realise by selling. This had social cost in increased repossessions and reduced labour mobility.

American house prices peaked in early 2006, followed by rapid decline and shocks to credit markets both in the US and Europe. Greenspan (2008) has stated that

“The current financial crisis in the US is likely to be judged in retrospect as the most wrenching since the end of the second world war. It will end eventually when home prices stabilise and with them the value of equity in homes supporting troubled mortgage securities.”

The UK cannot expect to be isolated from this crisis. Indeed, its effects are already apparent within the UK credit market. The International Monetary Fund (2008) has stated that

“The financial market crisis that erupted in August 2007 has developed into the largest financial shock since the Great Depression, inflicting heavy damage on markets and institutions at the core of the financial system. The turmoil was initiated by rapidly rising defaults on subprime mortgages in the context of a major U.S. housing correction...”

This will clearly have an effect on UK house prices. The housing market within the UK has experienced a prolonged period of growth since the fall of 1989 to 1992. However, this now seems set to change. Two major UK mortgage lenders, the Nationwide (2008) and the Halifax (2008a), have both reported year-on-year growth in house prices of only 1.1% for March 2008, whilst the International Monetary Fund (2008) has suggested that

“Countries that look particularly vulnerable to a further correction in house prices are Ireland, the United Kingdom, the Netherlands, and France. In these economies, it is difficult to account for the magnitude of the run-up in house prices on the basis of those countries’ fundamentals. Furthermore, a
weakening housing market can also present a direct drag on growth from reductions in residential investment.”

Given the importance of the market, considerable effort has been put into forecasting overall market movements and individual property prices. This research addresses the former.

1.2 Research Aim

The aim of this research was to assess the potential for applying Artificial Intelligence (AI) techniques to time series in order to forecast residential property market movements. In particular, the research sought to:

- evaluate the application of Artificial Neural Network models and genetic algorithms to residential property price time-series data;
- determine relationships over time between macro-economic (large-scale, national economic), socio-economic (combination of social and economic factors) and residential property transaction attributes at both national and regional levels;
- identify and rank the most significant inputs and, where possible, identify relationships between them.

1.3 Thesis Structure

Chapter 2 examines the background to modelling of the property market, and reviews some of the techniques applied to determining residential property prices.

Chapter 3 describes some of the background to the use of artificial networks. It examines the two software packages used in initial experiments, and compares features offered by them. It explains the reasons for choosing winGamma, in particular for its inclusion of a genetic algorithm stage in the training process and its ability to use the whole of the training set without the need for partitioning part of the set for validation.
Chapter 4 outlines the steps in designing neural network forecasting models. It discusses the availability, selection and pre-processing of data for use in house price forecasting models. A number of other issues relating to model building, training and implementation are also examined.

Chapter 5 examines experiments to forecast regional housing markets and sets out the rationale for combining the UK and regional data into a single dataset. Experimental results, including comparisons with the 1999 Budget forecast, are reported, and methods for optimising network input are discussed.

Chapter 6 examines the use of sensitivity analysis to identify and rank the most significant network inputs at different times in the market cycle. The measure of changes in the house price index itself was found to have the greatest effect on future changes in prices. The use of prediction surfaces to investigate relationships between particular pairs of inputs is described.

Chapter 7 examines the use of committees of networks to produce forecasts, and examines the results obtained for the extended forecasting horizon from 2002 to 2007. Forecasting results from committees of networks trained with post-1998 data are reported and compared with one-year ahead forecasts by the Nationwide Building Society. Changes in the housing market are discussed.

Chapter 8 summarises the research and makes suggestions for further work. It concludes that neural networks can successfully be used to produce time series forecasts of changes in the housing market, particularly when combined in simple committees of networks, and that changing conditions in the market can be incorporated into models. Sensitivity analysis and prediction surfaces were used to identify and rank input variables, and to investigate relationships between variables. Forecasts for the period 2008 to 2010 and possible implications of credit restrictions are discussed.
Chapter 2 – LITERATURE REVIEW

This chapter examines the background to modelling of the property market, and reviews some of the techniques applied to determining residential property prices.

2.1 Introduction

The property market is typically viewed at three levels:

- National (i.e., UK)
- Regional / sub-national (e.g., South East, Wales)
- Urban / sub-market

This research concentrates on the national and regional.

The following sections examine the background to modelling of the property market, and review some of the techniques applied to determining residential property prices.

2.2 Residential Property Market Models

Girouard and Blöndal (2001) examined the role of house prices in influencing consumption and residential investment in OECD countries. Movements in real house prices, mainly cyclic fluctuations about an upward trend, have been closely correlated with the business cycle.

Meen and Andrew (1998) identified the main variables expected to influence house prices at the national and regional levels as:

- incomes
- interest rates (real or nominal)
- the general level of prices
- household wealth
- demographic variables
• the tax structure
• financial liberalisation
• the housing stock

However, measures of some of these variables are not readily available at the regional level, so models of regional house prices are typically much simpler than their national counterparts (Meen and Andrew, 1998). Miles and Andrew (1997) developed the Merrill Lynch forecasting model using just four variables (real house price [log of the house price index divided by the retail price index], real incomes [log of UK total personal disposable income at constant prices], retail prices [log of the retail price index], mortgage interest rate). The clearest conclusion from the model is that real house prices are strongly linked to movements in personal disposable income.

Meen (1996) has suggested that, although most time-series studies of UK housing markets are carried out on national data, housing markets may be better characterised as a series of sub-national markets. Ashworth and Parker (1997) examined determinants of house prices in each of the eleven regions of the UK. They concluded that there are broad similarities in the structure of house price equations across regions in England and Wales (but not Scotland or Northern Ireland), indicating that the source of differences in English and Welsh regional house prices should probably be sought in different regional incomes, opportunity costs, and housing starts. Adair et al (1998), in examining the divergent behaviour of the Northern Ireland housing market relative to the national UK market, concluded that the primary factor influencing performance is disposable income, with risk arising from political instability a secondary factor.

Meen (1999) suggests that changes in regional house prices can be decomposed into three components: (i) movements that are common to all regions; (ii) variations reflecting differences in economic growth between the regions; (iii) structural differences in regional housing markets.
UK national and regional level models have developed primarily from the macroeconomic approach to market modelling, and have not been integrated with modelling at the urban level. \textit{“In an ideal world, regional models should synthesise the national and urban literatures. In practice, one theoretical framework that can join together the two spatial extremes does not exist.”} (Meen and Andrew, 1998)

### 2.3 Predicting Property Prices

Efforts to predict the housing market at the urban or sub-market level have centred more on predicting actual house prices than on forecasting changes in value over time. At the sub-market level, property valuation has centred on arriving at current prices for individual properties rather than forecasting a time series.

The traditional method for valuing residential property is Direct Capital Comparison (Jenkins, 2000), whereby valuers select comparable properties sold in the open market and make \textit{“an allowance in money terms”} (Millington, 1994) for any differences between the subject property and the comparable properties. This is a subjective method that relies heavily upon the experience of the valuer.

Investigators have examined a number of alternative techniques to Direct Capital Comparison. The most significant of these are Multiple Regression Analysis (MRA), Expert Systems and Databases, Linear Programming, and Artificial Neural Networks (ANN). MRA is used extensively in property analysis (Antwi, 1995), and the use of hedonic (regression-based) models is one of the most commonly used approaches in the academic literature for the removal of the element of quality change in the production of indices (Meen and Andrew, 1998).

One reason for the use of ANN is that they do not require an array of \textit{a priori} knowledge, which is frequently a prerequisite for MRA (Tay and Ho, 1992). As an alternative to MRA, ANN techniques have been applied successfully to value houses over a limited time period within a sub-market on the basis of attributes of the houses (Borst, 1991; Tay and Ho, 1991/2; Do and Grudinsky, 1992; Tay and Ho, 1992). Worzala et al (1995), using a similar methodology to Do and Grudinsky
Stuart D. Paris (1992), did not show ANN superior to MRA and they concluded that “Any appraiser who plans on using this new technology should do so with caution”. Subsequently, Lenk et al (1997) asked rhetorically, “Should artificial neural networks bypass the human valuer?” and replied firmly in the negative. McGreal et al (1998) investigated the application of neural networks to the prediction of residential values. They concluded that “the evidence stemming from this study suggests that more research, testing and evaluation of neural networks on larger data-sets are necessary before any decision to utilise these methods in valuation practice is adopted.” Nguyen and Cripps (2001) compared the predictive performance of ANN and MRA for single family house sales in Tennessee using as inputs a number of property attributes, such as area and number of bedrooms. Their results showed that ANN performed better than MRA when a moderate to large training data sample size was used, and they suggested this as a plausible explanation of why some previous papers had obtained varied results when comparing ANN and MRA. They concluded that with sufficient training data ANN perform better than MRA.

In 1995, a programme of research involving a comparative study of residential valuation techniques and the development of a house value model and estimation system was initiated at the University of Glamorgan (Lewis et al, 1997; Jenkins et al, 1998; Almond, 1999; Lewis, 1999). The researchers concluded that the valuation of residential property is too important, economically and socially, to be determined solely by the traditional means employed by chartered surveyors and estate agents, and that the subjective methods of valuation employed by professionals needed to be augmented by an objective methodology. To this end, methods for the data collection and its subsequent encoding for use within AI algorithms were developed. These algorithms circumvented the biases prevalent in the traditional valuation process and provided objective valuations of houses. This work and related projects (Lewis et al, 1997; McGreal et al, 1998) focussed upon the implementation of algorithms designed to produce reliable estimates of the open market value of a property, the current measure of value adopted in the approval of mortgage valuations.
Neural networks have continued to be applied to problems within the housing market, including accounting for environmental variables in valuation models (Din et al., 2001) and market segmentation using Self Organising Maps (Kauko et al., 2002).

Limsombunchai et al (2004) compared the predictive power of the hedonic model with an artificial neural network model for house price prediction in Christchurch, New Zealand. They included a number of attributes in the models, including physical attributes of each house, amenities around the house and geographical location. Selim (2008) used hedonic methods and ANN to examine house prices in Turkey with models containing 46 variables relating to building and locational characteristics. Both studies concluded that artificial neural network models outperformed hedonic models in predicting house prices. However, these activities concentrate on the current state of the market and take no notice of historical trends or what the subsequent value of the property might be. The open market value measure was used throughout the nineteen eighties and nineties property cycle and did nothing to mitigate the effects of disastrous overheating, with David Clarke, chief surveyor of the Halifax Building Society, concluding that "What consumers really want to know ultimately is - should I buy it, am I paying too much?" (Clarke, 1999).

Applying general economic theory, if the price of open market value of dwellings is determined by supply and demand, the value is discovered when simultaneous equations representing a function of demand and a function of supply are solved. Given the multitude and complexity of factors that contribute to both the supply and demand functions, house-price determination studies invariably limit the number of variables with the intention of reducing the problem to manageable proportions. The outcome of this is that the models generated can normally be applied only within narrow time and space zones because of the restrictions imposed by the reduction.
2.4 Forecasting

The terms ‘forecasting’ and ‘predicting’ are often used similarly to refer to the estimation of time series, cross-sectional or longitudinal data (data in which many units are observed over multiple time periods), and similar techniques may be applied to these different data. In the case of regression analysis, for instance:

“If the data are measured over time, then it will be called a time series regression. If the data measurements are all taken at the same time, it will be referred to as cross-sectional regression”. (Makridakis et al, 1998)

However, within the context of this research, ‘forecasting’ is used “in the customary sense of assessing the magnitude which a quantity will assume at some future point of time” (OECD, 2007)

Although the term ‘prediction’ is often used synonymously with ‘forecast’, “in statistical contexts the word may also occur in slightly different meanings; e.g. in a regression equation expressing a dependent variate y in terms of dependent x’s, the value given for y by specified values of x’s is called the “predicted” value even when no temporal element is involved” (OECD, 2007). It is this latter meaning which has been used in the previous section.

Makridakis et al (1998) suggest that forecasting techniques fall into two major categories, quantitative and qualitative methods, with a further category of unpredictable in cases when little or no information is available (for instance, predicting the emergence of new technologies). Qualitative forecasting techniques may be used when “little or no quantitative information is available, but sufficient qualitative knowledge exists” (Makridakis et al, 1998), and the inputs are mainly the product of judgement and accumulated knowledge.

Quantitative forecasting techniques are used when sufficient quantitative historical data are available. Makridakis et al (1998) outline three conditions which must exist for quantitative forecasting to be applied. These are:

- Information about the past is available.
This information can be quantified in the form of numerical data.

It can be assumed that some aspects of the past pattern will continue into the future.

The two main methods identified within quantitative forecasting are time series forecasting (Makridakis et al., 1998) and causal, explanatory or econometric forecasting. Although the term time series forecasting is commonly applied to techniques that use the past behaviour of a particular variable to forecast future values of that variable, the desired outcome of both methods is a forecast of the future values of a particular time series. Chatfield (1996) uses the term univariate to refer to forecasts of a given variable based only on past observations of the variable. He uses the term multivariate for time series where:

“Forecasts of a given variable depend at least partly on values of one or more other series, called predictor or explanatory variables....Methods of this type are sometimes called causal models.” (Chatfield, 1996)

De Gooijer and Hyndman (2006), in their review of 25 years of research into time series forecasting, consider both univariate and multivariate methods. For clarity, the term univariate time series forecasting (Section 2.4.1) has been applied to those techniques that use only the past behaviour of a particular variable to forecast its values. Multivariate forecasting methods are considered in Section 2.4.2, causal forecasting.

2.4.1 Univariate time series forecasting

Kendall and Ord (1990) suggest that it is convenient to consider a time series as a mixture of four components:

- a trend, or long-term movement;
- fluctuations about the trend of greater or less regularity (a cyclic component);
- a seasonal component;
- a residual, irregular, or random effect.
A trend represents a long-term movement in a time series which, together with any seasonal, cyclic or random components, may be regarded as generating the observed values.

A cyclical component is a non-seasonal component that varies in a recognisable pattern, although cycles may vary in length and magnitude.

“The seasonal component is that part of the variations in a time series representing intra-year fluctuations that are more or less stable year after year with respect to timing, direction and magnitude” (OECD, 2007).

The irregular component of a time series is the random variation in the time series that is left once the systematic variations due to the trend, cyclic and seasonal components have been removed.

One method of time series analysis is decomposition, in which the series is broken down into trend, seasonal variation, cyclic changes and the residual fluctuations. Chatfield (1996) suggests that this approach “is particularly valuable when the variation is dominated by trend and/or seasonality”. Makridakis et al (1998) suggest that in some circumstances the distinction between trend and cyclical components may be “somewhat artificial”, in which case they may be left as a single trend-cycle component. The OECD (2007) states that “In practice, statistical agencies do not estimate the trend but rather focus on the trend-cycle component”.

One way of detecting trend (or trend-cycle) in a time series is to smooth the data. Smoothing techniques are used to reduce the irregular component and, if suitably specified, they may also be used to remove seasonality. The most common type of smoothing technique is moving average smoothing. A moving average is calculated by averaging a fixed number of consecutive terms. The average ‘moves’ over time because each data point of the series is sequentially included in the average and the oldest data point is removed. Once the trend or trend-cycle has been identified, the time series can be further decomposed to identify the seasonal and irregular components. Forecasting can be undertaken by projecting the individual
components into the future and recombining them to produce a forecast of the underlying time series. However, Makridakis et al (1998) conclude that “in practice it rarely works well”.

Another forecasting technique is that of exponential smoothing. This is a weighted moving average technique that uses past values of the data to forecast future values. The most recent data are assumed to provide the best guide to the future, so weights exponentially decrease as observations get older. Single exponential smoothing (SES) is the simplest exponential smoothing method. It uses just weighted averages of past values of the data and forecast errors, and is suitable for data that has no trend and no seasonality. Additional methods have been developed to deal with different situations, of which the best known are Holt’s linear method (additive trend, no seasonality), Holt-Winters’ additive method (additive trend, additive seasonality), and Holt-Winters’ multiplicative method (additive trend, multiplicative seasonality) (De Gooijer and Hyndman, 2006).

Forecasting techniques which have been studied extensively are the Autoregressive Moving Average (ARMA) and the Autoregressive Integrated Moving Average (ARIMA) models. The iterative cycle for time series identification, estimation and testing is frequently referred to as the Box-Jenkins methodology, named after the statisticians George Box and Gwilym Jenkins who developed it. The term autoregressive (AR) refers to the fact that the model is a form of regression in which the variable of the series is related to past values of itself at varying time lags. The term moving average (MA) in this context is not the moving average of the observations (as used above in determining trend), but refers to a moving average of the series of past errors. ARMA models can only be used when the data are stationary, although they can be extended to non-stationary series by differencing of the data series. In this case they are called autoregressive integrated moving average (ARIMA) models. These techniques may be extended to multivariate models, with the vector ARMA (VARMA) and vector ARIMA (VARIMA) representing multivariate generalisations of univariate ARMA and ARIMA models.
2.4.2 Causal forecasting

The term causal or explanatory forecasting model refers to one in which the variable to be forecast is related to one or more independent or explanatory variables. Explanatory variables are ones whose values are determined outside of the system being modelled.

Econometrics is a branch of economics that combines economic theory with statistics, and “econometric models often assume that an economic system can be described, not by a single equation, but by a set of simultaneous equations” (Chatfield, 1996). However, “Complex econometric models do not always give better forecasts than simpler time series approaches. It is important to distinguish between econometric models used for policy analysis and econometric models used for forecasting. They are two different things.” (Makridakis et al, 1998)

Regression analysis is one of the techniques often used in econometric forecasting models. Gujarati (1995) describes regression analysis as “the bread-and-butter tool of econometrics”.

Regression analysis refers to the modelling of a forecast variable as a function of a set of explanatory variables. Simple linear regression models the relationship between a single dependent variable $y$ whose value is dependent on the corresponding value of the single independent (explanatory) variable $x$. It assumes a linear relationship between $y$ and $x$. Multiple linear regression is an extension of simple regression. It is used to describe the relationship between one dependent variable and multiple explanatory variables. It may be expressed in the form:

$$y = A + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + ... + \alpha_n x_n \quad (2.1)$$

Multiple regression analysis finds the best numerical values of $\{A, \alpha_1, \alpha_2, \alpha_3...\alpha_n\}$ so as to minimise the squared difference between the actual and predicted values. Once these values have been found, forecasts / predictions may be produced by entering into the equation values for the different explanatory variables. Lewis (1999)
reported that “MRA [multiple regression analysis] has formed the major contribution to alternative valuation literature in the UK and US”.

Hedonic models, which are commonly used in property appraisal and economics, and in consumer price index calculations, are most commonly estimated using regression analysis. The House Price Index issued by the Department of Communities and Local Government is based on a hedonic model (ODPM, 2003).

Much of the work undertaken in time series forecasting (both univariate and multivariate) has been on linear series. De Gooijer and Hyndman (2006) state that:

“Compared to the study of linear time series, the development of nonlinear time series is in its infancy.”

and that:

“An artificial neural network (ANN) can be useful for nonlinear processes that have an unknown functional relationship and as a result are difficult to fit.”

Burger et al (2001) compared a variety of time-series forecasting methods to predict tourism demand for Durban, South Africa. They concluded that a back-propagation neural network model outperformed naive, moving average, decomposition, single exponential smoothing, ARIMA, multiple regression and genetic regression techniques.

2.5 Forecasting with Artificial Neural Networks

Little attention has been paid to the application of neural networks to forecasting house price changes over time. However, the problem of forecasting time series is not restricted to the housing market, and much effort has been directed to this in a wide range of problem fields.

Artificial neural networks have been applied to time series forecasting in a number of areas of finance and economics. Moshiri and Cameron (2000) compared the performance of back-propagation artificial neural network models with traditional econometric approaches to forecasting the inflation rate. Their results showed the
ANN models were able to forecast as well as all the traditional econometric methods, and to outperform them in some cases. Qi (2001) used neural network models to examine the relevance of various financial and economic indicators in predicting US recessions. He concluded that “Because there is little a priori knowledge about the true underlying function that relates financial, economic and composite indicators to the probability of future recessions, the NN models are an ideal choice for modeling these relationships”.

Tkacz (2001) examined the forecasting of Canadian GDP growth using neural network models. He found that, though neural networks were unable to outperform a naive no-change model when forecasting quarterly growth, they did yield statistically lower forecast errors for the year-over-year growth rate of real GDP relative to linear and univariate models.

Zhang et al (2004) compared the accuracy of univariate and multivariate linear models with the accuracy of univariate and multivariate neural network models in forecasting earnings per share. Both the multivariate linear models and the multivariate neural network models incorporated fundamental accounting variables as explanatory variables. They concluded that the neural network approach improved forecasting accuracy over linear models for both the univariate and multivariate models, but that “the improved forecasting accuracy is more pronounced when we include a collection of fundamental accounting variables”.

Kanas and Yannopoulos (2001) and Kanas (2001) compared the out-of-sample performance of monthly returns forecasts for the Dow Jones and the Financial Times indices using linear and artificial neural network models. They reported that the ANN outperformed the linear forecasts and that:

“the inclusion of nonlinear terms in the relation between stock returns and fundamentals is important in out-of-sample forecasting. This conclusion is consistent with the view that the relation between stock returns and fundamentals is nonlinear.”

Olson and Mossman (2003) compared the neural network forecasts of one-year-ahead Canadian stock returns with the forecasts obtained using ordinary least
squares and logistic regression techniques, using as input data 61 accounting ratios for 2352 Canadian companies. They concluded that “neural networks outperform corresponding traditional regression techniques for the problem at hand”.

Moshiri and Brown (2004) suggested that:

“The asymmetric business cycle suggests that major macroeconomic series, such as a country’s unemployment rate, are non-linear and, therefore, the use of linear models to explain their behaviour and forecast their future values may not be appropriate”.

A back-propagation neural network model and a generalised regression neural network model were used to forecast post-war aggregate unemployment rates in the USA, Canada, UK, France and Japan, and the out-of-sample forecast results obtained by the neural network models were compared with those obtained by several linear and non-linear times series models. They concluded that the artificial neural network models were able to forecast the unemployment series as well as, and in some cases better than, the other univariate econometric time series models.

Gradojevic and Yang (2006) investigated the application of ANN to forecasting changes in the Canadian/US dollar exchange rate using as inputs a number of macroeconomic and microeconomic variables. They concluded that neural network models consistently outperformed random walk and linear models.

In addition to their application in finance and economics, artificial neural networks have been applied to similar univariate and multivariate time series forecasting problems in a number of other areas of study. One such topic area is river flow, which has also been investigated for its potential to benefit from the use of neural networks. A number of studies have compared the application of neural networks to other forecasting methods such as autoregressive moving average (ARMA) models (Abrahart and See, 2000), autoregressive (AR) models (Tawfik, 2003) and Box-Jenkins / ARIMA models (Castellano-Mendez et al, 2004; Huang et al, 2004). In each case, the researchers reported encouraging results. Kim and Barros (2001), using multivariate back-propagation neural networks, have also reported that
“multisensor data cast into an expert system such as a neural network...can lead to significant gains in the forecast skill of extreme rainfall and associated floods”.

