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INFLATION FORECASTING IN GHANA - ARTIFICIAL NEURAL NETWORK MODEL APPROACH

BY

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DECLARATION

I wish to declare that the content of this work is the result of my effort through research and that the work has not been presented for any Certificate, Diploma or Degree elsewhere. Those whose works were read and partly used are duly acknowledged in the text. I therefore present this for the award of Master of Philosophy Degree in Economics.

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ABSTRACT

Price stability is the primary objective of monetary policy in Ghana. To achieve this mandate, the Bank of Ghana has adopted inflation targeting as its monetary policy framework. Indeed, inflation targeting requires good forecasting ability for the monetary authorities. Two approaches i.e. econometric and artificial neural network (ANN) models have been used by some central banks and researchers to forecast inflation. However, the Bank of Ghana and researchers in Ghana have used only econometric models to forecast inflation. This thesis uses both the econometric and ANN methods to predict inflation in Ghana. The econometric models (AR and VAR) and the ANN models (NAR and NARX) were applied to the monthly year-on-year inflation data from Jan. 1991 to Dec. 2011. The models were estimated using the data from Jan. 1991 to Dec. 2010 so as to forecast for the period Jan. 2011 to Dec. 2011. It was found that the forecast errors of the ANN models were lower than those of the econometric models; thus, the ANN predicts inflation better than the econometric models. The policy implication is for the Bank of Ghana and researchers in Ghana to use the ANN model in addition to the econometric models to forecast macroeconomic variables such as the inflation.

LIST OF ABBREVIATIONS

ACF	Autocorrelation Function
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
AR	Autoregressive Model
ARFIMA	Autoregressive Fractional Integrated Moving Averages Model
ARIMA	Autoregressive Integrated Moving Averages Model
ARIMAX	Autoregressive Integrated Moving Averages with Exogenous Input Model
ARMA	Autoregressive Model Moving Averages
ARX	Autoregressive with Exogenous Input Network Model
AS-AD	Aggregate Demand – Aggregate Supply Model
BIC	Schwarz Bayesian criterion
BoG	Bank of Ghana
BPN	Back-Propagation Network Model
BVAR	Bayesian Vector Autoregressive Model
CPI	Consumer Price Index
ECFM	Error Correction Forecasting Model
FFNN	Feed-Forward Neural Network Model
FIGARCH	Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
GRNN	Generalised Regression Neural Network Model
GSE	Ghana Stock Exchange
HQC	Hannan-Quinn criterion
IIP	Economic Growth
IS-LM	Investment Savings – Money Demand Money Supply Model
LM	Levenberg-Marquardt learning (iteration) method
M2+	Broad Money Supply
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLP	Multilayer Perceptron Neural Network Model
MPC	Monetary Policy Committee

MS	Money Supply
MS-AR	Markov Switching Model
MSFE	Mean Squared Forecast Error
NAR	Nonlinear Autoregressive Network Model
NARX	Nonlinear Autoregressive with Exogenous Input Network Model
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary Least Squares
PACF	Partial Autocorrelation Function
RMSFE	Root Mean Squared Forecast Error
SURE	Seemingly Unrelated Regression Estimation
UCM	Unobserved Components Models
VAR	Vector Autoregressive Model
VECM	Vector Error Correction Model
VIF	Variance Inflation Factor
WPI	Inflation
YoY	Year on Year

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CHAPTER I

INTRODUCTION

1.0 Background of Study

Price stability, as an important indicator of overall economic performance, is one of the main objectives of monetary policy (BoG Act, 2002). Over the past years, Ghana's monetary policy regime in the pursuit of this goal has evolved from direct controls to indirect monetary policy instruments regime (i.e. monetary targeting). While some argue that in all past regimes monetary policy performance have not been encouraging, others are of the opinion that those strategies were adopted in response to the demands of the times and are thus justified (Bawumia, 2010). In either case, a reform in the financial sector is necessary. For this reason, policymakers have sought to reform the financial sector once more in considerable effort to enhance the effectiveness of monetary policy.

The Bank of Ghana Act of 2002 (Act 612) granted independence to the central bank and also set the Bank of Ghana's primary objective as – to ensure price stability or low inflation in Ghana. Following the new arrangement, the Monetary Policy Committee (MPC) was established to formulate monetary policy in Ghana. The MPC has subsequently shown its commitment to attain and maintain a low stable inflation using the inflation targeting framework.

Inflation targeting is a framework for the conduct of monetary policy, in which the central bank uses its instruments in order to drive inflation near a preannounced target (Mishkin, 2001). The main characteristics of inflation targeting policy are described by Mishkin (2001) as; the public announcement of a well-defined numerical target for inflation; a commitment to price stability as the primary goal of monetary policy; an information inclusive strategy for deciding the setting of policy instruments; increased transparency of the monetary policy strategy; and increased accountability of the central bank for attaining its inflation objectives. Inflation targeters initially were industrialised countries since early 1990s; however, many emerging-market economies have also adopted this framework, spurred in part by the success of inflation-targeting countries in achieving and sustaining low levels of inflation (Mboweni, 2005). Bank of Ghana's adoption of inflation targeting in November 2002 (BoG, 2007), makes Ghana the second African country to do so after South Africa.

Inflation targeting puts price stability as the primary objective of monetary policy; however, the framework is more than simply announcing a target for inflation. Besides other prerequisites, practical implementation requires that policy makers are forward-looking. Forward-looking in inflation targeting framework means policymakers must be able to forecast inflation with a reasonable good degree of accuracy. This is because the inflation forecasts are used to initiate and guide policy discussions at the MPC in determining the policy stance to be adopted (i.e. in setting the policy rate or prime rate). That is to say, the magnitude of adjustment in the prime rate depends on the level of the deviation of forecasted inflation from the targeted inflation. This makes inflation forecasting crucial to central banks.

Moreover, accurately forecasting inflation is not only essential for inflation targeting policy as a guide to achieve price stability, it is also used to make monetary policy transparent and acquire credibility. For this reason, searching out models and consequently modelling inflation process for generating reasonable forecast of inflation are becoming quite important.

1.1 Statement of Problem

Price stability is the main objective of monetary policy in Ghana (BoG Act, 2002). In pursuing this goal, the Bank of Ghana (BoG) has adopted inflation targeting as its monetary policy framework. Under the inflation targeting regime, the central bank's goal of price stability is defined by the government's inflation target which is clearly spelt out in the budget statement for each fiscal year. For example in the 2012 fiscal year, the inflation target was set at 8.5% (Budget statement, 2012). Inflation targeting requires the BoG to be able to model and forecast inflation so that they can react to deviations of forecasted inflation from the target; hence, accurately forecasting the inflation is crucial to the process.