Another area in which neural networks have been applied is ecology. Maier et al (1998) used neural networks for modelling cyanobacteria in the River Murray, South Australia. They investigated methods of determining the relative significance of different input variables, and the use of lagged versus unlagged inputs in multivariate neural network models. They concluded that the neural networks were “relatively successful in providing a good forecast of both the incidence and magnitude of a growth peak of the cyanobacteria within the limits required for water quality monitoring.”

Electric load forecasting is an area that has received a great deal of attention, and is one in which neural networks have played a large part. Alfares and Nazeeruddin (2002) undertook a literature survey and concluded that:

“After surveying all these approaches, we can observe a clear trend toward new, stochastic, and dynamic forecasting techniques. It seems a lot of current research effort is focused on three such methods: fuzzy logic, expert systems and particularly neural networks.”

It is clear that, whilst neural networks have played little part in the forecasting of house price changes over time, they have been applied successfully to a wide range of other forecasting problems.

2.6 Conclusions

The forecasting of price changes in the housing market receives a considerable amount of media attention, particularly at times of rapid change or economic uncertainty. Forecasts of the changes are made by mortgage lenders, Government and economic commentators. However, the basis on which such forecasts are made has received far less attention than that applied to the production of valuations of individual properties at the time they are offered for sale.
The prediction of property values has been studied extensively using a wide range of techniques, including neural networks. However, little has been done to extend the application of neural networks into the forecasting of changes over time in the housing market. Neural networks have, though, been applied to forecasting problems in finance, economics and a range of other disciplines. They have been applied to univariate and multivariate forecasting problems, and have been shown to perform well in many situations when compared to standard forecasting techniques. In the process, a number of useful techniques have been described and extended.

Although the areas of study vary, the overall methodologies have relevance to the forecasting of changes in the housing market over time. The application of these neural network techniques is discussed in the following chapters.
Chapter 3 – ARTIFICIAL NEURAL NETWORKS

This chapter describes some background to the use of artificial neural networks. Two alternative software packages are described and compared.

3.1 Forecasting using Artificial Neural Networks

“Many ideas and activities familiar to the statistician can be expressed in neural-network notation. ... they include regression models from simple linear regression to projection pursuit regression, nonparametric regression, generalized additive models and others” (Cheng and Titterington, 1994).

Artificial intelligence techniques, especially Artificial Neural Networks (ANN), are being applied to a wide range of practical problems. ANN are not programmed but learn by example (McCluskey, 1997), and are used in such problems as financial predictions. There are several features that make ANN valuable for forecasting tasks (Zhang et al, 1998):

- They are data-driven self-adaptive methods that learn from examples and capture functional relationships among the data even if the underlying relationships are unknown or hard to describe.
- They can generalise. After learning the data presented to them (a sample), they can often correctly infer the unseen part of a population.
- They are universal functional approximators (Hornik, 1991). A network can approximate any continuous function to any desired accuracy – traditional statistical forecasting models frequently have limitations in estimating underlying functions due to the complexity of real systems.
- They are non-linear. Real world systems are often non-linear, and ANN are capable of performing non-linear modelling without a priori knowledge about the relationships between input and output variables.
Hill et al. (1996) compared neural networks with six traditional statistical methods to forecast 111 M-competition time series. They concluded that the neural network models were significantly better than traditional statistical and human judgement methods when forecasting monthly and quarterly data. For the annual data, neural networks and traditional methods were comparable. They also concluded that neural networks are very effective for discontinuous time series.

“This may be due to the fact that monthly and quarterly data usually contain more irregularities (seasonality, cyclicity, nonlinearity, noise) than the yearly data, and ANNs are good at detecting the underlying pattern masked by noisy factors in a complex system.” (Zhang et al., 1998)

Chakraborty et al (1992) showed neural networks to be better than traditional statistical methods for forecasting some multivariate time-series, although they speculated that statistical pre-processing of the data might further improve performance.

Kohzadi et al. (1996) compared artificial neural networks with ARIMA (Auto Regression Integrated with Moving Averages) models in forecasting monthly live cattle and wheat prices. Their results showed that ANN forecast more accurately and captured more turning points than ARIMA models.

3.2 Time Series Forecasting

Forecasting is the rational prediction of future events on the basis of related past and current information. Time series forecasting is a challenging problem that has long attracted the attention of investors and academics alike. The process is comparable with modelling, where the outcome of an unknown variable is generated from known or controllable variables.

A combination of statistical analysis and informed judgement can approximate the relationships between the known and unknown variables. When complete information about relationships is available, then statistical data is invariably more reliable since it reflects patterns in the data in an unbiased way (Hoptroff, 1993).
Many time series consist of members that are serially dependent in the sense that one can estimate a coefficient or a set of coefficients that describe continuous members of the series from specific, time-lagged (previous) members. This process of autoregression can be summarised in the equation:

\[ y_t = A + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \alpha_3 y_{t-3} + \ldots + z_t \]  

(3.1)

Where \( y \) represents the values of the series at point \( t \), \( A \) is a constant, \( \alpha_1, \alpha_2, \alpha_3 \), etc are linear regression coefficients, and a random error component is denoted by \( z_t \). In other words, each observation is made up of a random error component and a linear combination of prior observations. Once the next value in the sequence has been predicted, this can be substituted into the equation to make further predictions.

When observations of multiple variables are recorded, it may be possible to explain the variation in one variable by the variation in one or more other variables. If the value of \( y \) (the dependent variable) is dependent of the corresponding values of \( x_1, x_2, \) etc (the independent variables) this multiple regression relationship can be summarised in the equation:

\[ y = A + b_1 x_1 + c_2 x_2 + d_3 x_3 + \ldots + z_n \]  

(3.2)

However, the practical success of regression models are limited by their linearity, their ravenous data requirements, and because one needs to be reasonably skilled to obtain a good forecast.

Non-linear models, including artificial neural networks are potentially better than regression models. Indeed, it has been shown that an ANN using logistic functions can model any functional relationship, linear and non-linear (Bishop, 1995). It would be expected that such models are better than regression since regression is essentially a linear technique used in a non-linear problem domain. Zapranis and Refenes (1999) suggest that

“From the statistician’s point of view they [neural networks] are analogous to non-parametric, non-linear regression models. The novelty about neural
networks lies in their ability to model non-linear processes with few (if any) a priori assumptions about the nature of the generating process.”

However, although non-linear systems inherently demonstrate more potential than linear systems, their implementation is problematic. This arises from the fact that non-linear systems will attempt to fit all data encountered, including any noise present. Therefore, processing must be stopped once all useful information has been internalised but before any noise within the data is absorbed.

### 3.3 Artificial Neural Networks Basics

Artificial Neural Networks are being applied to a wide range of practical problems, for example, classification, noise reduction and prediction (Masters, 1993). The most common types of ANN are generally known as supervised and unsupervised networks, referring to the methods of training.

An unsupervised network is not supervised during training – that is, the network is presented with sample inputs, but no corresponding outputs are provided. Such networks are often used in classification problems, where it is assumed that (Masters, 1993):

“...each input arises from one of several classes, and the network’s output is an identification of the class to which its input belongs. The process of training the network consists of letting it discover salient features of the training set, and using these features to group the inputs into classes that it (the network) finds distinct.”

A supervised network is trained using inputs together with the corresponding desired outputs. An example of a supervised learning network is the multi-layered perceptron (MLP) network. A strength of MLP networks is their ability to cope with non-linear functions. They have been used successfully in a number of experiments to predict house prices in snapshots of limited housing markets. A typical simple multi-layered perceptron network is shown at Figure 3.1.
The MLP in Figure 3.1 consists of interconnected layers of neurons or nodes, which are connected together. The number of nodes in the input layer (which does no processing) depends on the number of characteristics being modelled. The weights associated with each processing node are adjusted using the error, which is obtained by comparing the actual output with the desired output. This type of network is referred to as a feed-forward back-propagation ANN (the signal feeds forwards through the network and the error adjustment is propagated backwards).

Despite the many satisfactory characteristics of an ANN, building a neural network for a particular forecasting problem is a nontrivial task. Modelling issues that affect the performance of an ANN must be considered carefully. First, an appropriate architecture, that is, the number of layers, the number of nodes in each layer, and the number of arcs that interconnect with the nodes must be determined. Other network design decisions include the choice of activation function for the processing nodes, the training algorithm, data normalisation methods, training data, and performance measures (Zhang et al, 1998).

### 3.3.1 The network architecture

An ANN is composed of an input layer, which corresponds to the length of the input vector, an output layer, which provides the forecast values, and one or more layers of hidden nodes. Both the number of input nodes and the number of hidden nodes...
have significant effects on ANN model building and predictive ability. Generally, the number of input nodes has much stronger effects than the number of hidden nodes on both in-sample fit and out-of-sample forecasting (Zhang et al., 2001).

3.3.1.1 The number of nodes in the input layer
The number of nodes in the input layer of a network corresponds to the number of variables in the input vector used to produce the forecast of future values. For univariate time series forecasting, a series of lagged observations (a window) is used, on the assumption that future values are related in some way to the series that precedes them. The window size is the number of consecutive data points used. In multivariate forecasting, the number of inputs is determined by the number of indicators (leading indicators or factors believed to influence the outcome) used. An input vector may consist of windows from more than one time series and a number of indicators, with the number of input nodes corresponding to the total number of observations used.

3.3.1.2 The number of nodes in the hidden layers
It has been shown that a single hidden layer is sufficient for an ANN to approximate any complex non-linear function with any desired accuracy (Hornik, 1991), although two hidden layers can result in a more compact architecture that achieves a higher efficiency than single hidden layer networks (Chester, 1990; Srinivasan et al., 1994; Zhang, 1994). The number of hidden nodes in each layer is usually determined by trial and error.

3.3.1.3 The number of nodes in the output layer
The number of output nodes corresponds to the forecasting horizon. In this series of experiments a single output was used to provide a single quarter ahead forecast.
3.4 Artificial Neural Network Software

Experimental work was undertaken using two software packages, NeuralWorks Professional II and \textit{winGamma}.

3.4.1 NeuralWorks Professional II

NeuralWorks Professional II is a commercially available software package that provides the facility to generate neural networks based on a number of standard neural network architectures, including feed-forward back-propagation models.

3.4.1.1 SaveBest

The SaveBest option available in NeuralWorks is a tool for determining the point at which to stop training, and a way of ensuring that only changes in network parameters which produce a lower error for the validation set (Section 4.5) are retained. The validation set is presented to the network after a user-defined number of training cycles. If this results in a lower error than in the previous training/validation cycle, training continues using the current network weights. If not, training resumes from the previous best network, and continues for a user-defined number of consecutive training/validation cycles. If no improvement occurs after this number of retries, training stops and the network with the best results during the run is saved.

3.4.2 \textit{winGamma}

The \textit{winGamma} software package is a non-linear analysis and modelling tool developed by the Department of Computer Science, Cardiff University. The package estimates the least Mean Squared Error (MSE) that any smooth data model (for example, a trained feed forward neural network) can achieve on the given data without over training. It can be used with multiple column input/output data files and single or multiple time series.
Chapter 3 – Artificial Neural Networks

The software may be used to build models by using linear regression or by using one of three different types of neural network training algorithms, including two layer feed-forward back-propagation models. It also includes a number of training set analysis options, including the Gamma test and the M-test, and model identification options, including genetic algorithms, which can be used in the model building process.

3.4.2.1 Gamma Test and Associated Tools

3.4.2.1.1 Gamma Test

The Gamma (near neighbour) test is a data analysis algorithm that estimates the Mean Squared Error (MSE) that can be achieved by a model constructed using this data. This test can be used to simplify the process of constructing a smooth data model, such as an ANN.

If a time series can be assumed to hide an underlying smooth model

\[ y = \hat{f}(v) + r \quad (3.3) \]

where \( y \) is a scalar output and \( v \) is an input vector, restricted to a close bounded set, and \( r \) represents noise, then the Gamma test can provide a data-derived estimate for the variance of \( r \) given that:

- the training and testing data are different sample sets;
- the training set inputs are non-sparse in input-space;
- each output is determined from the inputs by a deterministic process which is the same for both training and test sets;
- each output is subjected to statistical noise with finite variance whose distribution may be different for different outputs, but which is the same in both training and test sets for corresponding outputs (Stefansson et al, 1997)

Given this, small variations in \( v \), written \( \Delta v \), and \( y \), written \( \Delta y \), should be constant between points in the time series that are close together. The gradient, \( \Delta y/\Delta v \), between neighbours is more or less constant. Therefore, for each small successive
section of the time series, if $\Delta v$ is decreased to zero then $\Delta y$ should also tend to zero provided there is no noise within the data (Connellan and James, 2000). With property prices, although $\Delta v$ tends to zero, $\Delta y$ does not because of the noise within the data, with the Gamma test providing an estimate for this noise.

The test is applied in turn to each point within the time series. The distance between it and the nearest neighbour in terms of the input vector $v$, and the corresponding output scalar value $y$ is found, and the process is repeated for $n$ nearest neighbours. The two corresponding values, $\delta$ (Delta) and $\gamma$ (Gamma), are then plotted on a Gamma Scatter plot - $\delta$ is the squared distance of an input vector $v$ from one of its near neighbours and $\gamma$ is one half of the squared distance between the two corresponding output ($y$) values.

Figure 3.2 The Gamma Test
Mean values of Delta and Gamma are calculated for all the first nearest neighbours, all the second nearest neighbours, and so on up to n nearest neighbours (the maximum number which it has been decided to use - \textit{winGamma} includes an ‘increasing near neighbours’ test which assists in this choice by finding how the Gamma statistic varies with the number of near neighbours used to compute it). These mean values are then plotted on a graph and a linear regression line is fitted to them. This linear regression line provides two measures, namely:

- the intercept of the line on the Gamma axis when delta is zero, which gives the MSE, or Gamma statistic (this is the estimated variance of the errors for a model built using the data); and
- the gradient of the line, which provides an indication of the complexity of the model under analysis. Where, the steeper the line the more complex the relationship between y and v.
These measures provide a basis for constructing and training an ANN, with the training process being stopped once the MSE reaches the Gamma value. A more detailed discussion of the Gamma test algorithm is given by Stefánsson et al. (1997).

3.4.2.1.2 M-test

One method of judging the adequacy of a dataset for modelling is the M-test, which shows how the Gamma statistic estimate varies as more data are used to compute it. The M-test is used to establish whether there are sufficient data to provide an accurate estimate of the Gamma statistic. The algorithm starts from a small subset of the data and gradually adds more points from the analysis data set. If the Gamma
estimate asymptotes then this suggests that there are sufficient data. The point of asymptote provides an estimate for the minimum amount of data required to build a robust model.

3.4.2.1.3 Model Identification
A number of model identification options are included within winGamma. These may be used to assist in the selection of those inputs which might best be used to predict a selected output (some inputs may be noisy or irrelevant). They are all designed to produce an embedding – a selection of inputs chosen from all the inputs, and designated by a string of ‘1’ s and ‘0’ s called a mask. The mask 10111 for five inputs indicates that all inputs are to be used except the second. The options include:

- Full Embedding – this tries every combination of inputs to determine which combination yields the smallest absolute Gamma value. For n inputs there are \(2^n - 1\) possible embeddings.
- Genetic Algorithm – this searches the space of all masks using a Genetic Algorithm to find good embeddings. It is particularly useful when the number of inputs is too large to make a full embedding practical.

3.4.3 Comparison of NeuralWorks and winGamma
A set, called the validation set, is frequently used to determine when the training process should be stopped (the validated training procedure). Zhang et al (1998) state that

“It is common to use one test set for both validation and testing purposes particularly with small data sets.”

However, Adya and Collopy (1998) recommend that

“Comparison of forecasts should be based on ex ante (out-of-sample) performance. In other words, the sample used to test the predictive capabilities of a model must be different from the samples used to develop and train the model.”
Conforming to this recommendation means that the training set should be partitioned to provide a separate validation set. Hence, the proportion of the data held back for validation is not available to train the network, which may be a disadvantage in cases where the number of samples is limited.

Early experiments to produce forecasting models of the Nationwide UK House Price Index using *winGamma* produced better results than those using NeuralWorks (Wilson *et al.*, 2002). However, it was not clear whether this was as a result of using the whole of the training set or whether differences in the operation of the software were responsible. In order to investigate this, the combined UK and regional dataset (see Section 5.3.2) was used to train and test a series of networks using both *winGamma* and NeuralWorks. The final 12 Quarters of the dataset were removed and used as the test set to assess the forecasting ability of the trained networks. The remainder of the dataset was used in its entirety as a training set to train a series of networks using *winGamma*. The training set was then partitioned to produce a training set and a validation set, with 20% assigned randomly to the validation set and the remaining 80% assigned to the training set. *winGamma* was then used to produce a further series of networks trained using the reduced (80%) training set. Finally, NeuralWorks was used to produce a series of networks trained using the reduced training set and the validation set. Training was undertaken using the ‘SaveBest’ option.

The performance of each series of trained networks was assessed by using the test set to produce forecasts. The RMSE of the forecasts were then averaged for each series of networks. The results are graphed at Figure 3.4.
Chapter 3 – Artificial Neural Networks

Comparison of the results for the two series of networks trained using winGamma suggests that the training process benefits from the availability of the full dataset compared with the partitioned (80%) dataset. However, further benefit appears to arise from using winGamma in preference to NeuralWorks for the same training set. This may reflect better processes for avoiding local minima in the solution search space.

A real-time chart provides user feedback within winGamma during network training. The feedback produced during a typical training run is shown at Figure 3.5. The model Mean Squared Error (MSE) is shown on the chart together with the target MSE. The initial rapid fall in the model MSE corresponds to the (optional) network initialisation stage, which utilises genetic algorithms. After this initialisation stage, the network training is punctuated at intervals with a simulated annealing routine to avoid the confinement of the network weights to local minima.
Overall, there appeared to be a two-fold benefit to using *winGamma* with the full training set, and this was the approach adopted.
Chapter 4 – NEURAL NETWORK MODELLING ISSUES

This chapter outlines the steps in designing neural network forecasting models.

4.1 Introduction

Kaastra & Boyd (1996) suggest that designing a neural network can be split into eight steps. This eight-step design methodology is set out in Table 4.1.

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Table 4.1  Steps in designing a neural network forecasting model. Adapted from Kaastra & Boyd (1996).

4.2 Variable Selection

"Knowing which input variables are important in the market being forecasted is critical. This is easier said than done because the very reason for relying on a neural network is for its powerful ability to detect complex nonlinear relationships among a number of different variables. However, economic theory can help in
choosing variables which are likely important predictors.”  (Kaastra and Boyd, 1996)

Theoretical market models indicate that the main variables expected to influence house prices at both the national and regional levels are (Meen and Andrew, 1998):

- incomes
- interest rates (real or nominal)
- the general level of prices
- household wealth
- demographic variables
- the tax structure
- financial liberalisation
- the housing stock

However, measures of some of these variables are not readily available at the regional level. Hence models of regional house prices are typically much simpler than their national counterparts (Meen and Andrew, 1998).

The Merrill Lynch forecasting model (Miles and Andrew, 1997) uses just four variables:

- Real House Price (log of house price index divided by RPI)
- Real incomes (log of real disposable incomes at constant prices)
- Retail prices  (log of RPI)
- Mortgage interest rate (tax-adjusted interest rate)

The variables selected for use in this investigation were:

- House Prices
- Incomes (earnings)
- Retail Prices (RPI)
- Interest Rate (Bank of England rate)
- Unemployment (percentage claimant count)
These variables are similar to those used in the Merrill Lynch forecasting model, with the addition of the percentage (unemployed) claimant count. The rate of unemployment was included as it is often taken as a proxy variable for general economic conditions. In choosing the variables, it was necessary to identify ones for which sufficient historical data existed to train ANNs, and for which forecasts of future values were also available. Using variables for which forecasts were not available would merely replace one forecasting problem with another.

4.3 Data Collection

4.3.1 National and regional house price data

Three major sources of time-series data on national and regional house prices available in the UK are the Halifax plc and Nationwide Building Society indices, and the House Price Index (HPI) published by the Department for Communities and Local Government (CLG).

The House Price Index has been published since 1968 by CLG and its predecessors (the Office of the Deputy Prime Minister (ODPM), the Department for Transport, Local Government and the Regions (DTLR), the Department of the Environment, Transport and the Regions (DETR) and the Department of the Environment (DoE)). Until August 2005, the data used to produce the HPI was based on the Survey of Mortgage Lenders (SML) that ODPM (and predecessors) ran in conjunction with the Council of Mortgage Lenders (CML). From September 2005 the SML was replaced as the data source by the Regulated Mortgage Survey (RMS) (Council of Mortgage Lenders/BankSearch) (CML, 2006a). The RMS has greater market coverage than the SML – around 90% compared with less than 50% for the SML. It covers many of the same areas as the SML, and several new ones for which the SML had little or no data. However, certain types of loan are not reported in the RMS, most significantly buy-to-let and further advances. The CML compared data from both the SML and the RMS for April to August 2005 - for this overlap period the underlying market trends revealed in the RMS and the SML were similar (Tatch, 2006).
From the inception of the HPI in 1968 until the first quarter of 1992 the survey was based on a sample of Building Societies, but from the second quarter of 1992 the survey was extended to include all mortgage lenders who were members of the CML. It contained information on dwelling prices at national and regional level, which was collected and published every quarter from a five per cent sample survey. The sample size for each quarter was usually 8,500 to 9,000, which was considered to be sufficient for a quarterly index, but not large enough to be able to calculate a reliable monthly series (DETR, 2000). From 2001, an increasing number of lenders started providing details of all their completions. This substantial increase in data (to 25,000 cases per month) enabled ODPM to launch a new monthly series in September 2003 (backdated to Feb 2002) (CLG, 200-). CLG continues to produce a quarterly series, with quarterly inflation from 2002 Quarter 2 based on the average of the monthly mixed adjusted series.

The Nationwide index covers the period from the final quarter of 1973, and the Halifax index from 1983. There are frequently short-term differences in the inflation rates recorded by the three indices, although the general direction and magnitude of house price inflation as measured by all three indicators shows a broad consensus (Figure 4.1) (CLG, 2008b).
The main technical differences between the Halifax, Nationwide and HPI indices are as follows:

- **Timing**: the Halifax and Nationwide indices are based on mortgage approvals. The HPI is based on completions.
- **Sample differences**: the Halifax and Nationwide indices are based only on their own in-house data. The HPI uses data from a wide variety of mortgage lenders.
- **Index construction**: the Halifax and Nationwide use a regression approach; the pre-2003 HPI used a matrix approach. Both these approaches are valid but they may explain some of the difference (DETR, 2000).
- **Weights**: the Halifax and Nationwide use different sets of fixed weights. The HPI weights are revised every year - based on transactions during the three previous calendar years.

One reason commonly given for differences between the Halifax and Nationwide inflation rates is variation in their regional lending patterns. However, the weights that each lender applies to determine a national average should smooth out any such differences, so this is unlikely to be a significant factor (DETR, 2000).
A further source of residential property price information is HM Land Registry, which produces a Residential Property Price Report quarterly. The report, which covers all house purchase transactions in England and Wales whether bought via a mortgage or cash, provides information on average prices and sales volumes in the residential property market broken down by property type and by County and Unitary Authority. This information is available from the first quarter of 1995. Similar information is available by Local Authority and postcode (down to sector level) from the first quarter of 1999.

Some early experiments were carried out using the Nationwide Building Society data. However, later work utilised the government’s House Price Index. This was chosen because it:

- covers a longer time period (more market cycles)
- covers the whole UK
- is not based on data from a single lender.

### 4.3.2 Other data

Details of the individual data series used are set out at Appendix 1. The Bank of England was the source for the interest rate data. The other data series were obtained from the National Statistics Office. Forecasts of future values of the variables were taken from the series “Forecasts for the UK Economy - A comparison of independent forecasts” produced by the Macroeconomic Prospects Team of HM Treasury (HM Treasury, 2007).

### 4.4 Data Pre-processing

Hoptroff (1993) has identified one of the core advantages of neural network modelling as ease of use because

> “the whole process can be completely automated in computer software so that people with little knowledge of either forecasting or neural nets can prepare reasonable forecasts in a short space of time”.

Stuart D. Paris
Commenting on this, Faraway and Chatfield (1998) suggest that

“a good NN model for time series data must be selected by combining traditional modelling skills with knowledge of time series analysis and of the particular problems involved in fitting NN models” and that “there is plenty of scope for going badly wrong with NN modelling (as there is for many other sophisticated statistical techniques)”. 

Flood and Kartam (1994) suggest that

“there is a tendency among users to throw a problem blindly at a neural network in the hope that it will formulate an acceptable solution…”,

whilst Maier and Dandy (2000) observe that

“the rules governing traditional statistical models are seldom considered in the ANN model building process”.

Zapranis and Refenes (1999) state that

“Data pre-processing is an important step in application development, since various problems, such as trends in the mean, can lead to spurious fit and poor generalization.”

Much work has been undertaken in time series forecasting using traditional statistical techniques, with most of the probability theory of time series concerned with stationary time series (Chatfield, 1996). A time series is said to be stationary if there is no systematic change in mean (no trend), if there is no systematic change in variance and if strictly periodic variations have been removed. Zhang (1994) considers the application of neural networks to time series prediction and the general properties of time series. He outlines some of the most important properties from the traditional statistical approach and suggests that

“If a time series is not stationary, then most algorithms cannot be successfully applied. The time series need to be transformed to a stationary form first.”

However, Maier and Dandy (2000) state that

“until recently, the issue of stationarity has been rarely considered in the development of ANN models”.

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“until recently, the issue of stationarity has been rarely considered in the development of ANN models”.
Real-world economic time-series tend not to be stationary within the time frames for which forecasts are calculated, but one of the challenges is to develop ways of predicting these non-stationary series. (Clemen, 2001; Makridakis and Hibon, 2001) However, even though series may be non-stationary in the strict statistical sense, there is still likely to be benefit from applying standard techniques to eliminate (or minimise) trend and changes in variance. Refenes (1995) states that

“The independent and dependent variables will, in the majority of cases, require detrending, normalisation, and attention to statistical outliers.”

4.4.1 De-trending

Neural networks are universal approximators and might be expected to be able to model time series containing trend, cyclical components and seasonality. However, using ANN to forecast the House Price Index or the price directly might be of only limited effectiveness. For such a series with an overall upward trend, forecasts (and, in the case of multivariate models, some of the input variables) are likely to lie outside the range of the training set / normalisation. ANN do not extrapolate well beyond the range of the data used for training (Flood and Kartam, 1994), and poor forecasts could therefore be expected when the validation data contain values outside the range of those used for training (Maier and Dandy, 2000).

De-trending is a process of removing seasonal and/or general trends from the data. Masters (1993) suggests that a vital aspect of time-series processing, especially for neural networks, is the elimination of large-scale deterministic components such as obvious trends and seasonal variation.

Nelson et al (1999) have suggested that using data from which seasonality has been removed may allow the available network elements to be used more effectively. They compared the forecasts for neural networks using the 68 monthly time series from the M-competition (Makridakis et al, 1982) and concluded that, when there was seasonality in the time series, forecasts from neural networks estimated on deseasonalized data were significantly more accurate than the forecasts produced by
neural networks that were estimated using data which were not deseasonalized. They speculated that:

“if neural networks use deseasonalized time series then the neural networks can focus on learning trend and cyclical components. Neural networks that do not use deseasonalized time series, however, have to learn trend, cyclical components, and seasonality.”

A similar argument may be extended for the de-trending of data, leaving the network to concentrate on modelling movements away from the general trend. Refenes (1995) states that

“The existence of strong trends in the independent and/or dependent variables can lead to spurious correlations and regressions because it is easier for the network to learn the general features of the data than the actual relationship between the variables.”

He goes on to suggest that

“Approaches developed in statistical modelling methodology for preprocessing the input and output data should always be given serious consideration prior to training neural networks. Although it is not essential in certain cases, it is vital in the majority of cases.”

4.4.1.1 De-trending by ratio

In line with the suggestion by Kendall and Ord (1990) that an initial step for time series modelling should be trend removal, it was decided that benefits could be gained from the identification of a measure of prices that showed no overall trend – a long term indication of value. Kaastra and Boyd (1996) state that a

“popular data transformation is to use ratios of input variables. Ratios highlight important relationships ... while at the same time conserving degrees of freedom because fewer input neurons are required to code the independent variables.”

The conclusion from the Merrill Lynch forecasting model (Miles and Andrew, 1997) that real house prices are strongly linked to movements in personal disposable income suggested that the ratio of house prices and incomes / earnings might
provide such a measure. The graph at Figure 4.2, showing the House Price Index and the House Price Index – Average Earnings Index ratio, clearly demonstrates how the latter ratio highlights the market highs and lows. The market peaks of 1974 and 1989 followed by the subsequent market lows are clearly shown.

![Figure 4.2 House Price Index and House Price Index - Average Earnings Index Ratio](chart.jpg)

Gallin (2006) has examined the proposition that there exists a long-run equilibrium relationship between house prices and fundamentals, such as income, population and user cost. Using both US national data and a panel of 95 metropolitan areas over 23 years, he found little evidence of cointegration at the national level and none at the metropolitan level. He concluded that

“This does not mean that fundamentals do not affect house prices, and it does not mean that house prices cannot fall. It does mean that the level of house prices does not appear to have a stable long-run equilibrium relationship with the level of fundamentals such as income.”

Chen et al (2007), using data from Taiwan, suggest that house price is much more volatile than income so that the cointegration test cannot find their equilibrium
relationship. However, using alternative tests, they do obtain an equilibrium relationship between house price and income. They argue that

“These results imply that house and income may deviate from each other but will return to equilibrium level in the long run.”

If Chen et al are correct, this supports the argument for including the price to income ratio (here, HPI/AEI) as a long term indicator of market conditions.

As alternatives to using earnings in the ratio, the use of RPI and GDP per capita were considered. The ratio of house prices to RPI was not used as the resulting ratio still showed an obvious trend. In addition, Meen and Andrew (1998) suggest that the use of RPI in models can lead to problems because of its treatment of housing costs. Until 1995, movements in owner-occupier housing costs in the RPI were dominated by changes in mortgage interest rates, generating a highly volatile component into the index.

The ratio of house price to GDP per capita, like the ratio of house prices to earnings, resulted in an approximately trend free series. The two ratios produced very similar curves. This was expected, as the correlation between the two series is 0.998 for the period 1968 Q2 to 2001 Q3. It was decided to use the ratio of house price index to average earnings index (HPI/AEI) initially in preference to HPI/GDP for both practical and theoretical reasons:

- If models are to be useful for forecasting, they must use inputs that are available – forecasts of changes in earnings for some years ahead are more readily available than predictions of GDP per capita (which rely on forecasts of both GDP and changes in population).
- The SML series only included purchases for owner occupation, and did not include cash transactions. As the majority of such mortgage borrowers repaid their mortgages from earnings, the HPI/AEI ratio for this series can be considered as a crude measure of value.

Early results from experiments using the HPI/AEI ratio for national data were presented at the RICS Cutting Edge conference 2001 (Paris et al, 2001).
4.4.1.2 De-trending by differencing

An alternative to de-trending by using ratios is to apply a transformation to the data.

“If there is a trend in the series and the variance appears to increase with mean then it may be advisable to transform the data.” (Chatfield, 1996)

Two of the most common data transformations in both traditional and neural network forecasting are differencing and taking the log of a variable (Kaastra and Boyd, 1996). If the size of an effect is directly proportional to the mean, then the effect is said to be multiplicative and a logarithmic transformation can make the effect additive. The trend can then be removed by differencing (i.e., taking one value from a following value – annual differencing can be used to remove seasonality).

An examination of the HPI, AEI and RPI series suggests that they can all be transformed to series with linear trends by a logarithmic transformation and then approximately de-trended by differencing. An alternative approach, which produces similar curves once normalised, is to use the percentage change in the indices. Masters (1993) suggests that

“using the percent price change would remove the effect of absolute price, often the best choice of all”.

Use of the annual percentage change provides deseasonalised data, and was the approach adopted using datasets from the SML and the National Statistics Office.

4.4.2 Normalisation

Data normalisation is the process of standardising the possible numerical range that the input data vectors can take. It is particularly relevant in cases where input variables are of different range - without normalisation, the effects of a change in one can completely outweigh the effects of changes in other variables. Additionally, non-linear transfer functions will squash the possible output from a node into, typically, (0,1) or (-1,1). Refenes (1995) states that
“a target output which falls outside this range [of the transfer function] will constantly create large backpropogated errors and the network will be unable to learn the input-output relationship implied by the particular training pattern.”

Masters (1993) states that

“The rule of thumb employed by the author is to aim for the series to cover approximately 70 to 90 percent of the theoretical range of the output neuron’s activation function range. If predictions are excessively compressed, reduce the range as needed, but only as much as absolutely necessary.”

Azoff (1994) suggests that along channel normalisation should be performed as a single procedure on the whole of the available data (that is, the training and test sets should be combined and normalised together) - normalising the test set over only its own data can severely distort the test vectors, as the test set is usually a smaller sample set than the training set. It may not be possible to do this if forecasting future / completely unknown out-of-sample values, and it could be argued that the test data is no longer completely independent if it has been used in the normalisation process. However, although using the normalisation parameters of the training set subsequently to normalise the test set runs the risk that the test data will fall significantly outside the range of the training data, small departures from the range are not a problem (Azoff, 1994). In any event, normalising within a smaller range than the full range of the transfer function allows for the possibility of test set values lying outside the range used for normalisation without reaching the flat spot section of the function.
Given the range of the input variables and the time series being predicted, data normalisation was required before the training process could begin. Linear transformation (Srinivasan et al, 1994) was applied to the values within each time series.

\[
[a, b]: x' = \frac{(b - a)(x - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}})} + a \quad (4.1)
\]

An upper limit of 0.9 and lower limit of –0.9 were chosen so as to lie within the theoretical boundaries (-1 to +1) of the hyperbolic tangent (tanh) transfer function chosen for use in Neural Works. Although the transfer function within \textit{winGamma} has a different range (-1.5 to +1.5) to tanh, it was not necessary to renormalise the datasets as an examination of the input neurons weights showed that the values were linearly adjusted to lie within the range -1 to +1 irrespective of the input range.

External normalisation of each dataset was chosen in preference to within software normalisation (an option with both Neural Works and \textit{winGamma}). This was done so that individual datasets would be consistent across a number of inputs (for example, bank rate and bank rate 1 year previously would be normalised over the same range), to avoid normalisation over different ranges if datasets were partitioned, and to allow forecasts to be generated outside of the ANN software.

### 4.5 Training, Testing and Validation Sets

The data available for training and testing an ANN is commonly partitioned into three sub-sets called the training set, the validation set and the test set. The test set is different from the validation set, although the terms are sometimes interchanged in the literature. The usage adopted here corresponds with that of Bishop (1995) and of Stegemann and Buenfeld (1999).

\begin{itemize}
  \item \textbf{training set} - the data set used to train the neural network
  \item \textbf{validation set} - a set to test performance of the network during training, but not used for modifying the weights of the network
\end{itemize}
[This is part of the initial training data set, which is partitioned to provide the training and validation sets when validated training is used. It is not necessary to partition the data set when using winGamma.]

**test set** – an independent set of data which the neural network has not previously seen, which is used to test how well the neural network has learned to generalise.

Once a network has been trained using the training set (and the validation set where appropriate), its performance is tested by assessing its ability to forecast using the previously unseen test set data.

### 4.6 Neural Network Paradigms

#### 4.6.1 Number of input nodes

Getting the number of input nodes right is extremely important, since it largely determines the subsequent network design and its ability to forecast. A network should have sufficient nodes to allow the learning of the features embedded in the data, without so large a number that its prediction capability is adversely affected – a network with a large number of inputs may be unable to generalise sufficiently to produce a meaningful prediction. Zhang et al (1998) express the opinion that

> *the number of input nodes is probably the most critical decision variable for a time series forecasting problem since it contains the important information about the complex (linear and/or nonlinear) autocorrelation structure in the data*.

However, there is no widely accepted systematic way to determine the optimum length for the input vector (Zhang et al, 1998).

The choice of input variables for the networks was initially based on theory and availability (Section 4.2).
4.6.2 Number of hidden layers

Masters (1993) states that
"...there is no theoretical reason ever to use more than two hidden layers”, that
"...for the vast majority of practical problems, there is no reason to use more than
one hidden layer. Those problems that require two hidden layers are only rarely
encountered in real-life situation.” and that “...using more than one hidden layer is
almost never beneficial.”

He suggests that:
1. the additional layer through which errors must be back-propagated makes the
   gradient more unstable, and that
2. the number of false minima usually increases dramatically.

The winGamma model building module allows only for building neural networks
with two hidden layers. However, using only a single neuron in the second hidden
layer is equivalent to a single hidden layer network with the addition of a further
non-linear scaling unit on the output. A number of networks were constructed with
varying numbers of neurons in the second hidden layer. Those with more neurons in
the second hidden layer trained faster, but the best forecasts produced were no better
than the best produced by networks with a single neuron in the second hidden layer.
However, the forecasting ability of the networks with multiple neurons in the second
hidden layer appeared to be much more sensitive to changes in the network
architecture – beyond a critical point, a small increase in the number of neurons in
the second hidden layer produced a rapid deterioration in the forecasting ability. As
what was required was a robust architecture that would not need to be fine-tuned for
varying input vectors using test data (and thus compromising its independence),
networks with a single neuron in the second hidden layer (quasi single hidden layer
networks) were adopted.

4.6.3 Number of hidden nodes

Choosing an appropriate number of hidden neurons for a neural network is an
extremely important, but generally a non-trivial, task. Too few may mean that the
network has insufficient computational power to learn the potentially complicated relationships within the data. Masters (1993) states that

“One of the thorniest issues in neural network training is local minima in the error function”

and that

“...using fewer hidden neurons often increases the likelihood of the learning algorithm becoming trapped in a local minimum.”

However, he also warns that

“...an excessive number of hidden neurons may cause a problem called overfitting.”

The problem of overfitting may occur when a network has so many hidden neurons that the network learns not only the general features of the training data but also irrelevant details of individual cases. It will then lose its ability to generalise and perform poorly when presented with previously unseen data.

Hecht-Nielsen (1987), using Kolmogorov’s Mapping Neural Network Existence Theorem, suggests $2n+1$ as the upper limit for the number of hidden layer nodes needed in order to ensure that ANNs are able to approximate any continuous function (where $n$ is the number of input nodes).

Although Hecht-Nielsen sets an upper limit on the number of hidden neurons which will approximate any function, it does not address the problem of overfitting. A number of rules of thumb have been suggested for the ratio of training samples to weights, for instance, 2 to 1 (Masters, 1993) or 10 to 1 (Weigend *et al*, 1990). Rogers and Dowla (1994) have suggested that there should be at least as many training samples available as there are weights in the network. For a single hidden layer network with $m$ hidden nodes and $n$ input nodes, the number of weights is $m(n + 1)$. Together these relationships provide an upper limit for the number of hidden nodes of the lower of:

$$m \leq \frac{\text{number of training samples}}{(n + 1)} \quad (4.2)$$

and
A series of networks were trained and tested with the number of hidden neurons varied incrementally between three and 47 \((2n + 1)\). The forecasts of the best large networks showed little gain over those of the best small networks. However, the worst forecasts produced by the small networks showed larger errors than those produced by the large networks – that is, the small networks appeared to offer a greater potential for failing to approach a global minimum. Accordingly, the number of hidden neurons was set to a large number within the upper boundaries set by equations 4.2 and 4.3.

### 4.6.4 Number of output nodes

The number of output nodes corresponds to the number of predictions to be produced as the output from a single network. Kaastra and Boyd (1996) state that

“Deciding on the number of output neurons is somewhat more straightforward since there are compelling reasons to always use only one output neuron”.

Masters (1993) also suggests that, whilst multiple predictions from one network are possible, they are generally best avoided. He argues that, since most training algorithms choose the network connection weights in such a way that the average error is minimised, the output(s) with the largest error(s) would dominate at the expense of those with less. For a time series, he concludes that

“The net result is that the 1-ahead prediction will almost always be inferior to what it could be if it were done alone.”

A single output node was used throughout these experiments.

### 4.6.5 Transfer functions

The transfer, or activation, function determines the relationship between inputs and outputs of a node and a network. In general, the transfer function introduces a
degree of non-linearity into the ANN and, in theory, any differential function can qualify as a transfer function. However, in practice, only a small number of bounded, monotonically increasing and differential functions are used.

The hyperbolic tangent (tanh) appears to offer some advantages when used as the transfer function (Bishop, 1995; Maier and Dandy, 1998), and was chosen for use in Neural Works.

The transfer function implemented within the \textit{winGamma} software package consists of an activation function

\begin{equation}
act(x) = \sum_{j=1}^{n} w_{ij} x_j
\end{equation}

(4.4)

where \( w_{ij} \) is the weight of the connection from unit \( j \) to unit \( i \) and \( x_j \) is the output of unit \( j \). The sigmoidal used by each neural node as an output function is

\begin{equation}
\text{sigmoidal (act)} = 1.5 \left( \frac{2}{1 + e^{-act/0.8333}} - 1 \right)
\end{equation}

(4.5)

The two transfer functions are graphed at Figure 4.3.
4.7 Evaluation Criteria

“The most common error function minimized in neural networks is the sum of squared errors.” (Kaastra and Boyd, 1996)

The winGamma software package (Section 3.4.2) estimates the least Mean Square Error that any smooth data model can achieve on the given data without over training. This value, or any chosen alternative, is then used as the target MSE against which the training MSE is evaluated during training (Figure 3.5).

4.8 Neural Network Training

“Training is a technique used to minimise the error of a network. The network weights are adjusted until the error is at a minimum or a predefined limit has been reached.” (Durrant, 2001)

Various criteria are used to determine the point at which training should stop. These include stopping when a fixed number of training samples have been presented to the network, when there is no further improvement in the training error, when a target training error is achieved, or when there is no further improvement in the forecasts obtained using an independent validation data set.

Independent validation allows the training algorithm to extract what information it can from the data before identifying a point beyond which it may be misled by noisy or ill-conditioned data. The data available for training the network is split into two parts, the training set and the validation set. The validation set is not used for training, but only for independently assessing the quality of the mapping being obtained from the training set. Training continues until there is no measurable improvement in the error of fit of the validation set (see Section 3.4.1.1, SaveBest). This was the option adopted when using NeuralWorks.
The proportion of the data held back for validation is not available to train the network, which may be a disadvantage in cases where the number of samples is limited. An alternative approach is to use the whole of the training set without partitioning, and to terminate training at a pre-determined measure of error (see Section 3.4.2.1.1, Gamma Test).

The Gamma Test provides an estimate of the Mean Square Error that can be achieved by a model. This MSE may be used as the pre-determined training error value at which to stop training in order to avoid overfitting. This was the approach adopted for all later experiments using \textit{winGamma}. In the majority of models, the training MSE approached, but did not reach, the target (Gamma Test) MSE. A similar effect has also been reported by Margetts et al (2001).

The failure of the training MSE to achieve the target MSE may reflect a failure of the model to achieve a global minimum – the Gamma MSE provides a lower bound on the MSE of the output, it does not guarantee that any particular model can necessarily achieve it. The approach adopted in terminating training was therefore to determine how long the model took to settle to a value close to the target MSE, and to allow it to continue to train for an additional time approximately four times the initial period.

\section*{4.9 Implementation}

Once a network is trained it may be used to produce forecasts. In the case of a univariate model, the output from the model is used as the next input in a moving window. This iterative process can be carried out within \textit{winGamma}. In the case of a multivariate model, neither NeuralWorks nor \textit{winGamma} can iterate using the output values. In this case, the process of testing requires that, if the output variable is also an input variable (or is used to calculate an input variable), new input vectors must be prepared one at a time and presented to the network to produce the next forecast in the iteration. A typical process might be:
Step 1: Present $t$ input vector to the network to produce $t+1$ output value
Step 2: De-scale $t+1$ output value
Step 3: Use de-scaled $t+1$ output value to calculate related input variables (for instance, use percentage increase in HPI to calculate new value of HPI and HPI/AEI)
Step 4: Normalise input variables
Step 5: Prepare $t+1$ input vector
Step 6: Present $t+1$ input vector to the network to produce $t+2$ output value, etc.

Table 4.2 Steps in forecasting using a neural network forecasting model.

This is a slow and labour intensive process. However, both NeuralWorks and winGamma provide a facility to export the trained weights for each neuron. It is possible to use these weights to build a model of the network in another environment or program, and to incorporate the iterative process described above within the model. For the experiments using regional data, described in Chapter 5, iterative models were built in Microsoft Excel. In this way it was possible to produce a series of within-sample and out-of-sample forecasts in a single operation.

4.10 Conclusions

The eight-step design methodology set out in Section 4.1 for designing a neural network was followed. It was found to provide a useful framework, guiding a logical progression from initial problem definition to implementation.
Chapter 5 – FORECASTING: UK AND REGIONAL HOUSING MARKETS

This chapter examines experiments to forecast regional housing markets and sets out the rationale for combining the UK and regional data into a single dataset. Experimental results, including comparisons with the 1999 Budget forecast, are reported, and methods for optimising network input are discussed.

5.1 Introduction

Two paradigms of forecasting were developed initially. Firstly, multivariate forecasting models were constructed. Multivariate forecasts of a given variable are based on values of one or more other series, often called explanatory variables.