The Bank of Ghana uses several time-series econometric forecasting models such as the autoregressive (AR) model, error correction forecasting (ECF) model and a calibrated macroeconomic model to generate forecasts of the inflation to guide policy discussions at the Monetary Policy Committee (Addison, 2006 and Bawumia, 2010). These time-series econometric forecasting models are limited since they often assume linearity which is not consistent with the nonlinear nature of the real world (Moshiri et al, 1999). As a result, the Artificial Neural Network (ANN) models have also been used extensively to predict macroeconomic variables such as the inflation. The ANN model can find solution for very complex and non-linear problems (Moshiri & Cameron, 2000).

In fact, scores of empirical studies have compared the inflation forecasting performance of the ANN model with the econometric models and have concluded that the ANN models outperform the econometric models in the prediction of inflation (Ozdemir & Taskin, 2010; Duzgun, 2010; Hu et al, 2007; Haider & Hanif, 2007; Lee et al, 2007; Gungor & Berk, 2006; Nakamura, 2005; Suhartono, 2006; Moshiri & Cameron, 2000; Moshiri, 1997).

Some central banks e.g. The State Bank of Pakistan, CZECH National Bank, Bank of Canada and Bank of Jamaica have also used ANN models to predict various macroeconomic indicators like the inflation, GDP growth etc (Hlavacek et al, 2005; Tkacz & Hu, 1999; Serju, 2002 and Haider & Hanif, 2007).

In the review of relevant literature, it was observed that some studies on inflation forecasting have been conducted in Ghana (Sowa & Kwakye, 1991; Sowa, 1994, 1996; Kwakye et al, 1996; Lawson, 1996; Ewusi, 1997; Addison, 2001; Bawumia & Abradu-Otoo, 2003; Ocran, 2007; Bawumia, 2010; Owusu, 2010; Alnaa & Ahiakpor, 2011). However, none of these studies used the ANN methodology to predict the inflation. For that reason, the quest to investigate the forecasting performance of the ANN model and compare with econometric models in Ghana remains a worthwhile endeavour.

1.2 Objectives of the Study

The general objective of this study is to evaluate the forecasting performance of the ANN model by comparing forecasts from the ANN model with time-series econometric models in Ghana. The specific aims are to:

i. To estimate inflation using time series econometric models i.e. the autoregressive (AR) model and the vector autoregressive (VAR) model
ii. To forecast inflation using the estimated econometric models i.e. AR and VAR
iii. To estimate inflation using artificial neural network (ANN) models i.e. the nonlinear autoregressive (NAR) network model and the nonlinear autoregressive with exogenous input (NARX) network model
iv. To forecast inflation using the estimated ANN models i.e. NAR and NARX
v. To compare the forecasting performance of the AR and NAR models
vi. To compare the forecasting performance of the VAR and NARX models

1.3 Hypothesis of the Study

In order to compare the accuracy of forecasts of the ANN models and the time-series econometric models, as in the specific objectives five and six, we formulate the hypothesis that:

i. **Null Hypothesis (H_0):**

There is no significant difference between the Root Mean Squared Forecast Errors (RMSFE) of the ANN and the time-series econometric models.

ii. **Alternate Hypothesis (H_1):**

There is significant difference between the Root Mean Squared Forecast Errors (RMSFE) of the ANN and the time-series econometric models.

1.4 Justification of the Study

According to Governor Kohn (2005), nothing is more important to the conduct of monetary policy than the understanding and ability to predict inflation. The better the forecasts, the better the chances that policy choices will contribute to economic stability and efficient resource allocation. Needless to say, more work remains to be done and always will. As a result, this study is plausible to monetary policymakers because it evaluates the forecasting performance of the new ANN model in an attempt to improve Ghana's inflation prediction accuracy.

Finally, there exist considerable empirical literature on inflation forecasting in Ghana; however, most of these studies have used time-series econometric models before the ANN models. Thus, although the model predicts better, the use of ANN methodology in researches in Ghana is rare. This study has an important contribution to this question in literature.

1.5 Brief Methodology

The study was conducted using four models to predict the inflation. Two of the models were time-series econometric models i.e. the autoregressive (AR) model and the vector autoregressive (VAR) model. The other two were artificial neural network (ANN) models i.e. the non-linear autoregressive (NAR) network model and the non-linear autoregressive with exogenous input (NARX) network model. The autoregressive models i.e. the AR and NAR, predict the inflation from the past values of the inflation whereas the VAR and NARX also forecast the inflation from past values of the inflation and past values of predictor variables such as broad money supply (M2+) growth rate and exchange rate depreciation.

The data for the estimation and forecasting of the inflation were obtained from the Bank of Ghana. The data were monthly year-on-year series and covered the period January, 1991 to December, 2011: The data between January, 1991 and December, 2010 were used to estimate the models and that between January, 2011 and December, 2011 were used for the prediction. The root mean squared forecast error (RMSFE) criterion was used as the basis for comparing forecasts from the ANN models with the time-series econometric models.

1.6 Scope of the Study

This thesis is about inflation forecasting in Ghana using the ANN model. The study briefly examines the main forecasting techniques in economics. It also includes the concepts of the time-series econometric models used as well as some empirical discussions. The concepts of the ANN model and its empirical studies are thoroughly discussed. The inflation, theories of inflation and empirical studies are also looked at. The study finally highlights on the ANN model's performance for predicting macroeconomic variables.

The study was limited to the period 1991 – 2011. This period is chosen partly because it marks a period of about ten years before and after the start of the inflation targeting policy in Ghana and partly because of data availability.

1.7 Organisation of Study

The study is organised into five chapters. Chapter One deals with the introduction i.e. the background of the study, the problem statement, the objectives of the study, the study hypothesis, the justification of the study, a brief methodology and the scope of the study. Chapter Two is a review of the theoretical and empirical literature on inflation forecasting techniques, the theories of inflation and some empirical studies on the determinants of the inflation. Chapter Three focuses on the specification of the models used for the study as well as the type and sources of data and variables description. The forecasting strategy and evaluation method are also presented in the third chapter. The results obtained are discussed and analysed in the Chapter Four. Chapter Five presents the summary of findings, policy implications, recommendations and concluding remarks.

CHAPTER II

LITERATURE REVIEW

2.0 Introduction

This chapter is about the relevant inflation theories and forecasting models. Some empirical studies on the determinants of inflation and inflation forecasting conducted elsewhere and in Ghana are also reviewed. There are four main parts. Part one reviews inflation, theories of inflation and some empirical studies on the determinants of inflation. Part two presents an overview of forecasting techniques. Part three deals with the concepts of time-series econometric forecasting models and some empirical studies on the models. Finally, part four looks at the concepts of ANN forecasting models as well as some empirical studies conducted using the ANN technique.

2.1 Inflation

Inflation is a rise in the general level of prices of goods and services in an economy over a period of time (Barro, 1997). Sometimes inflation is simply described as an economic state where there is too much money chasing too few goods. That is, inflation results if growth in money supply is higher than the economic growth rate (Gokal & Hanif, 2004).