Secondly, univariate forecasting models were constructed. Univariate forecasts of a given variable are based on a model fitted only to past observations of the given series. Takens’ Theorem (Takens, 1981) suggests that all influences on a time series are coded into the single time series. As reported in Section 5.2, the multivariate models outperformed the univariate models. Additionally, as univariate models are based on a single time series, only multivariate models could be applied to the later work of modelling aggregated regional housing markets (Section 5.3.2), since this involved combining multiple time series within a single model.

5.2 National Housing Market

Modelling the housing market with ANN was undertaken at the national level using both univariate and multivariate forecasting models. Both the validation model (NeuralWorks) and the Gamma test (winGamma) were used in each case to determine when to terminate training.
A series of training and testing sets were prepared. Given that the period of greatest risk occurs during the first 3 years of the mortgage (Jenkins, 2000), predictions of open market value 12 quarters ahead were chosen as a useful target. Each testing set therefore consisted of twelve consecutive quarters of the total dataset, with the remainder forming the training set (training and validation sets in the case of the validation model).

The trained networks were used to make successive one period (quarter) ahead forecasts. This was done by rolling the sample forward one period, using the predicted measure of house prices as an input, and making another one-step ahead forecast and so on.

The results of these experiments suggested that:

- a multivariate approach using a limited number of attributes identified in economic models outperformed a univariate approach, and that
- the Gamma Test approach outperformed the validation model for the same inputs.

The better performance of the multivariate models over the univariate may simply be the result of having too little historical data for the ANN to learn the underlying model.

“.... all such applications depend on the availability of adequate amounts of good-quality data. Takens’ theorem only guarantees reconstruction in a mathematically idealized sense. It cannot possibly rescue us if we have poor or insufficient data” (Stark, 2000).

5.3 Regional Housing Markets

5.3.1 Modelling individual regional housing markets

The regional housing markets were modelled for individual regions using the techniques applied at the national level, using the Gamma test within winGamma to terminate training. Initial results for both univariate and multivariate models were
not promising. An examination of the SML datasets for the individual regions revealed significant variation from quarter to quarter – the series appeared to be ‘noisy’ (for example, Figure 5.1). This could reflect genuine variations within the regional markets, reacting to short-term local conditions. An alternative, and more likely, explanation is that this volatility reflects the limited sample size used to construct each index. The SML index was constructed from a 5% sample of owner occupation mortgage purchases using a matrix approach, with the sample split into over 300 cells and each cell representing a unique combination of the five variables allowed for in the mix adjustment. In Wales, for instance, the Land Registry recorded approximately 15,000 sales a quarter, of which just under three-quarters were financed by mortgage. A 5% sample thus represents a quarterly sample size of only approximately 550 sales.

![Figure 5.1 Wales: annual percentage change in House Price Index](image)

Figure 5.1 Wales: annual percentage change in House Price Index

One method of judging the adequacy of a dataset for modelling is the M-test, which shows how the Gamma statistic estimate varies as more data is used to compute it.
The M-test is used to establish whether there are sufficient data to provide an accurate estimate of the Gamma statistic. The algorithm starts from a small subset of the data and gradually adds more points from the analysis dataset. If the Gamma estimate asymptotes then this suggests that there are sufficient data. The point of asymptote provides an estimate for the minimum data required to build a robust model.

The M-test was applied to the individual regional datasets. An example for Wales is shown at Figure 5.2. The Gamma value has not reached a steady asymptotic value. The results suggest that insufficient data are available within the individual regional datasets to enable robust models to be constructed.

![Figure 5.2 M-test: Wales multivariate - HPI annual % change](image)

**5.3.2 Modelling aggregated regional housing markets**

An examination of the regional datasets shows that the Northern Ireland house price index exhibits much greater divergence from the UK average than any of the other
regional house price indices for the period from 1968. Adair et al (1998), in examining the divergent behaviour of the Northern Ireland housing market relative to the national UK market, conclude that the primary factor influencing performance is disposable income, with risk arising from political instability a secondary factor. In view of this, and the at times wide variation between the NI and UK indices, the Northern Ireland house price index was not included in the aggregated models.

The average prices within each region were not all the same when the indices were set at 100 (1990), but they could be considered as reflecting a regional value against which to track changes. In any event, use of de-trended series (such as the annual percentage increase) reflects movements independent of the starting value. Changes in each index reflect price movements within the region – each region may be affected by similar mechanisms but local circumstances. Ashworth and Parker (1997) examined determinants of house prices in each of the regions of the UK. They concluded that there are broad similarities in the structure of house price equations across regions in England and Wales, but not Scotland or Northern Ireland.

Meen (1999) suggests that changes in regional house prices can be decomposed into three components: (i) movements that are common to all regions; (ii) variations reflecting differences in economic growth between the regions; (iii) structural differences in regional housing markets. It appeared from this that it might be possible to find a suitable single model for the regional housing markets. Therefore, as an alternative to modelling the regions independently, the regional datasets were aggregated, with the addition of nominal variables to indicate the regions. Broadly speaking, it was expected that a single model could encompass Meen’s three components by training with data composed of:

i). national macroeconomic variables

ii). regional claimant count, acting as a proxy variable for regional economic conditions

iii). nominal variables to identify the individual regions
5.3.3 Regional input data

Although an ANN can approximate any function arbitrarily well if there are sufficiently many hidden layer nodes, too many nodes can lead to overfitting (Qi and Maddala, 1999). A network in which overfitting has occurred fits the training data very well (learning everything including spurious features and noise) but generalizes or forecasts very poorly (Zhang et al, 2001). There is therefore a need to keep the number of inputs to the ANN relatively low in relation to the number of data sets available for training. Hill et al (1996) state that

“when the number of parameters in a network model is too large relative to the size of a training set, the model tends to ”memorize” the data rather than “generalize” from it.”

Choosing input data for the ANN involved striking a balance between supplying additional, possibly useful information, and increasing the number of node weights and the solution search space. Earlier work and theory suggested that useful variables would be:

• Bank of England rate
• Percentage change over 12 months in RPI
• Percentage change over 12 months in average earnings
• Seasonally adjusted claimant count as a percentage rate
• Percentage change over 12 months in HPI
• House price index / average earnings index (HPI/AEI)

The UK data was aggregated with the regional data and included in the datasets (effectively treated as an additional region).

Input vectors consisted of normalised values of each variable for $t$ and $t-4$ (that is, current quarter and the corresponding quarter one year previously). Although this increased the number of variables, it was expected that changes in the values of the variables as well as their actual levels could be significant. Chen (1994) has reported that the use of indicators like the rate of change and momentum can lead to improvements in financial market predictions. Adding nominal variables further
increased the number of inputs by eleven. However, aggregating the data also increased the size of the training dataset by a multiple of eleven, leading to a significant improvement in the ratio of training vectors to hidden layer weights.

The M-test was applied to the aggregated regional datasets. An example is shown at Figure 5.3. The Gamma value has approached a steady asymptotic value, suggesting that sufficient data are available within the aggregated datasets to enable robust models to be constructed.

![Gamma value vs Unique data points graph](image)

**Figure 5.3** M-test: aggregated regional multivariate - HPI annual % change

### 5.4 Annual Percentage Increase in Regional HPI

Networks were trained to forecast the annual percentage increase in the UK and regional HPI for the last three years (1999-2001) of the dataset. It was also decided to prepare models that could predict three overlapping three-year periods covering 1987 to 1992. This period covered a rapidly rising market, an abrupt turning point (peak), and a rapidly falling market – between 1989 and 1992 real house prices fell by about 25%. In each case, the data relating to the three-year period to be forecast
were removed from the total dataset to become the test set, and the remainder used as the training set.

The variables used to train the networks were:
- Bank of England rate at time \( t \) and \( t-4 \)
- Percentage change over 12 months in RPI at time \( t \) and \( t-4 \)
- Percentage change over 12 months in average earnings at time \( t \) and \( t-4 \)
- Seasonally adjusted claimant count as a percentage rate at time \( t \) and \( t-4 \)
- Percentage change over 12 months in HPI at time \( t \) and \( t-4 \)
- House Price Index / average earnings index (HPI/AEI) at time \( t \) and \( t-4 \)
- Nominal variables

The trained networks were used to make successive one period (quarter) ahead forecasts. This was done by rolling the sample forward one period, using the predicted measures of house prices as inputs, and making another one-step ahead forecast and so on. The results for each region and each of the prediction periods are graphed against actual values and presented in Appendix 2.

The forecast results of the annual percentage change in the house price index (HPI\%) were used to calculate the HPI. The actual and predicted values of the house price index were used to calculate the average and root mean square errors both for the best network and for the average of all the networks. The results are tabulated below at Table 5.1. The dates shown for each series correspond to the data used in the testing set (that is, data excluded from the training process).
### Forecasting Period: 1987 Q1 - 1989 Q4

<table>
<thead>
<tr>
<th>Region</th>
<th>Average Error (%)</th>
<th>RMS Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Networks Averaged</td>
<td>Best Network</td>
</tr>
<tr>
<td>UK</td>
<td>-4.8</td>
<td>-1.8</td>
</tr>
<tr>
<td>London</td>
<td>4.8</td>
<td>-0.1</td>
</tr>
<tr>
<td>Wales</td>
<td>-9.2</td>
<td>1.3</td>
</tr>
<tr>
<td>East Anglia</td>
<td>-9.4</td>
<td>-4.9</td>
</tr>
<tr>
<td>North West</td>
<td>-1.4</td>
<td>-1.2</td>
</tr>
<tr>
<td>East Midlands</td>
<td>-6.3</td>
<td>-1.6</td>
</tr>
<tr>
<td>West Midlands</td>
<td>-8.1</td>
<td>-5.1</td>
</tr>
<tr>
<td>Yorkshire &amp; the Humber</td>
<td>-5.6</td>
<td>-1.8</td>
</tr>
<tr>
<td>South West</td>
<td>-6.3</td>
<td>-2.5</td>
</tr>
<tr>
<td>Scotland</td>
<td>-13.9</td>
<td>-13.1</td>
</tr>
<tr>
<td>South East</td>
<td>-9.5</td>
<td>-3.9</td>
</tr>
</tbody>
</table>

### Forecasting Period: 1988 Q3 - 1991 Q2

<table>
<thead>
<tr>
<th>Region</th>
<th>Average Error (%)</th>
<th>RMS Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Networks Averaged</td>
<td>Best Network</td>
</tr>
<tr>
<td>UK</td>
<td>-7.6</td>
<td>-1.1</td>
</tr>
<tr>
<td>London</td>
<td>-5.6</td>
<td>-1.1</td>
</tr>
<tr>
<td>Wales</td>
<td>-10.2</td>
<td>-4.0</td>
</tr>
<tr>
<td>East Anglia</td>
<td>-8.1</td>
<td>-2.1</td>
</tr>
<tr>
<td>North West</td>
<td>-15.5</td>
<td>-4.6</td>
</tr>
<tr>
<td>East Midlands</td>
<td>-10.5</td>
<td>-2.1</td>
</tr>
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<td>West Midlands</td>
<td>-6.5</td>
<td>-6.4</td>
</tr>
<tr>
<td>Yorkshire &amp; the Humber</td>
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<td>-5.7</td>
</tr>
<tr>
<td>South West</td>
<td>-10.6</td>
<td>-8.0</td>
</tr>
<tr>
<td>Scotland</td>
<td>-7.9</td>
<td>-0.1</td>
</tr>
<tr>
<td>South East</td>
<td>-8.0</td>
<td>-5.4</td>
</tr>
</tbody>
</table>

Table 5.1 Forecasting of House Price Index
### Forecasting Period: 1990 Q1 - 1992 Q4

<table>
<thead>
<tr>
<th></th>
<th>Average Error (%)</th>
<th>RMS Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Networks Averaged</td>
<td>Best Network</td>
</tr>
<tr>
<td>UK</td>
<td>3.5</td>
<td>2.1</td>
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<tr>
<td>London</td>
<td>5.2</td>
<td>-2.0</td>
</tr>
<tr>
<td>Wales</td>
<td>5.6</td>
<td>4.1</td>
</tr>
<tr>
<td>East Anglia</td>
<td>13.7</td>
<td>6.8</td>
</tr>
<tr>
<td>North West</td>
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<td>0.7</td>
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<td>East Midlands</td>
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<td>2.5</td>
</tr>
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<td>West Midlands</td>
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<td>-0.2</td>
</tr>
<tr>
<td>Yorkshire &amp; the Humber</td>
<td>-4.0</td>
<td>3.0</td>
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<tr>
<td>South West</td>
<td>12.1</td>
<td>5.3</td>
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<tr>
<td>Scotland</td>
<td>0.3</td>
<td>-1.1</td>
</tr>
<tr>
<td>South East</td>
<td>12.8</td>
<td>6.1</td>
</tr>
</tbody>
</table>

### Forecasting Period: 1999 Q1 - 2001 Q4

<table>
<thead>
<tr>
<th></th>
<th>Average Error (%)</th>
<th>RMS Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Networks Averaged</td>
<td>Best Network</td>
</tr>
<tr>
<td>UK</td>
<td>0.4</td>
<td>-0.7</td>
</tr>
<tr>
<td>London</td>
<td>-10.2</td>
<td>-4.2</td>
</tr>
<tr>
<td>Wales</td>
<td>1.4</td>
<td>-0.6</td>
</tr>
<tr>
<td>East Anglia</td>
<td>15.0</td>
<td>1.3</td>
</tr>
<tr>
<td>North West</td>
<td>1.9</td>
<td>-1.4</td>
</tr>
<tr>
<td>East Midlands</td>
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<td>-1.4</td>
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<tr>
<td>West Midlands</td>
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<td>-0.1</td>
</tr>
<tr>
<td>Yorkshire &amp; the Humber</td>
<td>-1.8</td>
<td>-3.0</td>
</tr>
<tr>
<td>South West</td>
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<td>1.2</td>
</tr>
<tr>
<td>Scotland</td>
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<td>-1.0</td>
</tr>
<tr>
<td>South East</td>
<td>5.6</td>
<td>0.8</td>
</tr>
</tbody>
</table>

Table 5.1 (cont) Forecasting of House Price Index
5.5 The Budget 1999

In March 1999, the Treasury (HM Treasury, 1999b) forecast the SML house price-earnings ratio for the UK for the period 1999-2001. The networks trained to forecast the annual percentage change in the SML house price index (Section 5.4) were tested using the actual values of the non-housing input variables that occurred during this period. Whilst this offered a good demonstration that the networks appeared to have captured the underlying relationships, the results could not be compared directly with the Treasury forecast, which used only data projections available prior to the Budget. Accordingly, the networks were also tested using the Treasury three-year assumptions about RPI and unemployment (HM Treasury, 1999a 1999b), and the range of projections for average earnings. The forecast results of the annual percentage change in the house price index were used to calculate values of HPI/AEI. These, together with the re-scaled Treasury forecast, are graphed at Figure 5.4 and Figure 5.5. Similar comparisons undertaken for the 2005 and 2008 budgets are detailed in Chapter 7.

![Figure 5.4 HPI/AEI: comparison of ANN and 1999 Budget forecasts](image-url)
The results shown as ‘UK – Model Prediction’ were those forecast using the actual 1999-2001 values of RPI, average earnings and unemployment in the models. The results shown as ‘UK – Model Prediction (Budget(1))’ and ‘UK – Model Prediction (Budget(2))’ were those forecast using in the models the varying estimates of average earnings and the Treasury assumptions of RPI and unemployment. These forecasts, together with the Treasury forecast, were used to calculate values for the UK house price index for the period Quarter 1 1999 to Quarter 4 2001. The average and RMS errors of these forecasts are tabulated at Table 5.2.

<table>
<thead>
<tr>
<th></th>
<th>Average error (%)</th>
<th>RMS Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>UK - Model Prediction</td>
<td>0.4</td>
<td>1.6</td>
</tr>
<tr>
<td>UK - Model Prediction (Budget (1))</td>
<td>-4.7</td>
<td>6.1</td>
</tr>
<tr>
<td>UK - Model Prediction (Budget (2))</td>
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</tr>
<tr>
<td>HMT Prediction</td>
<td>-13.8</td>
<td>14.6</td>
</tr>
</tbody>
</table>

Table 5.2 Comparison of ANN and 1999 Budget forecasts of HPI
Although the networks gave reasonable results, and clearly outperformed the 1999 Budget prediction, it was not possible to know whether a different set of variables and lags might have produced better forecasts. The next stage was to investigate methods for choosing the variables to include in the input vectors. What was sought was an objective way of choosing input variables, lags and methods of combining the regional data.

5.6 Optimising Network Input

The decision on which variables to use to train the networks to forecast the annual percentage change in HPI for the regions was based on earlier work and theory (Section 5.3.2). However, it was not clear whether the most appropriate inputs and lags had been chosen. Two methods for optimising the network inputs were investigated. These were the use of genetic algorithms within winGamma (Section 5.6.1), and an examination of the relationship between in-sample forecasts and out-of-sample forecasts (Section 5.6.2).

5.6.1 Model identification – genetic algorithm

The Model Identification options within winGamma are designed to assist in identifying the best choice of inputs for predicting a given output. The Full Embedding option tries every combination of inputs to determine which combination yields the smallest absolute Gamma value. Running this option for twenty inputs involves testing over a million combinations of inputs ($2^{20} - 1$), and takes about one day on a fairly fast PC. For each additional input included in the Full Embedding, the number of combinations (and hence the time to run the test) approximately doubles ($(2^{n+1} - 1)/(2^n - 1)$). As the intention was to examine a large number of candidate inputs, the Full Embedding option was impractical and the Genetic Algorithm was therefore used.
The Genetic Algorithm option searches the space of all masks using a Genetic Algorithm (GA) to find good embeddings. The parameters which can be used to control this search include (Jones et al, 2001):

*Population Size* The size of the population of masks being used throughout the search.

*Gradient Fitness* The weighting in the GA fitness function for masks giving a low gradient in the Gamma Test. Increasing this weighting will place more emphasis on the relative simplicity of the modelling function.

*Intercept Fitness* The weighting in the GA fitness function for masks with a low absolute value of the Gamma statistic. Increasing this weighting will place more emphasis on the model accuracy.

*Length Fitness* The weighting in the GA fitness function for masks with a given number of ‘1’s. Increasing this weighting will encourage the selection of masks with fewer ‘1’s and thereby place more emphasis on simpler models.

*Run Time* The maximum time selected to perform the GA.

For long masks (that is, a large number of inputs) and large data sets the GA requires runs of several hours.

The objective of using the Genetic Algorithm was to determine whether all the variables used in the previous models were useful, and to attempt to identify the best lags to use. Accordingly, two datasets were constructed, one with a window length of six for each variable (that is, values at $t$, $t-1$, ..., $t-5$) and one with window length twelve (that is, values at $t$, $t-1$, ..., $t-11$). The variables included were Bank of England rate, percentage change over 12 months in RPI, percentage change over 12 months in average earnings, seasonally adjusted claimant count as a percentage rate, House Price Index / average earnings index (HPI/AEI) and percentage change over 12 months in HPI. The input vectors were constructed by concatenating together the windows of normalised values for each of the variables, together with the corresponding normalised output value. Nominal variables were also included.
Alexander and Barrow (1994), using statistical tests, established that a set of relationships exists between regional house prices, and that the South-East appears to lead the rest of the country. This lead-lag relationship could represent leads/lags in economic conditions in the different regions, or it could be an indication that different regions react at different rates to national changes. If the latter, the inclusion of time as an input variable, together with the regional nominal variables, might improve forecasting performance. A normalised date variable was therefore included in the input vectors.

The two datasets were loaded into winGamma project files, and the Genetic Algorithm Model Identification option was then run a number of times with different fitness weightings (the three weightings chosen for GA fitness should sum to one). The results of each experiment were then analysed by totalling the number of times each lagged observation occurred within the final population of masks determined by the Genetic Algorithm. Examples are shown at Figure 5.6.

![Bank Rate and Claimant Count Graphs](image)

*Figure 5.6 Results of Model Identification Genetic Algorithm*
The results obtained varied depending on the relative weightings chosen for gradient, intercept and length fitness. The most common features were a very low occurrence in the final population of masks of HPI change at times $t$ and $t-1$, zero or low occurrences for date, and a relatively even distribution of the lagged observations for each of the other variables when examined across the series of experiments. No single observation or pair of lagged observations from each variable were obvious candidates for inclusion in the final dataset. It did appear likely that the information contained in the lagged observations of the first six quarters could all contribute to the model. However, the inclusion of all these inputs would have resulted in a very large input vector in relation the number of training examples available. It was therefore decided to proceed to the next step using the original choice of lagged variables at $t$ and $t-4$. This provided an indication of the current values and a year-on-year comparison, thus providing an indication of
movement and avoiding the introduction of possible seasonality. Although the value of changes in the House Price Index at time $t-4$ was a strong candidate for inclusion and the value at time $t$ was not, both were included for the same reasons.

### 5.6.2 Within-sample forecasts

The final MSE achieved by *winGamma* only measures how well a network has learned to forecast a single step ahead using the training set. These MSE results (which were, in any case, all of a similar order of magnitude) were not found to offer a useful guide to which networks might provide the best forecasts. However, the decision to produce out-of-sample forecasts by an iterative process within Microsoft Excel meant that it was also relatively straightforward to produce in-sample forecasts at the same time. It was therefore decided to produce within sample forecasts covering three years (twelve quarters) to measure how well the networks had ‘learnt’ to forecast generally rather than just a single step ahead. Forecasts were produced for the period 1972 Q1 to 1974 Q4, and then at overlapping periods advanced by six quarters each time (1973 Q3 to 1976 Q2, 1975 Q1 to 1977 Q4, etc) until 1996 Q1 to 1998 Q4.

The initial series of networks were trained using as variables the Bank of England rate, the percentage claimant count, the percentage change over 12 months in HPI, RPI and average earnings, and the ratio HPI/AEI (Section 5.3.3). Each set of variables had been normalised using the total UK and regional data as a single dataset. An alternative would have been to normalise the data for each region separately – in essence, to normalise each in terms of its position within its measured range rather than on the basis of a numerical value across the UK as a whole.

A series of networks were trained for each of the combinations of variables set out in Table 5.3, normalised both by UK total and individually by region. The aim was to see whether in-sample forecasts could be used as a means of identifying those input selections most likely to produce the best out-of-sample forecasts.
Chapter 5 – Forecasting: UK and Regional Housing Markets

The trained networks were each used to produce forecasts for the UK and the regions - out-of-sample forecasts for the period 1999 Q1 to 2001 Q4, and in-sample forecasts for the periods 1972 Q1-1974 Q4 to 1996 Q1-1998 Q4. The results for each network were then used to produce a single average in-sample Root Mean Squared Error (RMSE) and a single out-of-sample RMSE. The results for all the networks with the same input variable selection were then used to produce a single average in-sample RMSE and a single average out-of-sample RMSE for that experiment. The average errors for all the experiments are graphed at Figure 5.7.