Inflation is of concern to many countries both developed and developing. This is because inflation affects directly and indirectly all economic units and several macroeconomic indicators like wages, interest rate, exchange rate, imports and exports etc. For instance, the currency loses its purchasing power when there is inflation. As a result, fixed income earners such as pensioners are affected because the value of their monthly remittances declines. Savings are discouraged because as prices surge, the value of savings declines if the rate of inflation exceeds the rate of interest. High inflation also translates into high lending rates for the private sector, the engine of growth.

What is more, decisions of economic units like investment decisions become difficult as expectations of future price movements are unstable in times of inflation. Inflation thus leads to uncertainty about future profitability of investment project and hence results in more conservative investment strategies than would otherwise be the case. The ultimately end result is lower levels of investment and economic growth. Inflation may also reduce a country's international competiveness, by making its exports relatively more expensive, thus impacting on the balance of payments. The costs associated with high inflation are evidently more.

Price stability is therefore one of the main objectives for policymakers in many countries. To achieve this mandate through the conduct of monetary policy, nothing is more important than the understanding and ability to predict inflation (Governor Kohn, 2005). Better outcomes inevitably begin with improved understanding of the theoretical and empirical framework of the inflation.

2.1.1 Theories of Inflation

The theories of inflation are important for the understanding of the determinants of the variable and its prediction. There are various schools of thought regarding the determinants of the inflation. In this study, the various theories are grouped into two broad categories as the demand-side and the supply-side theories.

2.1.1.1 Demand-side Theories of Inflation

The demand-side theories comprise the Keynesian and Monetarist views of inflation. These theories of inflation argue that inflation is mainly caused by excess demand for goods and services over supply in the economy. The Keynesian theory focuses on the short run demand pressures on the economy, hence emphasizing the short run Philips curve. Whereas the Monetarist theory while accepting the Keynesian approach in the short run, focuses only on money as a major determinant of inflation in the long run. That is, in the monetarist theory, both the short run Phillips curve which is negatively sloped and the long run Phillips curve which is vertical are equally important. Thus, both the Monetarist and Keynesian theories come under the umbrella of the expectation augmented Phillips curve.

2.1.1.2 Supply-side Theories of Inflation

The supply-side theories of inflation also comprise of mainly the new Classical and the Structuralist theories. These theories stress on factors that influence the inflation other than demand shocks. The new Classical theory emphasizes the supply side of the economy arguing that only supply shocks can influence prices. That is, in the new Classical theory, there is only one Phillips curve which is vertical. The Structuralist approach also examines structural and cost-push factors. The Structuralist dwells on structural factors such as whether the market works and cost-related pressures including import prices.

Determinants from both sides of the theories have been identified in empirical studies conducted in many countries. These studies are reviewed in order to identify the determinants that need to be used in the selected forecasting model in this study.

2.1.2 Review of Empirical Studies on Inflation Determinants

Several empirical studies exist to identify the determinants of the inflation and also to test the validity of the inflation theories in many economies. The empirical review of these studies is presented in three parts. The first part reviews studies conducted in the developed economies; then, those conducted in developing countries and in Ghana follow respectively.

2.1.2.1 Studies in Developed Economies

Altimari (2001) investigated the properties of monetary and credit aggregates as indicators for future price developments. He used quarterly data from 1980:Q1 to 2000:Q2. The results supported the idea that monetary and credit aggregates provide significant and independent information for future price developments in the euro area, especially at medium term horizons. De Grauwe and Polan (2005), using a sample of about 160 countries over the last 30 years, also found a strong positive relation between long-run inflation and the money growth rate.

In the United States, Dhakal et al (1994) investigated the major determinants of the inflation rate with US data. They found that changes in the money supply, wage rate, budget deficit, and energy prices are important determinants of the inflation rate. They emphasised that, the role of the money supply, however, is more important than other factors in explaining price changes.

Using the Canadian data, Caramazza and Slawner (1991) also investigated the relationship between money, output and prices. In general, they found that inflation is influenced both by money and the output gap. However, in a time-series analysis of retail food prices in Russian markets, Peterloy and Weaver (1998) indicated that distortions in relative prices were induced by the anticipated inflation rate, rather than by unanticipated inflation or a measure of inflation uncertainty.

2.1.2.2 Studies in Developing Economies

Some empirical studies have also been conducted on the determinants of inflation in the developing and emerging world economies. Frama and Carneiro (2002) analysed the annual Brazilian data from the period of 1980 to 1995. They concluded that there exist a negative relationship between inflation and economic growth in the short run although no such relationship exists in the long run.

In Turkey, Lim and Papi (1997) found, in a multi-sector analysis, that money supply growth plays a central role in the inflationary process in the Turkish economy during the period 1970 to 1995 besides exchange rates, inertial factors and public sector deficits. Dibooglu and Kibritcioglu (2004) also studied output and inflation in Turkey using quarterly data from 1980:Q1 to 2002:Q3. The empirical results showed that terms of trade, monetary and balance of payments shocks figure prominently in the inflation process. On the contrary, Us (2004) found that inertial inflation is not a monetary phenominon in Turkey but rather an outcome of a political misconduct which therefore showed the fiscal dominance.

In Africa, some studies have also been conducted. London (1989) examined the role of money supply and exchange rate in the inflationary process in twenty-three African countries. The results revealed that in the period between 1974 and 1985 the growth of money supply, exchange rate, expected inflation and real income were significant determinants of inflation in the sample countries. London's findings were supported by Tegene (1989) who on the other hand established the role of domestic money supply on inflation in six African countries. He evidenced a unit-directional causality from monetary growth to inflation in his study.

Chhibber et al (1989) analysed Zimbabwean inflation using both structuralists and monetary factors of the inflation. The results showed that nominal monetary growth, foreign prices, exchange and interest rates, unit labour costs and real income are the determinants of inflation in Zimbabwe. Elbadawi (1990) also conducted a research on the determinants of inflation in Uganda. His work revealed that rapid monetary expansion and the depreciation of parallel exchange rate were the principal determinants of inflation in Uganda. In an attempt to explain the inflation movement in Kenya using six-variables i.e. money supply, domestic price level, exchange rate index, foreign price index, real output, and the rate of interest, Ndungu (1993, 1997) also observed that the rate of inflation and exchange rate explained each other.

A research conducted by Laryea and Sumaila (2001) on the determinants of inflation in Tanzania established that output and monetary factors are the main determinants of inflation in the short-run while in the long-run, parallel exchange rate also influences inflation. In their conclusion, they emphasized that inflationary situation in Tanzania is basically a monetary phenomenon. Recently, Okhiria and Saliu (2007) examined the relationship between government expenditure, money supply, oil revenue, exchange rate, and inflation in Nigerian economy between 1970 and 2007. Their result confirmed a strong relationship among the variables although inflation rate and exchange rate showed only short term relationship.