Table 5.3 Input selection for winGamma networks

<table>
<thead>
<tr>
<th>Normalised by Region</th>
<th>Normalised by Total</th>
<th>Date</th>
<th>Nominal variables</th>
<th>AEI%</th>
<th>AEI%t-4</th>
<th>Bank rate</th>
<th>Bank rate-t</th>
<th>Claimant count</th>
<th>Claimant count%</th>
<th>RPI%</th>
<th>RPI%t-4</th>
<th>HP/AEI</th>
<th>HP/AEI-t</th>
<th>HP%</th>
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The trained networks were each used to produce forecasts for the UK and the regions - out-of-sample forecasts for the period 1999 Q1 to 2001 Q4, and in-sample forecasts for the periods 1972 Q1-1974 Q4 to 1996 Q1-1998 Q4. The results for each network were then used to produce a single average in-sample Root Mean Squared Error (RMSE) and a single out-of-sample RMSE. The results for all the networks with the same input variable selection were then used to produce a single average in-sample RMSE and a single average out-of-sample RMSE for that experiment. The average errors for all the experiments are graphed at Figure 5.7.
The points in Figure 5.7 appear somewhat scattered, possibly due to the relatively small number of networks, ten, trained in each experiment. However, the data return a Pearson’s correlation coefficient of 0.677 (significant at the level 0.005), which suggests that the average in-sample forecasting error may be used to help identify those experiments most likely to provide good average out-of-sample forecasts and those unlikely to do so.

On the basis of these results, it would appear that the networks trained using data normalised for the whole of the UK as a single dataset can be expected to outperform those trained using data normalised by region. Additionally, it appears that the inclusion of date has a neutral or slightly negative effect, and that the networks appear to benefit from the inclusion of nominal variables and lagged inputs for $t$ and $t-4$.

The fact that the inclusion of date in the input vector does not improve the forecasting ability of the networks may arise for a number of reasons. Two possible explanations are that:
• the extra input carries little or no useful additional information, but increases the solution space and complicates the model that the network is required to produce,

• the model attempts to generalise temporal variations when in reality the regions may lead or lag each other.

5.7 Network Selection

It was clear from the results at Section 5.4 that some trained networks forecast better than others. The next stage was to investigate possible methods of choosing those networks that were most likely to produce better forecasts. In particular, what was sought were criteria for judging which models were most likely to provide good forecasts without being able to test against forecasting data (that is, to build optimised models to be used to predict unknown, future values).

In addition to the average RMSE of forecasts for all the in-sample periods for each network model (Section 5.6.2), the minimum and maximum forecasting RMSE achieved by each model for individual time periods were also calculated. The average RMSE of forecasts is a measure of how well a network model has learnt the general structure of the data, but a relatively low average error value does not guarantee that the network has learnt all sections well. A network might produce forecasts with low errors for most of the range on which it had been trained, but perform badly under particular conditions. However, the maximum forecasting error does set an upper error limit on the network’s in-sample performance.

If each output is determined from the inputs by a deterministic process which is the same for both training and test sets, the out-of-sample forecasting RMSE for a network should generally lie within the limits of the minimum and maximum RMSE of that network (depending on whether the test data corresponds more or less to the sections of the training data that the network has learnt best). The out-of-sample forecasting RMSE would be expected to be the minimum or the maximum RMSE for the network on occasions. However, if it generally exceeds the in-sample
maximum, this could indicate that the training and test sets are dissimilar and that the network has failed to learn the conditions represented by the test set.

**Figure 5.8 Comparison of maximum in-sample RMSE and out-of-sample forecasting RMSE**

A comparison of in-sample and out-of-sample forecasting errors are graphed at Figure 5.8. The majority of the points fall to the right of the diagonal line defined by maximum in-sample RMSE equal to out-of-sample RMSE, suggesting that the training and test sets are representative of the same deterministic processes.

The graph also suggests that it may be possible to improve the choice of which networks to use for forecasting. It is not possible to choose the best networks on the basis of the in-sample RMSE, since some of the lowest out-of-sample RMSE are associated with moderately high maximum in-sample errors. However, eliminating networks with high maximum in-sample RMSE greatly reduces the chance of using networks with high out-of-sample forecasting errors.
5.8 Conclusions

The problem of limited data availability was addressed by aggregating data for the UK and the regions within single neural network models. These networks appeared able to model underlying relationships better and to generalise better. The fact that a single model was able to encompass the UK and the regions supports the view that each region may be affected by similar mechanisms but react to local circumstances.

Neural networks were demonstrated to be successful in producing time series forecasts of changes in the housing market. They successfully modelled the direction, timing and scale of annual changes in house prices, both for an extremely volatile and difficult period (1987 to 1991) and for the period 1999 to 2001. In the latter case, using HM Treasury’s own data from the 1999 Budget, the neural network models outperformed the 1999 Budget predictions of housing market changes.
Chapter 6 – FORECASTING: OPENING THE BLACK BOX

This chapter examines ways to identify and rank the most significant network inputs at different times in the market cycle, and discusses the use of prediction surfaces to identify relationships between particular pairs of inputs.

6.1 Introduction

One of the criticisms frequently levelled at neural networks is that they are black box systems - that is, they take input data, process them, and give output data. In general, precisely what is going on inside the network (inside the 'black box') is unknown. This means that the relationship between the input variables and the output variable(s) cannot readily be determined. However, it is possible to go some way to remedying this by using Sensitivity Analysis.

Sensitivity Analysis (SA) is the study of how the variation in the output of a model can be apportioned, qualitatively or quantitatively, to variations in the inputs to the model. In this way it is possible to rank the inputs of a network in order to arrive at their relative influence on the final output.

6.2 Sensitivity Analysis of Regional Networks

The strength of the relationship between the output variable and each of the input variables may be determined with the aid of sensitivity analysis. As part of this, each of the inputs is altered by a certain percentage (e.g., 5%) in turn whilst the other inputs remain fixed. The change in the output caused by the change in the input is calculated, and the sensitivity of each input is given by:

\[
\text{Sensitivity} = \frac{\% \text{ change in output} \times 100}{\% \text{ change in input}}
\]  

(6.1)
In order to undertake sensitivity analysis for the regional networks, input vectors were prepared for seven different quarters. These were 1982 Q1, 1986 Q3, 1988 Q3, 1989 Q3, 1992 Q4, 1996 Q2 and 2002 Q4, shown at Figure 6.1.

These dates were chosen for the following reasons:

- **1982 Q1** The annual percentage change in HPI was at a local minimum, showing a slight fall year on year (-0.2%). HPI/AEI was at a local minimum.

- **1986 Q3** The annual percentage change in HPI showed an annual increase approximately half the following maximum (1988 Q4), with the annual rate steadily increasing. HPI/AEI was rising.

- **1988 Q3** The annual percentage change in HPI was extremely close to the local maximum value, one quarter before the turning point (already at the turning point in some regions). HPI/AEI was approaching the local maximum value, four quarters before the turning point.
• 1989 Q3  The annual percentage change in HPI showed an annual increase approximately half the preceding maximum (1988 Q4). The value of the annual rate of increase was rapidly falling. HPI/AEI was at a local maximum.

• 1992 Q4  The annual percentage change in HPI was at a local minimum, showing a fall year on year (-7.4%). HPI/AEI had gone through a period of rapid decrease, which was to be followed by a period of slow decrease to the local minimum (1996 Q2).

• 1996 Q2  The annual percentage change in HPI showed a low annual increase (+1.1%) following slow market recovery. This was to be followed by an increasing annual rate of increase. HPI/AEI was at a local minimum.

• 2002 Q4  The annual percentage change in HPI was at a local maximum, with HPI/AEI steadily rising.

A series of input vectors was prepared for each date. The first of each series was prepared by entering the actual value at the relevant date for each of the input variables. The output from this provided the baseline value from which to calculate changes. Each input was then increased in turn by five percent of the normalised range whilst the other inputs retained their actual value. A second set of vectors was then prepared in the same way, but decreasing each input in turn by five percent.

The ten networks with the best in-sample forecasts – that is, those with both low average and low maximum in-sample forecasting RMSE - were identified. The series of input vectors for each date were used to produce output values. Equation 6.1 was then used to calculate values of sensitivity for each input at each date. The value of sensitivity for each input was taken as the average of the two values for plus and minus five percent changes – this was done to minimise the effects of any asymmetry in the response of the network.

The results from the ten networks were combined to produce average sensitivity values for each input and date. The results are graphed at Appendix 3.
The absolute value of the sensitivity for the different input variables provides an indication of the relative effect that the variables have on the output. These have been ranked for the UK for each date, and are set out at Table 6.1. The input variables have been listed in order of their average rank. The ranked sensitivity for the different input variables for each date and region are tabulated at Appendix 3.

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<td>6</td>
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Table 6.1 Rank of input variables by date for UK

Table 6.1 shows that the input variable ranked first for its effect on the annual percentage change in the House Price Index at time \(t+1\) for all periods is the annual percentage change in HPI at time \(t\). There are a number of reasons why this may be so. The process of house purchase may take from a few weeks to several months, so that prices agreed in one quarter may not result in the completion of a sale until one or more quarters later. This will tend to smooth out changes in HPI so that the annual change in one quarter is likely to be a reasonable indicator of the change in the subsequent quarter. In addition, the perceived view of the housing market is also likely to affect buyer/seller behaviour. In a market where prices are perceived to be rising rapidly, a seller is more likely to feel confident in refusing to accept less than the asking price and a buyer is more likely to agree to meet it in fear that the purchase will be lost (and that prices may have risen further by the time a further property is found). Conversely, in a falling or stagnant market, a buyer may feel
more confident in seeking to negotiate a lower price, and a seller feel more constrained to accept in case the sale is lost. One of the key elements informing this buyer/seller behaviour is likely to be the widely published information on changes in property prices.

Chen et al (2007) reported similar results for the Taiwan housing market, stating that

“The results indicate that disturbance originating from house price itself inflicted the greatest variability on future prices.”

and that

“This result indicates that current changes in house price influence heavily people’s expectation of future price changes.”

The next most significant group of input variables consists of the annual percentage changes in RPI and average earnings at time $t$, and claimant count at times $t$ and $t-4$. These variables appear to act in pairs, and are discussed in more detail at Section 6.3.

In addition to the differing ranks of the input variables at different times, there are also differences in the overall sensitivity that the networks display at these times. This is clearly seen in the graphs at Appendix 3. The overall sensitivity may be quantified by calculating the average absolute sensitivity of all the inputs. If this is done, the values of overall sensitivity at different dates may be compared and ranked (Table 6.2).

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*Table 6.2 Rank of overall sensitivity by date for UK*

The overall sensitivity at the most sensitive period (1988 Q3) exceeds that at the least sensitive period (1992 Q4) by a factor in excess of six. The sensitivity values for each input at these two dates are combined in the graph at Figure 6.2.
The sensitivity analysis graphs (Appendix 3) show that changes in the House Price Index are relatively less sensitive to changes in all the variables during market lows (1982 Q1, 1992 Q4 and 1996 Q2). However, one variable, the ratio of House Price Index to Average Earnings Index at time $t-4$, is of relatively low rank when the market is buoyant but of high rank during the market lows. At these times its negative sensitivity has a major effect on the forecasts of changes in HPI. This may indicate that a major factor in determining price movement in a depressed market is whether real prices appear high in a historical context.

6.3 Prediction Surfaces

At first sight, some of the sensitivity analysis results appear counter-intuitive. In particular there appears to be a negative sensitivity with the annual rate of change of RPI at time $t$. It might have been expected that the House Price Index would
increase more during periods of high RPI increases - that is, share in the general inflation. However, examination of the results for other inputs suggests that the positive sensitivity with the annual rate of change of average earnings and the negative sensitivity with the annual rate of change of RPI may be linked. In effect, it may be the relationship between two linked variables which affects the House Price Index. In terms of the individuals who make house purchases, whether their pay increases are greater or less than general inflation may be far more significant than the absolute levels of increase.

The positive sensitivity for claimant count at time $t-4$ also appears to run counter to expectation. The market might be expected to fall when unemployment is high and vice versa. However, this input also appears to be linked to another, in this case the negative sensitivity for claimant count at time $t$. If claimant count at time $t-4$ is greater than claimant count at time $t$ (that is, unemployment is falling), then the net result is a positive effect on house price increases. If unemployment is rising, when claimant count at time $t$ exceeds claimant count at time $t-4$, the effect will be to suppress house price rises.

These results offer some support to the assertion by Masters (1993) that model building techniques which add a single input variable at a time to assess whether they lead to significant improvements in model performance may be unable to capture the importance of certain combinations of variables that might be insignificant on their own.

The apparent relationships between RPI and average earnings, and between claimant count measurements a year apart, are displayed in the prediction surfaces at Appendix 4. The results are displayed as both 3-D surface graphs and contour graphs. These surfaces were generated in a similar way to the sensitivity results, but by varying two input variables against each other whilst keeping all the others fixed. The output values were then plotted against the two input variables to produce the prediction surfaces. These were prepared for the same dates as those used for the sensitivity analysis.
6.3.1 Prediction surface – average earnings v RPI

A contour map of the 1988 Q3 prediction surface for annual changes in the UK House Price Index calculated for differing annual changes in average earnings and RPI is shown at Figure 6.3. The period 1988 Q3, of the ones chosen to model (Section 6.2), displays the highest sensitivity to changes in both average earnings and RPI.

[Contour map image]

Figure 6.3 Contour map of UK 1988 Q3 prediction surface - average earnings v RPI

Two lines, A - A' and B – B', on Figure 6.3 are displayed as cross-sections at Figures 6.4 and 6.5.
The cross-section A - A' at Figure 6.4 represents the line of the annual change in average earnings equal to the annual change in RPI. The neural network models predict that, so long as they are equal, the actual values of increases in average earnings and RPI have little effect on the annual rate of change in the House Price Index over most of the range.

Lines parallel to the line A – A'' in Figure 6.3 represent points for which the change in average earnings differ by a fixed amount from the change in RPI. Those to the upper left of A – A’ represent average earnings increases lagging behind inflation, those to the lower right average earnings increases exceeding inflation. The fact that the contours of Figure 6.3 lie roughly parallel to the line A – A' demonstrates that changes in HPI are relatively insensitive to the actual values of changes in average earnings and RPI so long as the difference between them is constant. Changing the value of this difference (moving in the direction B – B') does appear to have a greater effect.

Figure 6.4 UK 1988 Q3, cross-section A - A' - average earnings v RPI
Figure 6.5 UK 1988 Q3, cross-section B - B' - average earnings v RPI

The cross-section B - B' at Figure 6.5 represents the line running from low annual increase in average earnings and high annual increase in RPI (B) to high annual increase in average earnings and low annual increase in RPI (B'). Point B therefore represents a situation where pay increases lag significantly behind overall increases in inflation. This is characterised by a housing market showing very little growth – that is, a housing market which is failing to keep pace with overall inflation, and which is therefore demonstrating an effective reduction in the real value of property.

By contrast, B' represents a situation where pay increases show a significant lead over overall increases in inflation. This is characterised by a market of rapidly rising house prices, with increases exceeding inflation.

Although the slopes of the prediction surfaces differ for the different periods, the overall shapes are similar – the relationships are similar for different market conditions, although the magnitudes of the effect may differ. These results do suggest that increases in the House Price Index are indeed much more affected by whether pay increases are greater or less than general inflation, and that it is the
difference between these which is far more significant than the absolute levels of increase.

### 6.3.2 Prediction surface – claimant count

A contour map of the 1986 Q3 prediction surface for annual changes in the UK House Price Index calculated for differing claimant count rates at \( t \) and \( t-4 \) is shown at Figure 6.6. The period 1986 Q3 displays the highest sensitivity to changes in claimant count rate for both \( t \) and \( t-4 \).

![Figure 6.6 Contour map of UK 1986 Q3 prediction surface - claimant count rate](image)

Two lines, \( A - A' \) and \( B - B' \), on Figure 6.6 are displayed as cross-sections at Figures 6.7 and 6.8.
The cross-section A - A' at Figure 6.7 represents the line of equal claimant count rates at \( t \) and \( t-4 \) – that is, the rate of unemployment neither rising nor falling. The neural network models predict that, so long as they are equal, the actual values of claimant count rate have little effect on the annual rate of change in the House Price Index.

Figure 6.7  UK 1986 Q3, cross-section A - A' - claimant count rate
The cross-section B - B’ at Figure 6.8 represents the line running from a low claimant count rate at \( t \) and a high claimant count rate at \( t-4 \) (B) to a high claimant count rate at \( t \) and a low claimant count rate at \( t-4 \) (B’). That is, B represents a time of very rapidly falling unemployment, which is characterised by rapidly rising house prices. By contrast, B’ represents a time of very rapidly rising unemployment, which is characterised by a market showing very little growth.

The curve at Figure 6.8 is at its steepest around the point at which the claimant count rates at \( t \) and \( t-4 \) are equal. The regions to either side of this point represent the employment market moving into either rising or falling unemployment. The former could be interpreted as a downturn in the economy, which might be expected to lead to market pessimism. The latter could be interpreted as an upturn in the economy, which might be expected to lead to market optimism. Although the effects of increasing rates of fall or rise in unemployment are reflected in the magnitude of the annual change in the House Price Index, it appears that the main effects are manifested over quite a narrow region around a static employment market. The very
fact of an upturn or downturn in the employment market, and by proxy in the economy, appears to be the main driver on changes in the housing market. In a similar way to that identified in Section 6.3.1, although the slopes of the prediction surfaces differ for the different periods, the overall shapes are similar – the relationships are similar for different market conditions, although the magnitudes of the effect may differ.
Chapter 7 – Forecasting: Extending the Timescale

This chapter examines the use of committees of networks to produce forecasts, and examines the results obtained for the extended forecasting horizon from 2002 to 2007. Changes in the housing market are discussed. Forecasts for the period 2008 to 2010 and the impact of credit restrictions are discussed.

7.1 Introduction

Following the initial success of forecasting changes in the House Price Index for the UK and the Regions (Section 5.4), a further series of neural networks was trained using the original training data. That is, the training set used data covering the period from 1971 Q2 to 1998 Q4 with the variables:

- Bank of England rate at time $t$ and $t-4$
- Percentage change over 12 months in RPI at time $t$ and $t-4$
- Percentage change over 12 months in average earnings at time $t$ and $t-4$
- Seasonally adjusted claimant count as a percentage rate at time $t$ and $t-4$
- Percentage change over 12 months in HPI at time $t$ and $t-4$
- House Price Index / average earnings index (HPI/AEI) at time $t$ and $t-4$
- Nominal variables

The trained networks were each used to produce a set of in-sample twelve-quarters forecasts, as described in Section 5.6.2. The maximum Root Mean Squared Error for each network was then determined. These maximum RMSE values were then used to select the networks to be used for forecasting. As described in Section 5.7, it is not possible to choose the best networks on the basis of the in-sample RMSE, since low out-of-sample forecasting errors may be associated with networks with high maximum in-sample errors. However, eliminating networks with high
maximum in-sample RMSE greatly reduces the chance of using networks with high out-of-sample forecasting errors.

### 7.2 Committees of Networks

Choosing an individual network to produce forecasts is problematical. A network that has been selected as performing best (by testing on a validation set or by other means) may not have the best performance on new test data. One way round this is to combine a number of networks together to form a committee.

A simple committee of networks involves averaging the forecasts of a number of individual networks. An alternative approach, of actively combining the committee members during the forecasting process, was also considered. This active committee of networks was intended to examine the possibility that the committee might produce better forecasts if individual networks used the committee (that is, the averaged) predicted results for each period in the time series forecast as the input for the next input vector. This was tested by taking the ten networks with lowest in-sample maximum RMSE for the UK and combining them in a simple committee of networks. The same ten networks were then combined in an active committee of networks. The forecasting process for the active committee (similar to that set out in Table 4.2 for a single network) is detailed at Table 7.1.
Chapter 7 – Forecasting: Extending the Timescale

Table 7.1 Steps in forecasting using an active committee of networks.

The simple and the active committees were used to forecast changes in the House Price Index for the UK for the period 1999 Q1 to 2001 Q4. The RMS errors for the two committees are set out at Table 7.2, and the forecasts, together with the actual changes in HPI, are graphed at Figure 7.1.

<table>
<thead>
<tr>
<th>Table 7.2 Comparison of errors of active and simple committees of networks</th>
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<td>RMS error - active committee of networks:</td>
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<td>RMS error - simple committee of networks:</td>
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In the absence of any improvement of results by using active committees of networks, there appeared to be significant advantages to adopting simple committees of networks. They require little effort to produce, since only averaging of the predictions is required, whilst active committees require procedures to be built to share results at each step of the time series forecast. In addition, it is relatively easy to add any number of individual networks to a simple committee. These networks need not necessarily be trained using the same input variables or network architecture, since only the predicted values are utilised. Subsequent investigations were therefore undertaken using only simple committees of networks.

### Figure 7.1  Comparison of active and simple committees of networks

In the absence of any improvement of results by using active committees of networks, there appeared to be significant advantages to adopting simple committees of networks. They require little effort to produce, since only averaging of the predictions is required, whilst active committees require procedures to be built to share results at each step of the time series forecast. In addition, it is relatively easy to add any number of individual networks to a simple committee. These networks need not necessarily be trained using the same input variables or network architecture, since only the predicted values are utilised. Subsequent investigations were therefore undertaken using only simple committees of networks.

### 7.3  Extending the Forecasts

Simple committees of networks were used to predict changes in the House Price Index for the UK and the regions. The choice of networks for inclusion in the
committees was made by excluding those with a high maximum in-sample forecasting RMSE. Accordingly, only networks with a maximum RMSE less than twice the maximum RMSE produced by the ‘best’ network were selected for forecasting – the choice was somewhat arbitrary, but resulted in the selection of approximately thirty percent of the total of trained networks. Data on the Bank of England rate, claimant count, RPI and average earnings for the period 2002 Q1 to 2007 Q4 were added to the test data. The networks selected for inclusion in the committees of networks were then used to predict changes in the House Price Index for the period 1999 Q1 to 2007 Q4, using the procedure set out in Table 4.2.

The forecasts of annual changes in the House Price index by the individual networks were combined to produce a simple committee of networks forecast for each region. The result for the UK is graphed at Figure 7.2. The results for the regions are graphed at Appendix 5.

![Figure 7.2 Annual percentage change in HPI: simple committee of networks forecast - UK](image_url)
Although the committees of networks produce reasonable predictions of changes in the House Price Index until the end of 2001, they fail to forecast the increases in subsequent years. This may indicate that the networks have failed to learn the relationships fully. An alternative explanation is that there has been a change in the housing market in the period from 2002 – that is, the conditions prevailing in the market were not represented in any of the previous data used to train the neural networks. A comparison of the in-sample and out-of-sample forecasting errors for the UK for the period 2002 Q1 to 2004 Q4 are graphed at Figure 7.3. The points fall on or to the left of the diagonal line defined by maximum in-sample RMSE equal to out-of-sample RMSE, suggesting that the training and test sets may not be representative of the same deterministic processes (see Section 5.7).

The committees of networks were not unique in forecasting a slowdown in the housing market. Many commentators predicted a slowdown or even the possibility of the bursting of a housing ‘bubble’. Farlow (2002) suggested that:
“Today is probably the riskiest time in a generation to get on to the property ladder.”