2.1.2.3 Studies in Ghana

In Ghana, some empirical studies on inflation determinants have also been done. Chhibber and Shaffik (1991) conducted a study on the effects of bank and fund policy reforms on inflation in selected African countries and concluded that inflation in Ghana is indeed, a monetary phenomenon. However, Dordunoo (1994) argued that rapid exchange rate depreciation and resultant increases in import prices are the main causes of inflation in Ghana.

Sowa (1994, 1996) also estimated an inflation equation for Ghana, carefully examining fiscal consistency under different regimes. On the whole, he found that inflation was influenced more by output volatility than by monetary factors induced by the government's deficit. However, inflation was on target during periods characterized by a fiscal discipline regime and exceeded the target during periods marked by fiscal incoherence. This findings affirmed earlier results by Sowa and Kwakye (1991). Ghartey (2001) similarly found the fiscal deficit to be an inflationary factor in Ghana for the period 1972 to 1992, because an important amount of financing came from printing money.

In a study using the Ghanaian data from 1960 to 2003, Ocran (2003) found that in the short run inflation inertia, money growth, changes in Treasury bill rates and the exchange rate are important in determining the level of inflation. Bawumia and Abradu-Otoo (2003) also confirmed the existence of a long-run equilibrium relationship between inflation, money supply, the exchange rate and real income in Ghana for the period 1983 to 1999. Appiah and Boahene (2006) too established that the growth rate of real GDP and the growth of money supply are the main determinants of inflation in Ghana both in the short-run and the long-run, with money supply being the key determinant. Recently, Adu and Marbuah (2011) provided an empirical analysis of the factors accounting for inflation dynamics in Ghana. They found that real output, nominal exchange rate, broad money supply, nominal interest rate and fiscal deficit play a dominant role in the inflationary process in Ghana. They concluded that inflation in Ghana is explained by a combination of structural and monetary factors consistent with prior studies.

2.2 Overview of Forecasting Techniques

A forecast is any statement about the future. Since it is merely a statement about the future, anything can be forecast. Economists predict various macroeconomic variables such as the inflation. Forecasting is an important exercise for policymakers because the forecasts underpin forward-looking decisions. In policy formulation for instance, forecasts can confirm the appropriateness of the current policy stance or alert the policymakers to take policy response should the forecast outlook indicate a likely deviation from target. Therefore, researchers continue to search out methods for accurately forecasting macroeconomic variables to aid policy formulation. Some studies on economic forecasting techniques can be found in the literature (Hendry & Ericsson, 2001; Diebold, 1998; Allen & Fildes, 2001; Whitley, 1994; Box & Jenkins, 1976; Granger & Newbold, 1986; Harvey, 1989; Clements & Hendry, 1998, 1999, 2002; Hackl & Westlund, 1991; and Engle & White, 1999).

There are several methods of making forecasts; however, the main forecasting methods in economics are expert judgement, leading indicators, surveys, econometric systems of equations and time-series models.

- **Expert Judgement**

The term expert judgement or judgemental forecasting refers to the incorporation of forecasters' opinions and experience into the prediction process. In economic forecasting, Bolger & Önkal-Atay (2004), note that judgement may enter the forecasting exercise at many levels, from the choice of the variables to include, building structural equations, correcting for omitted variables, specifying expectations for economic indicators, and adjusting the model predictions in light of new information, to official announcements. According to Batchelor & Dua (1990), studies with economic forecasters indicate that judgement is given more weight than the modelling techniques in constructing predictions. In fact, judgement is the primary factor that the economist uses in converting mere statistical and theoretical techniques into a usable forecast (McAuley, 1986). Some recent studies (Alamsyah, 2003; Faust & Wright, 2011) also confirm that the role of judgement in forecasting is still important. So, judgement is usually part of a forecasting approach, but lacks validation when it is the sole component (Clements & Hendry, 2002).

- **Leading Indicators**

Some researchers use leading indicators to forecast macroeconomic variables. Leading indicators are indicators that usually change before the economy as a whole changes (Sullivan & Sheffrin, 2003). They are very useful in predicting the future direction of business cycle related variables like GDP, inflation, employment and the money supply. For example, the stock market returns usually begins to decline before the general economy declines from a peak and vice versa.

Stock & Watson (2003) reveals that in the 2001 recession although professional forecasters found the recession a difficult one to forecast, the leading indicator performed somewhat better than a benchmark autoregressive forecasting model. However, Leigh & Rossi (2002) in testing the predictive power of leading economic indicators on inflation concluded that the forecasting ability of individual indicators was unstable and needed to be used in a suitable combination to outperform the forecasting ability of autoregressive model. Leading indicators have also been used in forecasting studies by Chauvet (2000), Grasmann & Keerman (2001) and Simone (2001).

- **Surveys**

Surveys of consumers and businesses including forecasters may be informative about future events and therefore can be used to forecast. Several central banks conduct surveys yielding regional and sectoral information on the general economic outlook. For example in the U.S., surveys of expected inflation such as Livingston Survey of Professional Economists and Survey of Professional Forecasters by the Federal Reserve Bank of Philadelphia and the Survey by the Institute for Social Research at the University of Michigan have been conducted for dozens of years and have been the subject of many papers.

Carlson (1977) and Carlson & Parkin (1975) argue that survey data for inflation are the best available measures of expected inflation. However, some researchers (Prescott, 1977; Pearce, 1979; Keane & Runkle, 1990) also claim that surveys are not appropriate for prediction. Nevertheless, many recent studies also highlight the importance of survey data in forecasting macroeconomic variables (Hansson, Jansson & Löf, 2003; Banerjee et al, 2003; Ang et al, 2007; Abberger, 2007; Claveria et al, 2007; Thomas, 1999; Österholm, 2009; Białowolski et al, 2010; Łyziak, 2010; Kruger et al, 2010; Lui et al, 2010 and Martinsen et al, 2011).

- **Econometric Systems of Equations**

Econometric systems of equations also called structural models are the main tools in economic forecasting. These comprise equations which seek to model the behaviour of discernible groups of economic agents such as consumers, producers, workers, investors, etc. assuming a considerable degree of rationality (Clements & Hendry, 2002). These methods rely on statistical procedures to estimate relationships for economic models specified on the basis of theory and other information. This approach incorporates existing theoretical and empirical knowledge of how the economy works. The main advantages to economists of using these approaches according to Clement & Hendry (2002) are to provide a framework for a progressive research strategy leading to increased understanding over time and to provide forecasts and policy advice.

- **Time-Series Models**

Time-series models are popular forecasting methods and are often used to forecast macroeconomic variables. Time series models describe the historical patterns of data. These methods are based on the supposition that history provides some guide as to what to expect in the future i.e. the models assume that the data has all the relevant information to study the behaviour of a variable and it therefore suffices.

The time-series models and econometric systems of equations are the primary methods of forecasting in economics (Clements & Hendry, 2002; Alamsyah, 2003); however, Moshiri (1997) finds that the time-series models are better at prediction than the econometric systems of equations and therefore are being used in most of the cases. This is because time-series models are free of parameter restrictions and model misspecification problems. Therefore, this study uses only time-series econometric models to predict the inflation in the contest with the ANNs.

2.3 Concepts of the Time-series Econometric Forecasting Models

Time series models presuppose that any piece of data can be decomposed into a time trend, a cyclical element, a seasonal factor and an error or random term. Several techniques exist to break up a time series into these components and thereby to generate a means of forecasting future behaviour of the series. The most popular of these techniques are the univariate frameworks such as the autoregressive (AR) model and the autoregressive integrated moving averages (ARIMA) approach by Box & Jenkins (1976), and the multivariate framework like the vector autoregressive (VAR) model (Sims, 1980 and Doan et al, 1984). In this study, two of the time-series econometric models are used to predict the inflation. These are the AR and VAR models.

- **Autoregressive (AR) Model**

The autoregressive (AR) model is a one variable (univariate) time series analysis that describes the behaviour of a variable in terms of its own past values. AR (p) indicates an autoregressive model of order p. The AR (p) model is defined as:

$$X_t = \mu + \sum_{i=1}^{\rho} \varphi_i X_{t-i} + \varepsilon_t \qquad \textbf{(2.1)}$$

where $\varphi_1, \varphi_2, \ldots, \varphi_\rho$ are the parameters of the model, μ is a constant and ε_t is white noise.

In estimating the AR (p) model in this study, past values of inflation are used to forecast future values of the inflation. This is because the past inflation values are assumed to contain enough information in explaining the behaviour of future inflation values. The ordinary least squares (OLS) regression method is used to estimate and forecast for the model.

- **Vector Autoregressive (VAR) Model**

VAR is a multivariate time-series forecasting model which extends the univariate model by incorporating the lags of other explanatory variables to the lags of the dependent variable in the model. Sims (1980) criticized the conventional simultaneous structural models on the basis that they usually require an imposition of invalid restrictions on parameters and lag patterns. He then suggested a VAR model which is an atheoretic model and is viewed as an unrestricted reduced-form of a structural model. The only assumptions the VAR model needs are the accurate selection of the relevant variables and how they appear (level or first difference) in the model (Moshiri, 1997). The VAR model is generally specified as:

$$Y_t = C + A(L)\, Y_t + E_t \qquad \textbf{(2.2)}$$

where Y_t is a (nx1) vector of variables. A(L) is an (nxn) matrix of polynomials in the lag operator L with the lag length p: $A(L) = A_1L + A_2L^2 + \ldots + A_pL^p$, C is an (nx1) vector of constants and E_t is a (nx1) vector of random errors. The VAR model assumes all variables are endogenous, and so there is no exogenous variable. The equations of a VAR (p) model with two variables, say Y_{1t} and Y_{2t}, can be expressed as follows:

$$Y_{1t} = \alpha_{10} + \sum_{i=1}^{\rho} \alpha_{1i} Y_{1,t-i} + \sum_{i=1}^{\rho} \beta_{1i} Y_{2,t-i} + \xi_{1t} \qquad \textbf{(2.3)}$$

$$Y_{2t} = \alpha_{20} + \sum_{i=1}^{\rho} \alpha_{2i} Y_{2,t-i} + \sum_{i=1}^{\rho} \beta_{2i} Y_{2,t-i} + \xi_{2t} \qquad \textbf{(2.4)}$$

where ρ is the lag length and ξ_{1t} and ξ_{2t} are the error terms. In the VAR model, past values of both variables predict each of the variables. As with the AR (p) model, the ordinary least squares (OLS) regression method is used to estimate and forecast for the model.

2.3.1 Review of Empirical Studies on Time-series Econometric Forecasting Models

Several studies have been conducted to check the performance of the time-series models in predicting macroeconomic variables like the inflation. Moshiri (1997) forecasted Canadian inflation using three time-series models i.e. ARIMA, VAR and Bayesian VAR model. He compared their forecast performance with three structural models i.e. the inflation equation based on AS-AD model, the Fair's model and the monetary model. The results showed that, in general, the time series models forecast better than the structural models with BVAR having the lowest forecast error. Holden (1997) also compared forecasts from three BVAR models with annual forecasts produced each autumn from four prominent UK economic modelling organizations. He found that although the BVAR forecasts are inferior to those from the economic models, they contain information which could be used to improve the other forecasts. Kenny, Meyler and Quinn (1998) also found that the Bayesian VAR technique performs well in forecasting Irish Inflation.

Ponomarevay (2004) constructed a simple univariate model and a VAR model for Korea to forecast inflation and nominal income growth. The main result showed that both models forecast the inflation equally well. Bokhari and Feridun (2006) also used both ARIMA and VAR to forecast inflation in Pakistan. Their results indicated that inflation forecasts from both models were good. Robinson (1998) used a VAR model augmented by an error correction term to forecast inflation in Jamaica. He found that the model exhibited greater predictive accuracy when compared to other models. Tanasie and Fratostiteanu (2005) also used VAR to model and forecast inflation in Romanian. They concluded that the results obtained were significant and in strict accordance to the economic reality and theory.

Meyer et al (1998) considered ARIMA for forecasting Irish inflation and justified that ARIMA models are surprisingly robust with respect to alternative (multivariate) model. Salam, Salam and Feridun (2004) adopted the ARIMA framework for forecasting Pakistan's inflation. They concluded that the model has sufficient predictive powers and the findings were consistent with other studies. Marcellino (2006) also used the standard linear model to forecast GDP growth and inflation and compared them with the benchmark model. He concluded that, in general, linear time-series models can hardly be beaten if they are carefully specified and therefore still provide a good benchmark for theoretical models of growth and inflation.

On the contrary, Önder (2004) compared forecasts from time-series models, namely, the ARIMA model, VAR and VEC model and a native no-change model with those of the Phillips curve for the Turkish economy. He found that inflation forecasts obtained from the Phillips curve were more accurate. Other contrasting studies can also be found in the literature (Moser, Rumler & Scharler, 2004; and Kotłowski, 2008).

Some studies have also compared the forecasting performance of different time-series models; the results are however mixed. Fritzer, Moser and Scharler (2002) evaluated the performance of VAR and ARIMA models to forecast Austrian headline inflation. They found that while forecasting accuracy improved substantially for ARIMA models, VAR models outperformed the ARIMA models in terms of forecasting accuracy over the longer projection horizon i.e. 8 to 12 months ahead. Valle (2002) also used ARIMA and VAR models to forecast inflation in Guatemala. He found that the VAR models produced better forecasts of inflation in the period prior to the occurrence of the structural change whereas the ARIMA models outperform the VAR models for the period of structural change.