By 2004, the Centre for Economics and Business Research was suggesting that “average UK house prices will be no higher in 2007 than in 2004” (2004b) or that house prices might even show a fall (2004a; 2004c).

The value of the House Price Index forecast by the committee of networks was approximately 38 percent lower than the actual value in 2007. As explained in the following section, there have been a number of changes in the housing market. However, these changes may not be permanent. The International Monetary Fund (2008) has commented that

“The countries that experienced the largest unexplained increases in house prices were Ireland, the Netherlands, and the United Kingdom—by the end of the decade [1997 to 2007], house prices in these countries were about 30 percent higher than justified by fundamentals.”

and that

“Countries that look particularly vulnerable to a further correction in house prices are Ireland, the United Kingdom, the Netherlands, and France.”

7.4 Changes in the Housing Market

One of the most obvious changes in the housing market has been the increase in the value of the ratio of the House Price Index to the average earnings index, which is graphed at Figure 7.4. By mid 2002, this had equalled the previous peak value reached in 1989 Q3, and by 2007 Q3 the value for the UK was 36% higher than that reached eighteen years previously. This may, in part, reflect changes in market conditions brought about by the easier availability of credit, and the willingness of many lenders to advance greater multiples of income than in the past.
The ratio of house prices to earnings clearly has an impact on some potential purchasers. First time buyers have been particularly badly hit during recent years as the amount of deposit they have been required to find is linked both to the loan to value ratio (that is, the advance as a percentage of purchase price) and to the purchase price of property. Increases in the ratio of House Price index to average earnings index roughly equate to increases in real terms to deposit costs at a fixed loan to value ratio. The Council of Mortgage Lenders (Cunningham, 2005) has commented that:

“A major factor now limiting first-time buyer activity is the need to raise a deposit.”

and that:

“...the typical first-time buyer now [2005] needs to raise a deposit of £17,000, equivalent to over 50% of gross annual household income, compared with £6,150, equivalent to around a quarter of annual income, five years ago.”
Since stamp duty is also linked to the property price, an increasing number of first time buyers are also having to find this in addition to their deposit. The Council of Mortgage Lenders (2007) reported that the percentage of first time buyers paying stamp duty on their purchases had risen to 58% in April 2007 from 51% a year earlier.

However, not all potential buyers are affected by the need to find a deposit, since those moving from one property to another frequently own sufficient equity in their first property to meet this requirement. Benito (2006) suggests that former owner-occupiers are insulated from the effects of house price inflation by the capital gains they can realise on their current property, so that there is greater volatility of former owner-occupiers’ house price inflation than for first-time buyers. They are therefore less likely to compare their income to the price of a house (the HPI/AEI ratio) than they are to compare their income to their mortgage payments.

### 7.4.1 Mortgages

Mortgages are generally calculated so that a fixed periodic (usually monthly) payment results in the loan, plus interest accruing during the period of the loan, being paid off in full at the end of its term. Many mortgages are at a fixed interest rate for all or part of the term of the loan. For those periods not at a fixed rate, if the interest rate changes during the course of the mortgage, the repayment is recalculated.

If the loan principal (the amount borrowed) is $P$, the number of periodic payments is $N$, and the periodic interest rate is $r$ (expressed as a fraction, not a percentage), then the fixed periodic payment $c$ is given by the formula:

$$c = \frac{r}{(1 - (1 + r)^{-N})}P \quad (7.1)$$

The formula at equation 7.1 was applied using the value of HPI/AEI as the loan principal $P$, the Bank Rate for the interest rate $r$, and 300 (monthly payments over 25 years) as the number of payments $N$. The result would give an accurate
indication of mortgage payments only for a 100% mortgage at the Bank of England rate on an average priced property by someone on national average earnings. However, it may be taken as a broad indication of the cost of loan servicing for property purchase. The value, which may be considered as a mortgage cost index, was adjusted so that the average value for the period of the training set data (1970 Q1 to 1998 Q4) equalled one. This is graphed at Figure 7.5.

![Figure 7.5 UK mortgage cost index (1970 Q1 to 1998 Q4 = 1)](image_url)

For periods with the index value less than one, the cost of servicing loans was less than the average for the period 1970 Q1 to 1998 Q4. It is apparent from Figure 7.5 that, due to an extended period of low interest rates, loan repayments for property purchases (in real terms) remained less than the long-term average for an exceptionally long time. It was not until mid-2004 that the value returned to average. Even by the end of 2007, real loan servicing costs were still considerably less than the peaks reached in 1974, 1980 and 1989.

This long period of relative stability in interest rates might, by itself, have been sufficient to have an effect on those purchasing property. As purchasers became accustomed to consistently low interest rates, they may have felt that the major rises
of the past were less likely, so that taking out relatively large loans was perceived as less risky. However, in addition to this possible change in perceived risk, the actual risk has been reduced by the growth in both the availability and take-up of fixed rate mortgages. These products are offered with the rates of interest fixed for different periods of time, ranging from two, three or five years up to ten or even twenty-five years (although take-up of loans fixed for periods in excess of five years is still very low in the UK (HM Treasury, 2008c)). In this way, purchasers can insulate themselves from future changes in interest rates - if they can afford their repayments at the outset, they know that mortgage costs will not increase during the period for which the interest rate is fixed. Even risk averse house buyers now have access to suitable products. As most of these products are portable, purchasers can also be confident in committing to a long fixed term as they can take their mortgage with them if they move house.

Commenting in 2006 (CML, 2006b), the Director General of the Council of Mortgage Lenders, Michael Coogan said:

“The strong take-up of fixed-rate deals is encouraging because they give consumers confidence in their mortgage payments and allow them to plan ahead financially.”

Data from the Council of Mortgage Lenders (2006b; 2007) showed that, in April 2007, fixed rate mortgages accounted for 78% of all loans for house purchase and remortgage, compared with 71% for the same period in 2006 and 56% in 2005.

7.4.2 Mortgage lender behaviour

In addition to the influence on buyer behaviour that is exerted by interest rates and the availability of fixed rate mortgages, mortgage lenders also influence the housing market by their lending behaviour. One aspect of this, which is likely to have had a major influence in recent years, is the ready availability of mortgages. First-time buyers have been able to obtain 100% mortgages, thus easing the problem of the down-payment constraint. Benito (2006) has reported that, in England, 23% of first-time buyers had a 100% mortgage in 2003/04 compared with only 12% in 1993/94.
A further relaxation of lending behaviour is demonstrated at Figure 7.6, which graphs HPI/AEI with average mortgage advance/average income (CLG, 2008a).

From 2000 onwards, both HPI/AEI and the loan to income ratio exceeded the maxima recorded in the previous thirty years. Both measures increase in line with each other. This reflects the findings of McQuinn and O’Reilly (2008), who report the existence of co-integration between actual house prices and the level suggested by the average amount borrowed in the long run.

The increase in the loan to income ratio reflects the willingness of lenders to increase the multiple of income that they were prepared to lend to borrowers. This relaxation in lending, together with the easy availability of relatively cheap and fixed rate mortgage products, offers a probable explanation for the continued buoyancy of the housing market from 2000. The increasing credit restrictions of 2008 and the, apparently related, slowdown in the housing market adds further credibility to the proposal that the market was behaving atypically because of unusual financial conditions.
7.5 Reconvening the Committees

The mortgage cost index (Figure 7.5) was not explicitly included in the training data for the neural networks, although the variables from which it was derived (HPI/AEI and Bank of England rate) were. In order to investigate whether explicitly including it as an input variable would improve the forecasting ability of the committees of networks, a further series of networks were trained using data covering the period from 1971 Q2 to 1998 Q4. The variables used were the same as those set out in Section 7.1, with the addition of the mortgage cost index at times $t$ and $t-4$.

Networks were trained using *winGamma*, with different input masks to allow for different combinations of the training data variables. The mortgage cost index, HPI/AEI and the Bank of England rate were used in different combinations, with all the other variables used in all models.

Models trained using the mortgage cost index as a variable instead of the Bank of England rate produced forecasts that were similar, although slightly inferior, to those using the original training set. Those that used both appeared to be unstable – that is, the forecast changes in HPI showed large variations between adjacent quarters. This could be due to problems arising from collinearity of the two variables. However, a number of investigators (Tabrizi and Panahian, 200?; Yi and Prybutok, 2001; Gaudart *et al*, 2004) have reported that the prediction capabilities of neural networks are relatively unaffected by collinearity.
The graph of the two variables together (Figure 7.7) shows that the two curves are very similar over the training period, although they diverge thereafter. It may be this divergence, reflecting feedback into the mortgage cost index of increases in HPI affecting the exceptionally high values of HPI/AEI, which is at least partly the cause of the instability of the forecasts. Figure 7.8 shows the mortgage cost index and the Bank of England rate plotted against each other. The correlation between the variables is 0.90 for the period of the training set (1970 Q1 to 1998 Q4). However, the correlation falls to 0.75 when the period from 1999 Q1 to 2007 Q4 is also included. An examination of this graph also shows a divergence between the data up to 1998 and that for 1999 onwards. These results add further weight to the possibility that there has been a change in the housing market in the post-training period.
Models trained with only the mortgage cost index (that is, without HPI/AEI and the Bank of England rate) failed to predict the reduction in the rate of annual increase in the House Price Index in 2001. Instead, they registered a peak value in 2001 between the actual adjoining peaks of 2000 and 2002/3, and a fall in house prices from 2005 (Figure 7.9). This suggests that it is not just the mortgage costs that affect changes in house prices. The value of HPI/AEI, which provides an indication of house prices in real terms, also appears to be important.
These results suggest that the failure to predict the behaviour of the housing market in the period after 2001 is unlikely to be due to the choice of variables within those examined. It may be that other variables might have provided information that would have improved the forecasting achieved. That is a matter for further study (see Section 8.6). However, given the behaviour reflected in the graphs at Figures 7.4, 7.5, 7.6, 7.7 and 7.8, the general failure of the majority of forecasts to predict the major rises since 2001, and the shift in consumer behaviour towards fixed rate mortgage products, it is likely that there has been a change in market conditions. This was investigated using self-organising maps.

A self-organising map is an artificial neural network that is trained using unsupervised learning to produce a low-dimensional representation of the training sample vectors. The output of the self-organising map is typically represented as a two dimensional map in which samples with similar properties are mapped close together and dissimilar apart. Self-organising maps were trained using the Bank of England rate, HPI/AEI, claimant count and percentage changes in RPI and average
earnings for the period 1970 to 1998. A map for the UK and the regions is shown at Figure 7.10. The map records the number of neurons activated at each co-ordinate - more neurons are activated in regions with high training sample concentration and fewer where samples are scarce. The trained network was then tested using the data for the period 1999 to 2007. This is shown at Figure 7.11.

![Self-organising map: 1970 to 1998](image)

**Figure 7.10** Self-organising map: 1970 to 1998
The results from the self-organising maps demonstrate that the properties of the input vectors post-1998 differ from those in the period 1970 to 1998. This result adds further support to the proposal that there has been a significant change in the conditions of the housing market in the period since 1998. Neural networks do not predict well if conditions fall significantly outside those that have been used to train them.

### 7.6 Retraining the Networks

In order to test whether the forecasting ability of neural networks could be improved for the post-2001 period, new series of networks were trained and tested. Networks were trained and combined to form committees using the data and techniques described in Sections 7.1 and 7.2, with the addition to the training sets of data covering periods beyond 1998. By including data covering periods representing the new market conditions, the networks were given the opportunity to learn these new conditions. Forecasts produced by the new committees of networks for the periods...
2002 Q1 to 2004 Q4 and 2005 Q1 to 2007 Q4 are shown at Figure 7.12 together with the extended forecast (from Figure 7.2) of the committee of networks trained on pre-1999 data (included as ‘UK Predicted (Committee 1998)’). The Nationwide Building Society produces one-year ahead forecasts for the annual change in house prices. These have also been included at Figure 7.12.

![Figure 7.12](image-url)  

**Figure 7.12** Neural network and Nationwide forecasts of changes in HPI

The forecasts by the committees trained using datasets including post-1998 data show a significant improvement over that of the committee trained using only pre-1999 data, and they compare quite favourably with the shorter term forecasts of the Nationwide Building Society. It appears that, even with the addition to the training data of only a relatively small sample of the new market conditions, the networks have begun to incorporate this information in the models. If the current market conditions were to continue, it is likely that neural networks trained with additional data would be able to show further improvements in forecasts. However, the current credit crisis is already exerting pressure on factors such as the loan to
income ratio, which has been one of the major differences between the pre- and post-2000 housing markets. If this continues, market conditions may become more akin to those prevailing pre-2000 and the networks trained on pre-1999 data may once again produce useful forecasts of changes in house prices.

### 7.6.1 The Budget 2005

In the March 2005 Budget, the Treasury (2005b) forecast changes in the house price-earnings ratio for the three years 2005 to 2007. The committee of networks trained on pre-2005 data (Committee 2004) was used to prepare a forecast for comparison using the Treasury’s own data assumptions (HM Treasury, 2005a; 2005c). The networks were used to forecast annual changes in the house price index, and from this the house price-earnings ratio was calculated. The results, rescaled to 1995 = 100 in line with the Treasury forecast, are graphed at Figure 7.13.

![House price-earnings ratio: comparison of forecasts](image)

**Figure 7.13** House price-earnings ratio: comparison of forecasts
Chapter 7 – Forecasting: Extending the Timescale

The forecasts produced by the committee of networks, using both actual historic data and Treasury predictions, have clearly improved on the Treasury’s own prediction of the house price-earnings ratio for the three years 2005 to 2007.

7.6.2 The Budget 2008

The Treasury forecast changes in the house price-earnings ratio for the three years 2008 to 2010 in the March 2008 Budget (HM Treasury, 2008a). The committee of networks trained on pre-2005 data was again used to prepare a forecast for comparison using the Treasury’s own data assumptions (HM Treasury, 2008a; 2008b). The committee of networks trained on pre-1999 data (Committee 1998) was also used to prepare forecasts using the Treasury data. Both committees of networks were used to forecast annual changes in the house price index. The results are graphed at Figure 7.14.

![Graph showing annual percentage change in HPI from 2004 Q1 to 2010 Q3]

**Figure 7.14 Changes in HPI: comparison of forecasts for 2008-2010**
Both committees of networks forecast substantial decreases in the annual change in house prices from the 10.1% annual increase recorded by the CLG index for 2007 Quarter 4. The actual changes recorded for March 2007 to March 2008 by the Nationwide, Halifax and Land Registry, together with the 2007 Q1 to 2008 Q1 increase recorded by the Nationwide, are included for comparison. These show a substantial slow down in the housing market, in line with the forecasts.

Both committees of networks forecast relatively modest annual changes in house prices over the three-year period to the end of 2010. The committee of networks trained on pre-1999 data forecasts a fall in price of approximately nine percent over the three years, whilst the committee of networks trained on pre-2005 data forecasts a rise in price of approximately seven percent over the same period.

The forecasts are based on the Treasury’s assumptions about the economy over the next three years. However, the International Monetary Fund (2008) has forecast that growth will slow to 1.6% in the UK in both 2008 and 2009, compared with the Treasury’s assumptions of around 2% and 2.5%. Growth in the United States and the Eurozone is forecast to slow even more. This slowing may impact on the Treasury’s assumptions, including changes to earnings, inflation and unemployment. As set out in Section 6.3, the house price index is sensitive to changes in unemployment and to the relationship between prices and earnings. A significant slowing of growth might be expected to lead to increased downward pressure on the housing market. The forecasts may therefore need to be re-examined in due course in the light of the emerging impact of the forecast slowing of growth.

The predicted annual changes in the house price index were used to calculate the house price-earnings ratio for the period 2008 to 2010. The results, re-scaled to 1995 = 100 in line with the Treasury forecast, are graphed at Figure 7.15.
Figure 7.15 House price-earnings ratio: comparison of forecasts for 2008-2010

The values of the house price-earnings ratio for 2010 Quarter 4 forecast by the committee of networks trained on pre-2005 data and by the Treasury are very similar. However, the committee of networks trained on pre-1999 data forecasts that the ratio will fall rapidly. Given the apparent long run relationship between actual house prices and the average amount borrowed (Section 7.4.2), this fall may reflect possible behaviour as the housing market adjusts to the current credit restrictions imposed by lenders. The value of the house price-earnings ratio forecast for the end of 2010 is still significantly higher than the peak recorded in 1989, suggesting that further readjustment may occur.
Chapter 8 – CONCLUSIONS AND FUTURE WORK

This chapter summarises the research undertaken and the conclusions reached elsewhere in this thesis. It makes recommendations for future work.

8.1 Introduction

At the start of this thesis, the general aim of this research was stated as being to assess the potential for applying AI techniques to time series in order to forecast residential property market movements. In particular, the research sought to:

- evaluate the application of Artificial Neural Network models and genetic algorithms to residential property price time-series data;
- determine relationships over time between macro-economic (large-scale, national economic), socio-economic (combination of social and economic factors) and residential property transaction attributes at both national and regional levels;
- identify and rank the most significant inputs and, where possible, identify relationships between them.

The experimental research presented in the preceding chapters addressed these objectives.

8.2 Artificial Neural Networks and the Housing Market

Artificial neural networks have previously been used to produce estimates of the open market value, the current measure of value adopted in the approval of mortgage valuations, of a property. They have also been applied to the prediction of time-series data in a number of fields, including finance. This research sought to combine the two to forecast changes over time within the housing market.
One of the features that makes artificial neural networks valuable for forecasting is that they are data-driven, self-adaptive methods that learn from examples and capture functional relationships among the data. However, this means that they must be presented with sufficient data to enable them to learn the underlying relationships. In addition, the data must be representative of the different patterns of behaviour (for instance, different market conditions) which may be observed, and sufficient examples of the patterns must be available to take account of statistical variation or random noise. In practice, this means that at least one, and preferably more than one, business / market cycle should be represented in the training data. The initial choice of variables to be used to train the neural networks was therefore made on the basis of theory and the availability of data.

Experimental work was initially undertaken using two software packages, NeuralWorks Professional II and winGamma. However, winGamma was used for the majority of the work because it:

- is able to maximise the use of data by using the whole of the training dataset instead of partitioning it to provide training and validation datasets;
- appears to incorporate better processes for avoiding local minima in the solution search space, possibly due to the use of genetic algorithms and simulated annealing as part of the training process;
- incorporates a number of tools to assist with model identification and analysis.

One of the problems of forecasting the UK and regional housing markets is that there are only limited data from which to construct input vectors. The problem of forecasting seems to be exacerbated for the regions individually, probably due to ‘noise’ within the (pre 2002) small sample House Price Index data sets. However, by using a large number of input vectors (aggregating the UK plus the regions), networks appear better able to model underlying relationships and generalise better. Using this approach, it was possible to produce forecasts of changes in the housing market that successfully modelled the direction, timing and scale of changes in the annual movement in house prices, both for an extremely volatile and difficult period (1987 to 1991) and for the period 1999 to 2001. In the latter case, using
HM Treasury’s own data from the 1999 Budget, the neural network models outperformed the 1999 Budget predictions of housing market changes.

### 8.3 Model Building

Amongst the decisions to be made in the process of building neural network models, those relating to the choice of the input variables are perhaps the most critical. A network needs to have sufficient relevant inputs to allow the learning of the features embedded in the data. However, it should not be presented with so large a number that its prediction capability is adversely affected. Choosing which variables are relevant and how many to present is both difficult and important. A number of tools and techniques were investigated during this research.

The starting point was to identify which variables might be relevant to changes in the housing market. Although, in theory, it should be possible to present a large number of input variables to a neural network and allow it to learn which are irrelevant, in practice this is best avoided. In problem areas such as the housing market, which is relatively data poor, this could rapidly lead to a situation in which there were insufficient data to adequately train the network. A first step, therefore, was to assemble data on the basis of theory.

Early model building and testing suggested that the initial choice of input variables was a good starting point for further investigation. Two of the tools available within winGamma, the M test and genetic algorithm model identification, were used to inform and refine the choice. The former provided information on the adequacy of datasets for modelling. The genetic algorithm model identification option was used to assist in the choice of the input variables and appropriate lags.

Series of neural networks, trained using different combinations of input variables, were used to produce in-sample forecasts for overlapping three year intervals covering the whole of the period used in the training set. The average in-sample forecasting error for each series of networks was found to be a good indicator of the out-of-sample prediction capabilities of the networks. The ranking of the average
in-sample forecasting errors of series of networks appeared to be a useful technique for choosing input variables.

Although the average in-sample forecasting error was found to be a useful indicator in choosing network inputs, a way of refining the choice of individual networks was also sought. Some trained networks forecast better than others within the same series. The average forecasting error is a measure of how well a network model has learnt the general structure of the data, but a relatively low average error value does not guarantee that the network has learnt all sections well. However, the maximum forecasting error does set an upper error limit on the network’s in-sample performance. Whilst it was not possible to choose the best networks on the basis of the maximum in-sample error, since low out-of-sample forecasting errors could be associated with high maximum in-sample errors, eliminating networks with high maximum in-sample errors reduced the chance of using networks with high out-of-sample forecasting errors. This technique was used to choose networks for inclusion in simple committees of networks.

8.4 Interpreting the Input-Output Relationship

One of the aims of this research was to identify and rank the most significant inputs and, where possible, identify relationships between them. Because of the black box nature of neural networks, the relationship between input and output variables cannot readily be determined, although sensitivity analysis can go some way to overcoming this.

Sensitivity analysis determines how the variation in the output of a model can be apportioned to variations in the inputs to the model. Each of the inputs is altered by a certain percentage in turn whilst the other inputs remain fixed, and the change in the output caused by the change in the input is used to calculate the sensitivity. The inputs may then be ranked on the basis of their sensitivity in order to arrive at their relative influence on the final output.
The ten networks with the best in-sample forecasts were identified, and used to undertake sensitivity analysis for seven different dates. The dates were chosen to represent different market conditions. The results from the ten networks were combined to produce average sensitivity values for each input and date, and these values were used to rank the inputs.

The overall sensitivity at different dates may be quantified by calculating the average absolute sensitivity of all the inputs. There are clear differences in the overall sensitivity that the networks display at these times. Changes in the House Price Index were relatively less sensitive to changes in all of the variables during market lows (1982 Q1, 1992 Q4 and 1996 Q2).

The input variable annual percentage change in the House Price Index at time $t$ ranked first for its effect on the output, annual percentage change in HPI at time $t+1$. The next most significant group of input variables consisted of the annual percentage changes in RPI and average earnings at time $t$, and claimant count at times $t$ and $t-4$. These variables appeared to act in pairs. The apparent relationships between RPI and average earnings, and between claimant count measurements a year apart, were investigated by generating prediction surfaces. These surfaces were generated in a similar way to the sensitivity results, but by varying two input variables against each other whilst keeping all the others fixed. The output values were then plotted against the two input variables to produce the prediction surfaces.

### 8.5 Review of Results

This research sought to assess the potential for applying Artificial Neural Networks to forecast changes in the residential property market. Successful models were trained to forecast annual changes in the House Price Index for a number of periods. The fact that a single model was able to encompass the UK and the regions supports the view that each region may be affected by similar mechanisms but react to local circumstances.
The input variables used to train the networks were chosen on the basis of theory and then refined using various tools and techniques. They are ones that are readily accessible to and understood by house buyers. This was an additional reason for their choice initially - individuals make housing purchases, usually on the basis of only limited information, which was broadly mirrored in the input vector. Their decisions are likely to be driven by a number of factors such as how secure they feel in employment; whether they can afford a particular type of property; whether the price is high or low / rising or falling (in real terms). Although consumer behaviour is not necessarily explicit in econometrics, it may be implicit (for example, supply and demand).

The forecasts of the annual percentage increase in the House Price Index were improved when the generated series of the ratio of the House Price Index to the average earnings index (HPI/AEI) was included in the input vector. The market could be expected to behave differently under different conditions – HPI/AEI and its movement may be considered as indicators of the state of the market (high / low, rising / falling) in real terms.

The individuals who make housing purchases are unlikely to make direct numerical comparison with past prices. Although they may be aware of previous prices – for instance, “I paid £4500 for my first house in 1971” - they are more likely to consider whether the current price seems reasonable for the time and location. In this context, HPI/AEI and its movement can be seen as a crude measure of market conditions, and, in the process of model building, can be considered as a proxy variable to quantify consumer behaviour. Sensitivity analysis revealed that HPI/AEI at time $t-4$ was of relatively low rank when the market was buoyant but of high rank during the market lows. At these times its negative sensitivity had a major effect on the forecasts of changes in HPI. This may indicate that a major factor in determining price movement in a depressed market is whether real prices appear high or low in a historical context – in effect, is it a bargain in a buyers market.

Although house purchasers could be expected to look at the real price of property, their overriding consideration is likely to be whether they can afford to make the
purchase – a factor of how much they can borrow, how much they can afford to repay, etc. This goes some way to explaining why the generated ratio HPI/AEI appears to help in forecasting – it is linked to both the lending behaviour of the mortgage lending institutions and, together with interest rates, how much borrowers can afford to repay now and in the future. This also helps to explain the difficulties experienced in forecasting from 2002 onwards – lending institutions altered their behaviour and borrowers were able to guarantee cheap fixed rate loans.

The annual percentage change in HPI at time $t$ was consistently ranked first for its effect on the network output. There are a number of reasons why this might be so, including the smoothing effect introduced by the differing times taken to complete property purchases and the feedback effect into purchaser perceptions and behaviour of this widely published aspect of the housing market.

The prediction surfaces of the apparent pairings of the input variables annual percentage changes in RPI and average earnings at time $t$, and claimant count at times $t$ and $t-4$ were investigated to determine relationships between these variables. Using the shapes of the prediction surfaces, it was possible to deduce the likely relationships between the paired variables.

The results suggested that changes in HPI are relatively insensitive to the actual values of changes in average earnings and RPI so long as the difference between them is constant. However, in a situation where pay increases lag significantly behind overall increases in inflation, the housing market could be expected to show little growth. Conversely, in a situation where pay increases show a significant lead over overall increases in inflation, the housing market could be expected to demonstrate a rapid rise.

A similar effect appears to operate for the claimant count measurements a year apart. In the case of the rate of unemployment neither rising nor falling (that is, the values at time $t$ and $t-4$ equal), the neural network models predict that the actual values of claimant count rate have little effect on the annual rate of change in the House Price
Index. However, falling unemployment results in rapidly rising house prices, whilst rising unemployment has the opposite effect and acts to depress price increases.

Although the neural network models trained on pre-1999 data have predicted changes in the House Price Index up to the end of 2001 with success, they have clearly failed to do so for the following period. As argued in Chapter 7, this appears to be due to significant changes in the housing market. In particular, there has been an extended period of low interest rates and a relaxation by lending institutions on the income multiplier which they are prepared to offer in setting the upper limits on loans. In addition, borrower behaviour has also been altered by the growth in both the availability and take-up of fixed rate mortgages. Together these have resulted in market conditions unlike any of those that were used to train the neural networks.

Neural networks do not predict well if conditions fall significantly outside those that have been used to train them. Accordingly, further series of networks were trained using datasets that included post-1998 data. Despite the availability of only limited additional data for training, the networks produced significantly improved forecasts for the post-2001 period. This suggests that the networks have begun to incorporate in the models information about the new market conditions.

The International Monetary Fund has suggested that by 2007 house prices were “about 30 percent higher than justified by fundamentals”. This is of the same order of magnitude as the difference between actual prices and those predicted by the committee of networks trained on pre-1999 data (Section 7.3). Although the availability and take-up of fixed rate mortgages might have resulted in some additional buoyancy in prices, it is interesting to speculate how the market would have behaved if lending had been constrained (in particular, the loan to income ratio) to the pre-2000 conditions. If the market had behaved as predicted, price increases would have slowly decreased over the period from 2002 to zero growth by the end of 2007. However, prices would not have fallen, as is now predicted by the pre-1999 networks.
Both the 2008 Budget and the committee of networks trained on pre-2005 data forecast that the house price-earnings ratio will fall only slightly (about 5%) over the next three years (equivalent to a small increase in house prices). By contrast, the committee of networks trained on pre-1999 data forecasts a fall of approximately four times this (about 20%) over the same period. The International Monetary Fund has suggested that the UK appears “particularly vulnerable” to a correction in house prices. The increasing credit restrictions now being applied may presage this correction. Certainly, lending criteria now appear to be more like those applied pre-2000, so the correction suggested by the pre-1999 networks may be a more likely outcome. If the predicted slowing of growth has a negative impact on employment or earnings, however, even this may prove to be optimistic.

8.6 Suggestions for Future Work

The improvement observed when values of the variables were included for both $t$ and $t-4$ suggests that it is both the current value and the change in the value of variables that are important. However, it is possible that, by including only $t$ and $t-4$ values, additional useful information is being discarded. Increasing the number of input values for a particular variable might improve predictions, but it could also degrade the ability of networks to forecast. A further area for investigation is therefore that of reduction of dimensionality – ways of retaining the essential information within a dataset, but using a reduced input set to do so.

The input variables chosen to train the neural networks have produced good forecasts in the period to the end of 2001. However, it is possible that other indicators might have produced better forecasts, or enabled the networks to predict more accurately for the period from 2002 onwards. A candidate list of other potential input variables is at Table 8.1.
<table>
<thead>
<tr>
<th>HM Treasury Forecast</th>
<th>ONS Series</th>
<th>Office For National Statistics: Series Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td>ABMI</td>
<td>Gross Domestic Product: chained volume measures: Seasonally adjusted</td>
</tr>
<tr>
<td>Private consumption</td>
<td>ABJR + HAYO</td>
<td>Household final consumption expenditure: National concept CVM NAYear SA Final Consumption Expenditure of NPISHs CVM SA</td>
</tr>
<tr>
<td>General government consumption</td>
<td>NMRY</td>
<td>General Government: Final consumption expenditure: P3: CVM SA</td>
</tr>
<tr>
<td>Gross fixed investment</td>
<td>NPQT</td>
<td>Total Gross Fixed Capital Formation CVM SA £m</td>
</tr>
<tr>
<td>Change in inventories (2003, £bn)</td>
<td>CAFU</td>
<td>Changes in inventories including alignment adjustment - CVM NAYear SA</td>
</tr>
<tr>
<td>Domestic demand</td>
<td>YBIM</td>
<td>Total domestic expenditure (aligned) - P.3+P.5: CVM SA</td>
</tr>
<tr>
<td>Exports (goods and services)</td>
<td>IKBK</td>
<td>Balance of Payments: Trade in Goods &amp; Services: Total exports: CVM SA</td>
</tr>
<tr>
<td>Imports (goods and services)</td>
<td>IKBL</td>
<td>Balance of Payments: Imports: Total Trade in Goods &amp; Services: CVM SA</td>
</tr>
<tr>
<td>CPI (Q4)</td>
<td>D7G7</td>
<td>CPI ANNUAL RATE 00: ALL ITEMS- estimated pre-97 2005=100 From 1989 Q1</td>
</tr>
<tr>
<td>RPIX (Q4)</td>
<td>CDKQ</td>
<td>RPI: Percentage change over 12 months- All items exc. mortgage interest payments From 1976 Q1</td>
</tr>
<tr>
<td>Sterling index (Q4, Jan 2005=100)</td>
<td>BK67</td>
<td>Monthly average, Effective exchange rate index, Sterling (Jan 2005=100) From 1980 Q1</td>
</tr>
<tr>
<td>M4 growth</td>
<td>VQJW</td>
<td>Money stock M4: annual % change SA</td>
</tr>
<tr>
<td>RHDI</td>
<td>NRJR</td>
<td>HN: Real households disposable income: CVM SA</td>
</tr>
<tr>
<td>Employment growth</td>
<td>DYDC</td>
<td>UK Workforce jobs (SA): Total - thousands (LMT table B11)</td>
</tr>
<tr>
<td>Claimant unemployment (Q4, mn)</td>
<td>BCJD</td>
<td>Total Claimant count SA (UK) - thousands From 1971 Q1</td>
</tr>
<tr>
<td>Manufacturing Output</td>
<td>CKYY</td>
<td>IOP: Industry D: Manufacturing: CVMSA NAYear=100</td>
</tr>
<tr>
<td>Current account (£bn)</td>
<td>HBOP</td>
<td>BoP Current Account Balance SA £m</td>
</tr>
<tr>
<td>Public Sector Net Borrowing</td>
<td>ANNX</td>
<td>Public sector finances: Net Borrowing (B.9g): £m CPNSA</td>
</tr>
</tbody>
</table>

Table 8.1 Candidate variables for neural networks

The variables have all been chosen as they are both forecast by HM Treasury and available as historical datasets from the Office for National Statistics. Unless otherwise indicated, all ONS datasets extend back at least as far as 1968 Q2, the beginning of the House Price Index.

The benefit of including individual datasets from this list could be determined using the techniques described earlier. In particular, genetic algorithm model identification and in-sample forecasting performance could be used identify possible
candidates for inclusion. Sensitivity analysis could then be applied to enable a final determination of which to include.

The current credit crisis is already exerting pressure on factors such as the loan to income ratio, which has been one of the major differences between the pre- and post-2000 housing markets. If this continues, market conditions may become more similar to those prevailing pre-2000. This could be tested using the self-organising maps, and the existing networks could be tested for their forecasting ability in the new period. Their forecasting ability could be taken as an indication of how far conditions had returned to those existing pre-1999 (suggesting that there are long-term relationships, such as the price to income ratio, within the housing market) and how well the networks had learnt these.

### 8.7 Conclusions

Neural networks were demonstrated to be successful in producing time series forecasts of changes in the housing market, particularly when combined in simple committees of networks. They successfully modelled the direction, timing and scale of annual changes in house prices, both for an extremely volatile and difficult period (1987 to 1991) and for the period 1999 to 2001. In the latter case, using HM Treasury’s own data from the 1999 Budget, the neural network models outperformed the 1999 Budget predictions of housing market changes.

Poor forecasting results for the period 2002 onwards were linked to new conditions in the housing market, including changes in the loan to income ratio. Neural networks trained with a subset of post-1998 data added to the training set improved their forecasting performance, suggesting that they had begun to incorporate the new conditions into the models. The accuracy of three-year forecasts produced by the committees of networks were comparable to one-year ahead forecasts produced by a major mortgage provider (the Nationwide Building Society) and, using data from the 2005 Budget, they outperformed HM Treasury’s own predictions.
The problem of limited data availability was addressed by aggregating data for the UK and the regions within single neural network models. These networks appeared able to model underlying relationships better and to generalise better. The fact that a single model was able to encompass the UK and the regions supports the view that each region may be affected by similar mechanisms but react to local circumstances.

Sensitivity analysis was used to identify and rank the network inputs under different market conditions. The measure of changes in the house price index itself was found to have the greatest effect on future changes in prices.

Sensitivity analysis and prediction surfaces were used to identify and investigate the next most significant group of input variables. Changes in the house price index appeared to be affected by the relationship between changes in RPI and average earnings – which was greater and by how much appeared to have more effect on changes in house prices than the actual levels of either. A similar relationship also appeared to exist between claimant count measurements a year apart – whether unemployment was rising or falling appeared to have a greater effect on changes in house prices than the actual levels of unemployment.

The committees of networks trained using pre-1999 and pre-2005 data have produced differing forecasts for price changes within the housing market over the period 2008 to 2010. How the market reacts during this period, together with observed changes in the credit market, may provide an indication of whether there are long-term relationships within the market, and how well neural networks are able to model these.
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A1.1 Department for Transport, Local Government and the Regions

DTLR Mix Adjusted Index (1990 = 100): All Dwellings

**Description:** House Price Index  
**Source:** Department for Transport, Local Government and the Regions  
**Period:** 1968 Q2 to 2002 Q1  
**Series**  
UK  
Wales  
Scotland  
North West  
Yorkshire & the Humber  
East Midlands  
West Midlands  
East Anglia  
London  
South East  
South West

**Description:** Annual Percentage Change in House Price Index  
**Source:** Department for Transport, Local Government and the Regions  
**Period:** 1969 Q2 to 2002 Q1  
**Series**  
UK  
Wales  
Scotland  
North West  
Yorkshire & the Humber  
East Midlands  
West Midlands  
East Anglia  
London  
South East  
South West
Appendix 1: Data Sources

A1.2 Communities and Local Government

CLG Mix Adjusted Index (Feb 2002 = 100): All Dwellings
Table 591

Description: House Price Index
Source: Communities and Local Government
Period: 1968 Q2 to 2007 Q4
Series
UK
Wales
Scotland
Yorkshire & the Humber
East Midlands
West Midlands
London
South West
Period: 1992 Q2 to 2007 Q4
Series
East 4
South East 4
Period: 1999 Q1 to 2007 Q4
Series
North West 5

Notes
1 Data up to and including 1992 was based on returns from Building Societies only. Data from 1993 onwards is based on returns from all mortgage lenders.
2 Based on mortgages completed and adjusted for the mix of dwellings sold.
3 Quarterly index calculated as the average of the monthly mix-adjusted series.
4 Data not available on a Government Office Region prior to 1992 Q2.
5 Data not available on a Government Office Region prior to 1999 Q1, as it had previously been split between North West (excluding Merseyside) and Merseyside.
6 From September 2005, data are collected via the Regulated Mortgage Survey (RMS) of the Council of Mortgage Lenders (CML)/Bank Search. 2005 Q3 data are based on combined data from the Survey of Mortgage Lenders (SML) and the Regulated Mortgage Survey (RMS).
Appendix 1: Data Sources

<table>
<thead>
<tr>
<th>Description</th>
<th>Annual Percentage Change in House Price Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source</td>
<td>Communities and Local Government</td>
</tr>
<tr>
<td>Period</td>
<td>1969 Q2 to 2007 Q4</td>
</tr>
<tr>
<td>Series</td>
<td>UK</td>
</tr>
<tr>
<td></td>
<td>Wales</td>
</tr>
<tr>
<td></td>
<td>Scotland</td>
</tr>
<tr>
<td></td>
<td>Yorkshire &amp; the Humber</td>
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<td></td>
<td>East Midlands</td>
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<tr>
<td></td>
<td>London</td>
</tr>
<tr>
<td></td>
<td>South West</td>
</tr>
<tr>
<td>Period</td>
<td>1993 Q2 to 2007 Q4</td>
</tr>
<tr>
<td>Series</td>
<td>East 4</td>
</tr>
<tr>
<td></td>
<td>South East 4</td>
</tr>
<tr>
<td>Period</td>
<td>2000 Q1 to 2007 Q4</td>
</tr>
<tr>
<td>Series</td>
<td>North West 5</td>
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</table>
### A1.3 Office for National Statistics

<table>
<thead>
<tr>
<th>Description</th>
<th>Source</th>
<th>Series</th>
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</thead>
<tbody>
<tr>
<td><strong>Average Earnings Index for the Whole Economy</strong></td>
<td>Office for National Statistics</td>
<td>LNNC: Average earnings, Headline rate (change in the index values - last 3 months compared to a year ago), seasonally adjusted</td>
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<td><strong>Average earnings index, seasonally adjusted</strong></td>
<td></td>
<td>LNMQ:</td>
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</table>

<table>
<thead>
<tr>
<th>Description</th>
<th>Source</th>
<th>Series</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Percentage changes in RPI: all items</strong></td>
<td>Office for National Statistics</td>
<td>CZBH: RPI: Percentage change over 12 months - all items</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Description</th>
<th>Source</th>
<th>Series</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Estimates of claimant count (the number of people claiming unemployment related benefits) in the UK; as a percentage rate. Seasonally adjusted</strong></td>
<td>Office for National Statistics</td>
<td>BCJE: Claimant count rate SA %: UK</td>
</tr>
<tr>
<td>Gender: All</td>
<td></td>
<td>DPBI: Regional Claimant count rate SA %: Yorkshire &amp; the Humber</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DPBJ: Regional Claimant count rate SA %: East Midlands</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DPBM: Regional Claimant count rate SA %: South West</td>
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<tr>
<td></td>
<td></td>
<td>DPBN: Regional Claimant count rate SA %: West Midlands</td>
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<tr>
<td></td>
<td></td>
<td>DPBP: Regional Claimant count rate SA %: Wales</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DPBQ: Regional Claimant count rate SA %: Scotland</td>
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<tr>
<td></td>
<td></td>
<td>DPP: Regional Claimant count rate SA %: East</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DPDR: Regional Claimant count rate SA %: South East</td>
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<tr>
<td></td>
<td></td>
<td>IBWC: Regional Claimant count rate SA %: North West</td>
</tr>
</tbody>
</table>
Appendix 1: Data Sources

A1.4 Bank of England

**Description:** Bank Of England Money Market Intervention Rates: Changes In Bank Rate, Minimum Lending Rate, Minimum Band 1 Dealing Rate, Repo Rate and Official Bank Rate

**Source:** Bank of England

**Series**
- Bank Rate: Changes as they occurred, up to 22 Jun 1972
- Minimum Lending Rate: Changes as they occurred, 16 Oct 1972 to 11 Mar 1981
- Repo Rate: Changes as they occurred, 6 May 1997 to 4 Aug 2005
- Official Bank Rate: Changes as they occurred, 3 Aug 2006 onwards
APPENDIX 2: REGIONAL HOUSE PRICE FORECASTS
A2.1 UK

[Graph of UK House Price Forecasts]

- Annual percentage change in HPI
- UK Actual
- UK Predicted: Average
- UK Predicted: Best Network

[Graph of UK House Price Forecasts 2]

- Annual percentage change in HPI
- UK Actual
- UK Predicted: Average
- UK Predicted: Best Network
A2.2 Wales

[Chart showing annual percentage change in HPI for Wales from 1986 Q1 to 1998 Q4, with lines representing actual and predicted values.]

A2.3 Scotland

[Graph showing annual percentage change in HPI for Scotland Actual and Predicted: Average and Best Network over time from 1986 Q1 to 2002 Q4.]

[Graph showing annual percentage change in HPI for Scotland Actual and Predicted: Average and Best Network over time from 1998 Q1 to 2002 Q4.]

Stuart D. Paris
A2.4 North West

[Diagram showing annual percentage change in HPI from 1986 Q1 to 2002 Q1, with lines for NW Actual, NW Predicted: Average, and NW Predicted: Best Network.]
A2.5 Yorkshire & the Humber

[Graphs showing annual percentage change in HPI for Yorkshire & the Humber from 1986 Q1 to 2002 Q1, with lines for Y&H Actual, Y&H Predicted: Average, and Y&H Predicted: Best Network.
A2.6 East Midlands

![East Midlands House Price Forecasts](chart)

**EM Actual**  
**EM Predicted: Average**  
**EM Predicted: Best Network**

![East Midlands House Price Forecasts](chart2)

**EM Actual**  
**EM Predicted: Average**  
**EM Predicted: Best Network**
Appendix 2: Regional House Price Forecasts

A2.7 West Midlands

[Graph showing annual percentage change in HPI for West Midlands from 1986 Q1 to 2002 Q1, with data points indicating actual and predicted values using average and best network methods.]
A2.8 East Anglia

![Graph showing annual percentage change in HPI from 1986 Q1 to 1993 Q1 for East Anglia. The graph compares actual data with predicted data using average and best network models.](image-url)
A2.9 London
Appendix 2: Regional House Price Forecasts

A2.10 South East

![Graph showing annual percentage change in HPI for South East from 1986 Q1 to 2002 Q4, with data points for Actual, Predicted: Average, and Predicted: Best Network.](attachment:image.png)
A2.11 South West

[Graph showing annual percentage change in HPI for South West from 1986 Q1 to 2002 Q1, with lines indicating actual and predicted values.]

- SW Actual
- SW Predicted: Average
- SW Predicted: Best Network
APPENDIX 3: SENSITIVITY ANALYSIS
A3.1 Input Sensitivity Graphs - UK

A3.1.1 Sensitivity Graph – UK: 1982 Q1

A3.1.2 Sensitivity Graph – UK: 1986 Q3
A3.1.3 Sensitivity Graph – UK: 1988 Q3

A3.1.4 Sensitivity Graph – UK: 1989 Q3
Appendix 3: Sensitivity Analysis

A3.1.5  Sensitivity Graph – UK: 1992 Q4

1992 Q4

A3.1.6  Sensitivity Graph – UK: 1996 Q2

1996 Q2
Appendix 3: Sensitivity Analysis

A3.1.7 Sensitivity Graph – UK: 2002 Q4

2002 Q4

![Bar graph showing sensitivity analysis of various economic indicators for the UK in 2002 Q4. The x-axis represents different economic indicators, and the y-axis shows the sensitivity values ranging from -80 to 120.]
A3.2 Input Sensitivity Graphs - Wales
A3.3 Input Sensitivity Graphs - Scotland

Scotland: 1982 Q1

Scotland: 1986 Q3

Scotland: 1988 Q3

Scotland: 1989 Q1

Scotland: 1992 Q4

Scotland: 1996 Q2

Scotland: 2002 Q4
A3.4 Input Sensitivity Graphs - East Anglia
A3.5 Input Sensitivity Graphs - London

London: 1982 Q1

London: 1986 Q3

London: 1988 Q3

London: 1989 Q3

London: 1992 Q4

London: 1996 Q2

London: 2002 Q4
A3.6 Input Sensitivity Graphs - North West

NW: 1982 Q1

NW: 1986 Q3

NW: 1988 Q3

NW: 1989 Q3

NW: 1992 Q4

NW: 1996 Q2

NW: 2002 Q4
A3.7 Input Sensitivity Graphs - East Midlands

EM: 1982 Q1

EM: 1984 Q3

EM: 1988 Q3

EM: 1992 Q3

EM: 1992 Q4

EM: 1996 Q2

EM: 2002 Q4
Appendix 3: Sensitivity Analysis

A3.8 Input Sensitivity Graphs - West Midlands

WM: 1982 Q1

WM: 1986 Q3

WM: 1988 Q3

WM: 1992 Q4

WM: 1996 Q2

WM: 2002 Q4
A3.9 Input Sensitivity Graphs - Yorkshire & the Humber
A3.10  Input Sensitivity Graphs - South West

SW: 1982 Q1

SW: 1984 Q3

SW: 1988 Q3

SW: 1989 Q3

SW: 1992 Q4

SW: 1996 Q2

SW: 2002 Q4
Appendix 3: Sensitivity Analysis

A3.11 Input Sensitivity Graphs - South East

SE: 1982 Q1

SE: 1986 Q3

SE: 1988 Q3

SE: 1992 Q4

SE: 1996 Q2

SE: 2002 Q4
## Appendix 3: Sensitivity Analysis

### A3.12 Ranked Input Sensitivity – UK and the Regions

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## Appendix 3: Sensitivity Analysis

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## Appendix 3: Sensitivity Analysis

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APPENDIX 4: PREDICTION SURFACES
A4.1 UK 1982 Q1

A4.1.1 Prediction Surface – Average Earnings v RPI

1982 Q1

HPI% (t+1) vs RPI% (t) vs AE% (t)

1982 Q1
A4.1.2 Prediction Surface – Claimant Count

1982 Q1

1982 Q1
A4.2 UK 1986 Q3

A4.2.1 Prediction Surface – Average Earnings v RPI
A4.2.2 Prediction Surface – Claimant Count

1986 Q3

[3D graph showing prediction surfaces for HPI\%(t+1), CC\% (t), and CC\% (t-4) with different color-coded areas representing varying percentage ranges.]