Webb (1995) examined several forms of VAR models to forecast the inflation rate in the United States. In general, he showed that VAR models which take into account different monetary regimes, either by adding dummy variables or by splitting the data into different sub-periods, produce better forecasting results. Wright (2011) used the Bayesian VAR in a real-time forecasting exercise in Maryland and found that it generally outperforms a benchmark univariate autoregressive model. Biswas et al (2010) also found that BVAR model performed better than VAR model in case of inflation as well as IIP growth forecast in India. Some of these studies that also compare different time-series models in inflation prediction can be found in the literature (Clements & Galvão, 2011; Clark & McCracken, 2006; Berger & Stavrev, 2008; Lack, 2006; Heidari, 2010; and Mayr & Ulbricht, 2007).

In Ghana, Atta-Mensah and Bawumia (2003) presented a vector error correction forecasting model (VECFM) based on broad money (M2+). The results indicated that the model forecasts inflation, M2+ growth, output growth, interest rate and the exchange rate with a reasonable good degree of accuracy. Recently, with monthly inflation data from 1990 to 2009, Owusu (2010) also used the ARIMA model to perform in-sample and out-of-sample inflation forecast in Ghana. He found that the model has sufficient predictive power and the findings were consistent with other studies. Alnaa and Ahiakpor (2011) also used the ARIMA model to predict inflation in Ghana using monthly inflation figures from the period 2000:M6 to 2010:M12. By making a comparison of co-integration and ARIMA models, they found that the ARIMA model is efficient in predicting inflation in Ghana.

2.4 Concepts of the Artificial Neural Network (ANN) Forecasting Models

The Artificial Neural Network (ANN) theory grew out of Artificial Intelligence research, or the search in designing machines with cognitive ability. And so, the ANN methodology was developed in an effort to model the way the human brain process information. The human brain learns by experience: It receives information and recognises the pattern; the brain then generalises and is able to predict based on the information received. It is this way of information processing by the brain that the ANN model tends to mimic. Although ANN models are too far from the way the human brain performs, by mimicking the basic features of the biological neural networks, they have succeeded in doing certain jobs very well (Moshiri, 1997).

2.4.1 Human (or Natural) Neural Network

The human brain or the central nervous system is made up of interconnected units called neurons. This system or group of interconnected neurons working together to perform the functions of the brain (i.e. learning) is the neural network. By definition, neurons are basic signalling units of the nervous system of a living being in which each neuron is a discrete cell whose several processes are from its cell body. Figure 2.1 below shows the biological structure of the human neuron.

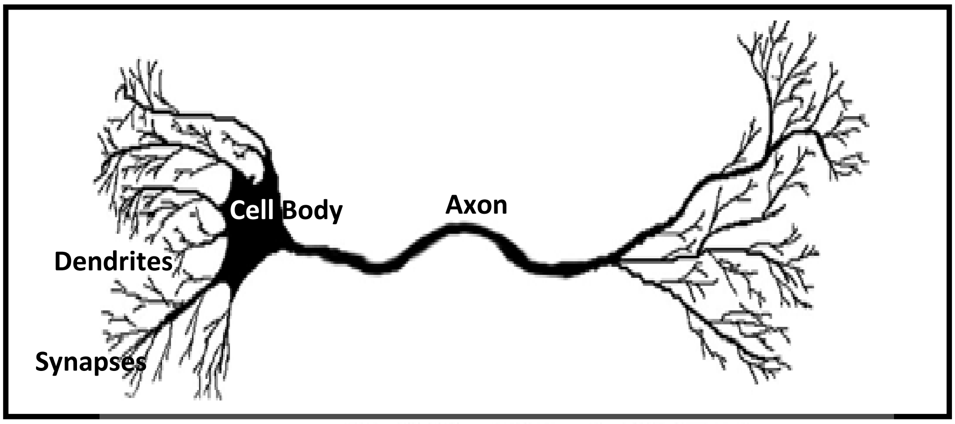


Figure 2.1 Biological Model of Human Neuron (artist's conception)

The biological neuron has four main regions to its structure: The *cell body*, the *dendrites* or *membrane*, the *axon* and the *synapses*. The cell body is the heart of the neuron. The human neuron receives signals through synapses located on the dendrites or membrane. When the signals received is strong enough (i.e. surpasses a certain threshold), the cell body is activated and emits another signal through the axon. The emitted signal (or action potentials) is sent to activate other neurons within the system. As similar signals continue to cross the threshold, the network recognises the path of the signals, assumes a pattern, and as a result generalises that if the signal is like this, then the output should be that. That is, the network is able to predict based on the pattern of the signals received.

2.4.2 Artificial Neural Network

The artificial neuron is a mimic of the natural human neuron. The human brain contains approximately ten billion (10^{10}) neurons, each connected on average to ten thousand (10^4) other neurons, making a total of 10^{15} synaptic connections (Larose, 2004). Therefore, a mimic of the way biological networks perform may appear more than complex. Artificial neural networks only represent an attempt at a very basic level to imitate the type of nonlinear learning that occurs in the networks of neurons found in nature.

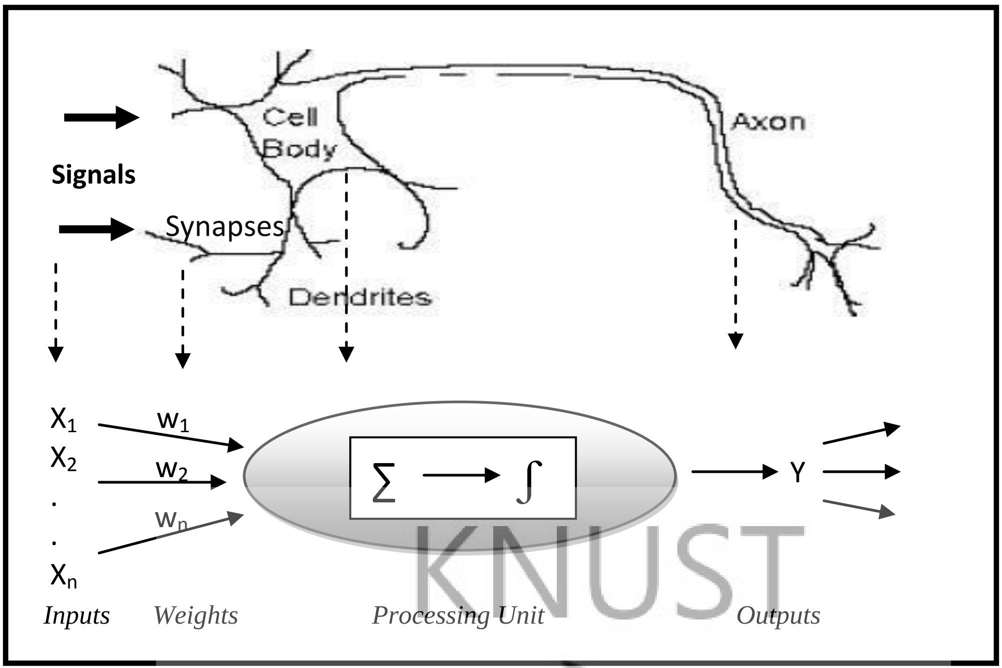


Figure 2.2 Natural and Artificial Neurons (a relational sketch)

As shown in figure 2.2, a natural neuron uses the synapses located on the dendrite to gather inputs (signals) from other neurons and combines the input information, generate a nonlinear response when some threshold is reached, which it sends to other neurons using the axon. Similarly, the artificial neuron collects inputs (x_i) from input neurons, attaches weights and combines them through a combination function such as summation ($\sum$). It is then activated by a function ($\int$) to produce an output response (y), which is sent to other neurons.