1986 Q3

[2D graph showing prediction surfaces for HPI\%(t+1), CC\% (t), and CC\% (t-4) with different color-coded areas representing varying percentage ranges.]
A4.3 UK 1988 Q3

A4.3.1 Prediction Surface – Average Earnings v RPI

1988 Q3

1988 Q3
A4.3.2 Prediction Surface – Claimant Count

1988 Q3

HPI\%(t+1)

CC\% (t)

CC\% (t-4)

1988 Q3

HPI\%(t+1)

CC\% (t)

CC\% (t-4)
A4.4 UK 1989 Q3

A4.4.1 Prediction Surface – Average Earnings v RPI
A4.4.2 Prediction Surface – Claimant Count

1989 Q3

HPI\%(t+1)

CC\%(t-4)

CC\%(t)

1989 Q3

HPI\%(t+1)

CC\%(t-4)

CC\%(t)
Appendix 4: Prediction Surfaces

A4.5 UK 1992 Q4

A4.5.1 Prediction Surface – Average Earnings v RPI

![Graph showing prediction surfaces for Average Earnings (AE) vs RPI, with 1992 Q4 data points and color-coded regions for different percentage ranges.]
A4.5.2 Prediction Surface – Claimant Count

1992 Q4

1992 Q4
A4.6 UK 1996 Q2

A4.6.1 Prediction Surface – Average Earnings v RPI

The diagrams illustrate the prediction surfaces for Average Earnings (AE) and RPI for 1996 Q2. The surfaces are color-coded to represent different percentage ranges, allowing for visual analysis of the relationship between AE and RPI.
A4.6.2 Prediction Surface – Claimant Count

1996 Q2

HPI\%(t+1) vs. CC\% (t) vs. CC\% (t-4)

1996 Q2

HPI\%(t+1) vs. CC\% (t) vs. CC\% (t-4)
Appendix 4: Prediction Surfaces

A4.7 UK 2002 Q4

A4.7.1 Prediction Surface – Average Earnings v RPI

2002 Q4

HPI\% (t+1)

RPI\% (t)

AE\% (t)

HPI\% (t+1)

RPI\% (t)

AE\% (t)
A4.7.2 Prediction Surface – Claimant Count

2002 Q4

2002 Q4
APPENDIX 5: REGIONAL HOUSE PRICE FORECASTS
1999 Q1 TO 2007 Q4
A5.1 UK: HPI Forecast 1999 Q1 TO 2007 Q4

A5.2 Wales: HPI Forecast 1999 Q1 TO 2007 Q4
A5.3 Scotland: HPI Forecast 1999 Q1 TO 2007 Q4

![Scotland HPI Forecast Graph]

A5.4 North West: HPI Forecast 1999 Q1 TO 2007 Q4

![North West HPI Forecast Graph]
A5.5 Yorkshire & the Humber: HPI Forecast 1999 Q1 TO 2007 Q4

A5.6 East Midlands: HPI Forecast 1999 Q1 TO 2007 Q4
A5.7 West Midlands: HPI Forecast 1999 Q1 TO 2007 Q4

![Graph showing annual percentage change in HPI for West Midlands Actual and West Midlands Committee of Networks from 1999 Q1 to 2007 Q4.]

A5.8 East Anglia/East: HPI Forecast 1999 Q1 TO 2007 Q4

![Graph showing annual percentage change in HPI for East Anglia/East Actual and East Anglia/East Committee of Networks from 1999 Q1 to 2007 Q4.]

Stuart D. Paris
A5.9 London: HPI Forecast 1999 Q1 TO 2007 Q4

A5.10 South East: HPI Forecast 1999 Q1 TO 2007 Q4
A5.11 South West: HPI Forecast 1999 Q1 TO 2007 Q4

![Graph showing annual percentage change in HPI from 1999 Q1 to 2007 Q4 for South West Actual and South West Committee of Networks.](image-url)
APPENDIX 6: PUBLISHED PAPER

"Residential property price time series forecasting with neural networks."
Residential property price time series forecasting with neural networks

I.D. Wilson1,*, S.D. Paris, J.A. Ware, D.H. Jenkins
School of Technology, University of Glamorgan, Pontypridd, Mid Glamorgan, Wales CF37 1DL, UK

Abstract

The residential property market accounts for a substantial proportion of UK economic activity. Professional valuers estimate property values based on current bid prices (open market values). However, there is no reliable forecasting service for residential values with current bid prices being taken as the best indicator of future price movement. This approach has failed to predict the periodic market crises or to produce estimates of long-term sustainable values (a recent European Directive could be leading mortgage lenders towards the use of sustainable valuations in preference to the open market values). In this paper, we present artificial neural networks, trained using national housing transaction time series data, which forecasts future trends within the housing market. © 2002 Elsevier Science B.V. All rights reserved.

Keywords: Gamma test; Neural network; Forecasting

1. Introduction

Today’s mortgage valuation process is not able to perform a socially useful role, with property valuation wholly dictated by current market forces (the open market value). This is because lenders, who manage this process, have been able to offload the risk on to consumers and insurance companies. Major changes in the housing market can have a significant impact on the economy as a whole. The fall in UK house prices between 1989 and 92 (which fell by about 25%) was a period during which the savings rate almost doubled (from just over 6 to around 12%), GDP stagnated and business confidence declined [1]. Many individuals were left in a situation of negative equity, where they had paid (and were usually still paying) more for their homes than they could realise by selling. This had a significant social cost in terms of increased repossessions and reduced labour mobility. This experience has led to a recent European Directive which may lead mortgage lenders toward the use of sustainable values in preference to open market value. Therefore, it can be seen that the development of models that provide a sustainable value for properties would be of great usefulness to the consumer.

The consumer would be able to make informed decisions based upon pricing models that give a clearer indication of the real, sustainable value of property. Accurate valuations would forecast negative equity and facilitate movement between jobs in today’s mobile labour market.

The aim is that, by drawing upon economic, social and residential property transaction data at the national, regional and sub-regional level, appropriate valuation functions can be identified. The results of this preliminary, national, stage of this EPSRC funded project are presented in this paper.

First, the reader is presented with a background to traditional, linear, and non-linear approaches to forecasting. Next, an overview for the data is provided, along with an examination of the methodology that underpins the experimental work undertaken. Finally, conclusions are drawn and the plans for future work are explained.

2. Traditional time series forecasting

Forecasting is the rational prediction of future events on the basis of related past and current information. Time series forecasting is a challenging problem that has long attracted the attention of investors and academics alike. The process is comparable with modelling, where the outcome of an unknown variable is generated from known or controllable variables. A combination of statistical analysis and informed judgement can approximate the relationships between the known and unknown variables. When complete information about relationships is available, then a reliance upon the statistical data is invariably more reliable since it reflects patterns in the data in an unbiased way [2].

Most time series consist of members that are serially dependent on the sense that one can estimate a coefficient
or a set of coefficients that describe continuous members of the series from specific, time-bounded (previous) positions. This process of autoregression can be summarized in the equation:

\[ y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \epsilon_t \]

(1)

where \( y_t \) represents the values of the series at point \( t \), \( \beta \) is a constant, \( \beta_1, \beta_2, \ldots \) are the linear regression coefficients, and a random error component is denoted by \( \epsilon \). In other words, each observation is made up of a random error component and a linear combination of prior observations.

Independent of the autoregressive process, each member in the series can also be affected by the past error \( e \), which cannot be accounted for by the autoregressive component, that is:

\[ y_t = \mu + \epsilon_t - \phi_1 y_{t-1} - \phi_2 y_{t-2} - \cdots \]

(2)

where \( y_t \) represents the value of the series at point \( t \), \( \mu \) is a constant and \( \phi_1, \phi_2, \ldots \) are the moving average model parameters. In words, each observation is made up of a random error component \( \epsilon \) and a linear combination of prior random errors.

Once the next value in the sequence has been predicted, this can be substituted into the equation to make further predictions. However, the practical success of models of this type are limited by their linearity, their insufficient data requirements, and because one needs to be reasonably skilled to obtain a good forecast.

3. Non-linear time series forecasting

Non-linear models, including artificial neural networks (ANN), are potentially better than regression models. Indeed, it has been shown that an ANN using logistic functions can model any functional relationship, linear and non-linear [1]. It would be expected that such models are better than regression since regression is essentially a linear technique used in a non-linear problem domain.

However, although non-linear systems inherently demonstrate more potential than linear systems, implementation of such a problem is problematic. This arises from the fact that non-linear systems will attempt to fit all data encountered, including any noise present. Therefore, processing must be stopped once all useful information have been internalized but before any noise within the data is absorbed.

Independent validation allows the training algorithm to extract what information it can from the data before identifying a point, beyond which it may be misled by noisy or ill-conditioned data. Ill-conditioning usually arises when similar, or linearly dependent, input data are associated with very different output data.

Here, the data set is split into two parts, the training set and the test set. The test set is only used for independent validation; it is not used for training, but only for independently assessing the quality of the mapping being obtained from the training set. If the quality of the testing set is good, then the error in predicting the output from the independent test set will fall during training. This process continues until there is no measurable improvement. Instead, the error will increase providing an indication that the model may have begun to assimilate noise within the training set, and a useful heuristic for ending the modelling process. The fall in the measure of error happens before the rise because there is a strong tendency for the best fit to the underlying model to be located close to the unbiased starting point. Therefore, the best fit to the underlying model is located at the point where the validation set measure of error is minimized.

Unfortunately, partitioning the data set in this way is, itself, problematic when the data set is small. For large data sets, this is not a problem, but most property data sets cover long periods, punctuated by a relatively small number of statistical measures. Here, partitioning the data set into two parts might take valuable data points away from the training set and consequently impede the ANN's ability to extrapolate a reliable model from the time series. An alternative approach, where the data is not partitioned and training is instead terminated at a pre-determined measure of error would be advantageous.

One such measure, the Gamma (or near neighbour) test can provide an estimate for the best root mean squared error (MRSE) test can be achieved by a continuous or smooth (bounced first partial derivatives) data model [4]. This simple technique promises to provide a mean for simplifying the design process for constructing a smooth data model such as an ANN.

4. The Gamma test

The Gamma (or near neighbour) test is a data analysis algorithm that estimates the MSE that can be achieved by a model constructed using this data. This test can be used to simplify the process of constructing a smooth data model, such as an ANN. An overview of the technique is provided here.

If a time series can be assumed to have an underlying smooth model

\[ y = y(x) + \epsilon \]

(3)

where \( y \) a scalar output and \( \epsilon \) is an input vector, restricted to a close bounded set \( v \subseteq \mathbb{R}^n \), and \( \epsilon \) represents noise, then the Gamma test can provide a data-derived estimate for the variance of \( \epsilon \) given that:

- the training and testing data are different samples sets;
- the training set inputs are non-spars in input space;
- each output is determined from the inputs by a deterministic process which is the same for both training and test sets;
- each output is subjected to statistical noise with finite
variance whose distribution may be different for different sets, but which is the same in both training and test sets for corresponding outputs [4].

Given this, small variations in \( y \), written \( \Delta y \), and \( y \), written \( \Delta y \), should be constant between points in the time series that are close together. The gradient, \( \Delta y/\Delta x \), between neighbours is more or less constant. Therefore, for each small successive section of the time series, if \( \Delta x \) is decreased to zero then \( \Delta y \) should also tend to zero provided there is no noise within the data [5]. With property prices, although \( \Delta y \) tends to zero, \( \Delta y \) does not because of the noise within the data, with the Gamma test providing an estimate for this noise.

The test is applied to each point within the time series, in turn. The distance between it and the nearest neighbour in terms of the input vector \( x \), and the corresponding output scalar value \( y \) is found, and the process is repeated for \( n \) nearest neighbours. The corresponding, squared, \( x \) and \( y \), distances are plotted on a graph and a linear regression line is then fitted to the points. This, linear regression line provides two useful measures, namely:

- the intercept of the line on the y-squared axis when \( \Delta y \) is zero, which gives the MSE, or Gamma value; and
- the gradient of the line, which provides an indication of the complexity of the model under analysis, where the steeper the line the more complex the relationship between \( y \) and \( x \).

These measures provide a basis for constructing and training an ANN, with the training process being stopped once the MSE reaches the Gamma value. For a fuller discussion of the Gamma test algorithm, the reader is directed to the work of Steffansson et al. [4].

5. Literature review

This section presents a background to the property market, and provides an overview of previous work related to determining residential property prices.

The property market can be viewed at three levels:

- National (i.e. UK);
- Regional/sub-national (e.g. South East Wales); and
- Urban/sub-market.

Theoretical market models indicate that the main variables expected to influence house prices at both the national and regional levels are [6]:

- incomes;
- interest rates (real or nominal);
- the general level of prices;
- uncertainty factors; and
- demographic variables;

- the tax structure;
- financial liberalisation;
- the housing stock.

However, because measures of some of these variables are not readily available at the regional level, models of regional house prices are typically much simpler than their national counterparts [6]. The Merrill Lynch forecasting model [7] uses just four variables:

- real house price (log of house price index divided by RPI);
- real incomes (log of real disposable incomes at constant prices);
- retail prices (log of RPI); and
- mortgage interest rate (tax-adjusted interest rate).

UK national and regional level models have developed primarily from the modelling of the market at the macro-economic level. These models have not been integrated with modelling at the urban level.

At the sub-market level, property valuation has centred on arriving at current prices for individual properties rather than predicting a time series. The traditional method for valuing residential property is direct capital comparison [8]. Here, valuers select comparable properties sold in the open market and make ‘an allowance in money terms’ [7] for any differences between the subject property and the comparable properties. This subjective method relies heavily upon the experience of the valuer. This paper builds upon the work of other researchers, grouped here into the following classes:

- general, related models [6,9,10,11];
- hedonic (a measure of general, overall opinion) regression analysis models [12–14]; and
- artificial intelligence [15,16], including ANNs [17–19].

6. Forecasting using artificial neural networks

Despite the many satisfactory characteristics of an ANN, building a neural network for a particular forecasting problem is a non-trivial task. Modelling issues that affect the performance of an ANN must be considered carefully. First, an appropriate architecture, that is, the number of layers, the number of nodes in each layer, and the number of arcs that interconnect with the nodes must be determined.

Other network design decisions include the choice of activation function for the processing nodes, the training algorithm, data normalisation methods, training data, and performance measures [20].

In this section, an overview of the fully connected-feedforward back-propagation ANN implemented is provided with special attention being given to how training data was presented and how performance was measured.
6.1. The network architecture

Our ANN is composed of an input layer, which corresponds to the length of the input vector, an output layer, which provides the forecast values, and two layers of hidden nodes. It has been shown that a single hidden layer is sufficient for an ANN to approximate any complex non-linear function with any desired accuracy [21]. However, recent findings have shown that two hidden layers can result in a more compact architecture that achieves a higher efficiency than single hidden layer networks [22–24].

6.1.1. The number of nodes in the hidden layers

It is important that the network has generalised across the time series and not simply fitted the inputs to their corresponding outputs. Therefore, the number of hidden nodes in each layer was determined by trial and error, with large numbers of nodes in the hidden layers being incrementally pruned to a minimum whilst still producing relatively good forecasting capabilities. The gradient statistic provided by the Gamma test [4] provides a heuristic for estimating the complexity of the underlying model, and hence the number of nodes that will be required, but no significant results can be reported here.

6.1.2. The number of nodes in the input layer

The number of nodes in the input layer corresponds to the length of the window, or the number of lagged observations used to discover the underlying pattern in a time series. This is the most critical decision variable for a forecasting problem, since the vector contains important information about complex (linear and/or non-linear) structure in the data. However, there is no widely accepted systematic way to determine the optimum length for the input vector [20]. Given this, varying length vectors were used during our experiments with the best window length being selected. The Gamma test may provide a meaningful approach to determine a near optimum length for the input vector [4], and a detailed analysis of this will form a significant part of our continued research.

6.1.3. The number of nodes in the output layer

For the time series forecasting problem described in this paper, the number of output nodes corresponds to the forecasting horizon. Here, two types of forecasting were considered, namely: one-step-ahead, which requires only one output node, and multi-step ahead. Experiments with these two approaches to make multi-step forecasts, the iterative and direct methods, were made. The iterative method requires only a single output node, with forecast values being substituted into the input vector to make further predictions. The second, direct method provides for multiple output nodes that correspond to the forecasting horizon, with this approach generating the best predictions.

6.2. Activation function

The transfer, or activation, function determines the relationship between inputs and outputs of a node and a network. In general, the transfer function introduces a degree of non-linearity into the ANN and in theory, any differential function can qualify as a transfer function. However, in practice, only a small number of bounded, monotonically increasing and differential functions are used. It has been suggested [25] that sigmoid (logistic) transfer functions, such as the sigmoid function:

\[ f(x) = \frac{1}{1 + \exp(-x)} \]  

(4)

provide better results and a more robust learning when dealing with average behaviour, with hyperbolic tangent function (tanh):

\[ f(x) = \tanh(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)} \]  

(5)

providing better results if the problem involves learning about deviations from the average, such as the forecasting problem. Experimentation with both the logistic and tanh functions led the authors to adopt the tanh function.

6.3. Data normalisation

Non-linear transfer functions will squish the possible output from a node into, typically, (0,1) or (−1,1). Given the range of the property time series being predicted, data normalisation was required before the training process could begin. Here, linear transformation [22] was applied to the time series values, with an upper limit of 1 and lower limit of −1 so as to coincide with the theoretical boundaries of the transfer function.

\[ a,\bar{H} : x^i = (b - a)x^i - x_{min} + x_{max} - x_{min} \]  

(6)

Of the methods for input normalisation reported in literature [26], the external method (all the training data is normalised into a specific range) was selected since it is the most appropriate procedure for a time series forecasting problem.

6.4. Performance measure

Although there can be many performance indicators associated with the construction of an ANN the decisive measure of performance is the prediction accuracy it can achieve beyond the training data. No universally accepted measure of accuracy is available, with a number of different measures being frequently presented in literature [27]

\[ \sum(x_i - \bar{y}_i)^2/N \]  

(7)

The performance measure shown before, adopted by the authors, is the root mean squared error (RMSE) function. The RMSE provides a measure of the difference between the actual (desired) and predicted value, where \( x_i \) is the individual forecast error and \( N \) is the number of error terms.
6.5. Partitioning of the time series

Typically, training and test data sets are used during the ANN creation process. In this paper, the training set was used to construct the ANN’s underlying model of the time series and the test set was used to measure the accuracy of this model. A third set, called the validation set, was used to determine when the training process should be stopped (the validated training procedure) [28]. As was mentioned earlier, this paper presents two approaches to timing when the training procedure should be stopped.

First, the normalised data set was converted into input/ output vectors, using an overlapping moving window (shown in Fig. 1). Next, the set of vectors was partitioned into a training set and a test set. The M-compartment convention of retaining the last eight quarterly points for testing, mapped to input/ output vectors, was adopted [29]. The remaining vectors were partitioned into a validation set (20%) and training set (80%) for where the validation set was used to indicate when training should end. This validation set was created by removing every fifth vector from the test set. Partitioning the test set in this way provides a meaningful validation set drawn from across the whole range of values present. Where the Gamma-test statistic was used to stop the training procedure, there was no need to partition the vectors since the whole training set is presented during training.

7. Experimental work

The investigation consisted of three parts. ANN forecast- ing models were constructed using the validated training procedure (the validation model). Similarly, ANN forecasting modes were constructed using the Gamma test statistic model (the Gamma model). Comparisons between the best results from each approach were then made.

7.1. Data source

Takens’ theorem suggests that all influences on a time series are coded into the single time series [30]. Therefore, a single indicator (the housing price index provided by the Nationwide Building Society, shown in Fig. 2) was selected to model the projected movements in property prices.

The time series is modelled by presenting a moving window of five input and eight output values to the ANN. Here, the ANN learns the relationships between a past quarter and the next y quarters. Experimental results are outlined below.

7.2. Results using the validation model

Here, the weights within the ANN are adjusted using the training portion of the training/validation set. However, the RMSE, which is used to determine when the training process stops, is not calculated across training set. Instead, the validation set (see Section 6.5) is presented to the ANN at regular intervals with the resultant RMSE across this data set being used to determine how well the ANN has modelled the time series. This iterative training process continues until the RMSE generated by the validation set shows no improvement (see Section 3).

Upon completion of the training procedure outlined before, the test set was presented to the ANN, the best of which producing predictions with a 3.9% error whose trend line falls below the actual trend (see Fig. 3).

7.3. Results using the Gamma test model

Here, the weights within the ANN are adjusted using the whole of the training set. This iterative training process

![Fig. 2. Nationwide building society housing price index.](image-url)
8. Conclusion

The work has shown that promising forecasting models can be produced using an ANN that provide a meaningful measure to facilitate the consumers short-term (2 years) decision making process. Given that the models constructed using the outlined Gamma test procedure performed the validated approach, this work has shown that the Gamma test provides a significant measure of the robustness of an underlying continuous or smooth model. The experience of the authors strongly suggests that the Gamma test is of practical utility in area of time series modelling.

9. Future work

Given these promising, initial, experiences with the Gamma test, it is the authors’ intention to explore whether related documented measures [4], based upon the Gamma test, show equal promise. In addition, work will be extended to include modular networks that map trends within related economic measures such as the retail price index, unemployment rate and interest rate to the housing price index. Ultimately, it is the authors’ intention to produce long-term (5 years) forecasts for regional, sub-regional and local property markets.

References