2.4.3 The Mathematical Model

The mathematical equivalence of the ANN model is presented in two parts. The first part is the mathematical processes that occur in a single neuron. The second also presents the computations that go on in the multilayer network (i.e. a network of more than one neuron).

2.4.3.1 The Basic Single Neuron Model

The fundamental building block for neural networks is the single neuron model such as Figure 3.3. There are three distinct functional operations that take place in a neuron. These are the weight function, the net input function and the transfer function.

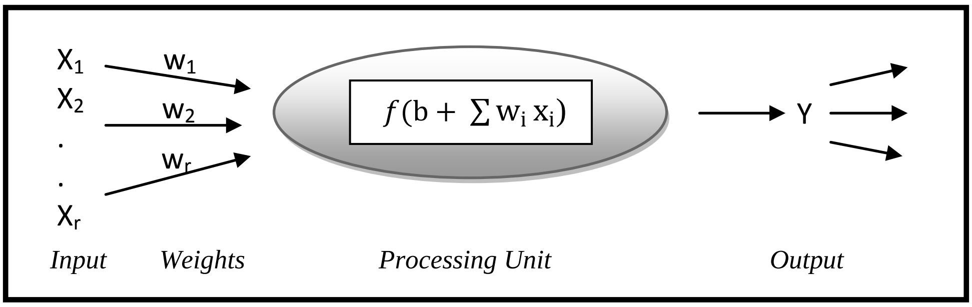


Figure 2.3 The basic structure of the Artificial Neuron Model

- **The Weight Function**

First, the inputs, (x: x_1, x_2,..., x_r) are fed into the neuron. Each input is multiplied by a random weight (w_i) to form the product and summed ($\Sigma w_i x_i$). The inputs and weights are the same as the variables and parameters, respectively, in linear regression models. For many types of neural networks, the weight function is a product of a weight times the input, but other weight functions (e.g., the distance between the weight and the input, $|w - x|$) are sometimes used.

- **The Net Input Function**

Next, the weighted input ($\Sigma w_i x_i$) is added to a bias (**b**) to form the net input (**n**). That is, the net input becomes: $n = b + \Sigma w_i x_i$. The bias is similar to the constant in linear models. The most common net input function is the summation of the weighted inputs with the bias, but other operations, such as multiplication, can be used.

- **The Transfer or Activation Function**

The net input is then passed through the transfer function (***f***), which produces the output (**y**). The three processes can be shown as follows:

$$y = f(b + \sum \mathrm{w_i}\, \mathrm{x_i}) \qquad \textbf{(2.5)}$$

There exist many types of transfer or activation functions. The most popular ones are the linear function and the nonlinear sigmoid function. If the function is linear, it only transfers the net "n" value to the output unit that is, f (n) = n. This is similar to the linear regression model in econometrics:

$$y = b + \sum w_i x_i \qquad \textbf{(2.6)}$$

However, if the function is nonlinear like the "log-sigmoid" or "hyperbolic tangent sigmoid" function, then the function is continuous and generates values between 0 and 1, and -1 and +1 respectively. The sigmoid function is very popular because it is relatively simple to calculate its first derivative during weight adjustment in back-propagation. The sigmoid function is similar to the logit model and has the following forms:

$$y = tansig\ (b + \sum w_i x_i) \quad \text{and} \quad y = logsig\ (b + \sum w_i x_i) \qquad \textbf{(2.7)}$$

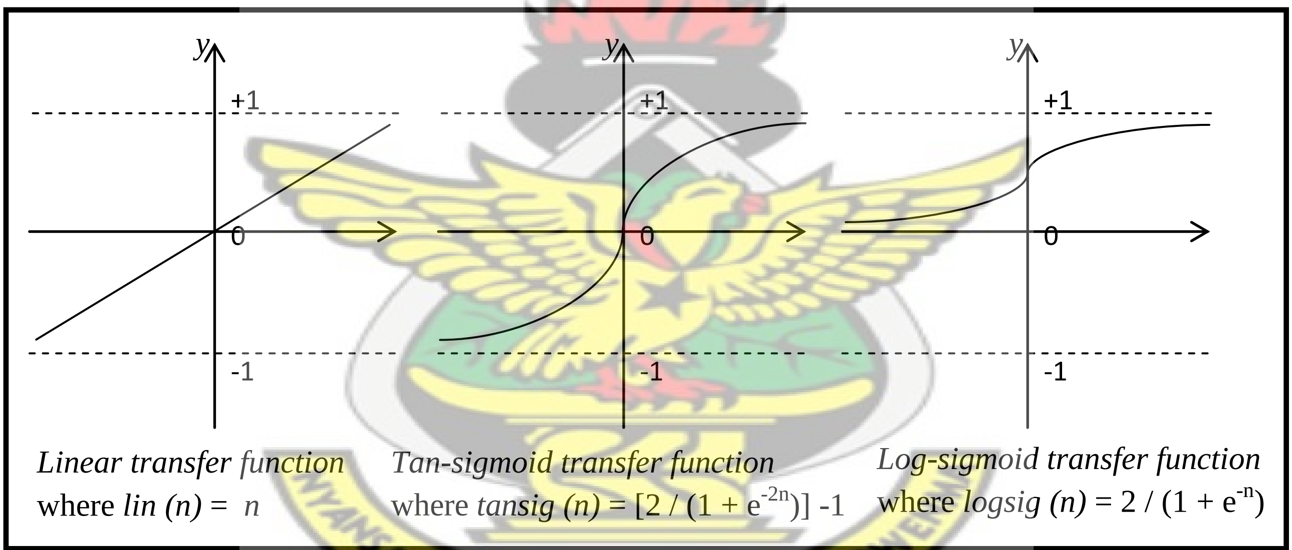


Figure 2.4 Three commonly used transfer (activation) functions

Finally, the output (y) generated by the network is compared with the target or desired output, and the error is calculated. The objective is to minimize the error. This is done by applying a "learning" or iteration procedure through which the network adjusts the weights (**w_i**s) in the direction in which the error is minimized.

2.4.3.2 Multilayer Neural Network Architecture

The basic single neuron model is very powerful in learning patterns; however, it cannot learn all types of patterns. The multilayer ANN models which have intermediate layer, called the hidden layer, are able to learn all kinds of patterns and thus are good at prediction. In the multilayer model, the inputs are first processed in the hidden units and the outputs of the hidden units become the inputs of the output units. The output units finally produce the outputs or forecasts. Figure 2.5 below shows the flow of network processes in the multilayer architecture.

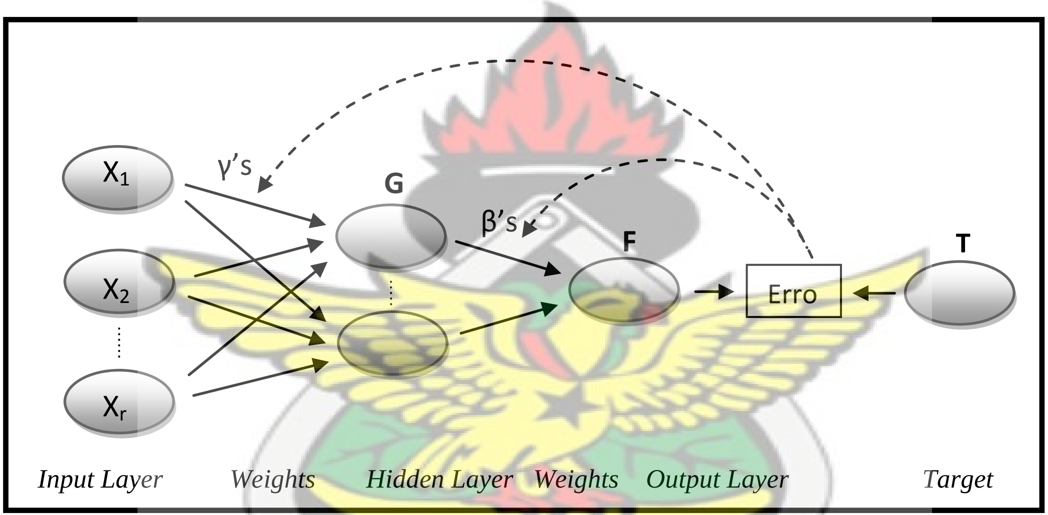


Figure 2.5 A Multilayer ANN with 'r' input units, 'q' hidden units and 'h' output units

The mathematical processes of the multilayer ANN model are as follows: First, inputs from the input layer enter the network through the hidden layer units. Each hidden layer unit receives the inputs, multiplies them by their correspondent weights and adds them all together with a bias (**b**). That is, the hidden layer unit (j) calculates:

$$\mathrm{net_j} = b_j + \sum \gamma_{ji}\, \mathrm{x_i}, \quad \mathrm{i} = 1, 2, \ldots, \mathrm{r} \qquad \mathrm{j} = 1, 2, \ldots, \mathrm{q} \qquad \textbf{(2.8)}$$

where (x_i) is the input of the unit (i) and (γ_{ji}) is a weight connecting the input unit (i) to the hidden unit (j). The output of the hidden layer unit (j), (G_j), is a transformation of the net, as follows:

$$\mathrm{G_j} = G(\mathrm{net_j}) \quad \textbf{(2.9)}$$

where (G) is an activation function mostly the nonlinear tan-sigmoid function. The output units receive the outputs of the hidden layer units (Gs) as their input. The process in the output layer units is exactly the same as that of the hidden layer units. That is, the output unit calculates the net, the sum of product of the inputs and weights, and bias as follows:

$$\mathrm{net_h} = \mathrm{b_h} + \sum \beta_{\mathrm{hj}} \mathrm{G_j}, \quad \mathrm{j} = 1, 2, \ldots, \mathrm{q}. \quad \mathrm{h} = 1 \quad \textbf{(2.10)}$$

where "$\mathrm{net_h}$" is the net value for the output unit (h), (β_{hj}) is the weight connecting the hidden unit (j) to the output unit (h) and (G_j) is the output of the hidden unit (j), which is input for the output unit (h). The output unit then applies a transfer function, (*f*), to the ($\mathrm{net_h}$). The output of the output layer unit (h) is defined as:

$$\mathrm{F_h} = f(\mathrm{net_h}) \quad \text{or} \quad \mathrm{F_h} = f(\mathrm{b_h} + \sum \beta_{\mathrm{hj}} G(b_j + \sum \gamma_{\mathrm{ji}} \mathrm{x_i})) \quad \textbf{(2.11)}$$

That is, the multilayer ANN mathematical model has the function of function form.

Finally, the network compares the outputs or forecasts (Fs) and the target outputs (Ts), and calculates the error (i.e. Root Mean Squared Forecast Error or RMSFE). The objective is to minimize the error; so, the computed errors are returned to the network in order to adjust the connection weights (γs and βs), hence back-propagation. The weight adjustment process, which is called learning, is done by a specific learning rule.

2.4.4 Learning (Training) Rules

There are several rules for training a network in order to minimise the error through adjusting the weights. The commonly used learning rule is the "generalized delta rule". In the delta rule, the weight is updated for each unit in the output layer as follows:

$$\beta_{\mathrm{hj}}(\mathrm{t}+1) = \beta_{\mathrm{hj}}(\mathrm{t}) + \eta \nabla_{\mathrm{hj}} \quad \textbf{(2.12)}$$

where $\beta_{hj}(t)$ is the weight connecting the hidden layer unit (j) to the output layer unit (h) at time (t), (η) is the learning rate (usually less than 1), and (∇_{hj}) is the gradient vector associated with the weight (β_{hj}). The gradient vector is the set of derivatives for all weights with respect to the output error. The network calculates the gradient vector on a layer-by-layer basis using the chain rule for partial derivatives. Therefore, the gradient descent algorithm requires that the activation function be differentiable. According to Wasserman (1994), the components of the output layer gradient vector may be evaluated as follows:

$$\nabla_{hj} = \partial E / \partial \beta_{hj}$$

$$= (\partial E / \partial F_h)(\partial F_h / \partial \beta_{hj})$$

where E is a function of the error, RMSFE, and:

$$\partial E / \partial F_h = \partial\, [n^{-1} \sum (T_{ht} - F_{ht})^2]^{1/2} / \partial F_h = \delta_h$$

$$\partial F_h / \partial \beta_{hj} = G\,(Net_j)$$

Therefore, the output layer gradient vector may now be written as:

$$\nabla_{hj} = \delta_h\, G\,(Net_j) \qquad \textbf{(2.13)}$$

The weight update rule for each neuron in the hidden layer is also as follows:

$$\gamma_{ji}\,(t+1) = \gamma_{ji}\,(t) + \eta \nabla_{ji} \qquad \textbf{(2.14)}$$

where γ_{ji} (t) is the value of the weight connecting the input layer unit (i) to the hidden layer unit (j), η is the learning rate and ∇_{ji} is the gradient vector which is calculated as follows:

$$\nabla_{ji} = \partial E / \partial \gamma_{ji} = \sum_h (\partial E / \partial F_h)(\partial F_h / \partial G_j)(\partial G_j / \partial Net_j)(\partial Net_j / \partial \gamma_{ji})$$ where,

i. $\partial F_h / \partial G_j = \beta_{hj}$

ii. $\partial G_j / \partial Net_j = g'(Net_j)$

iii. $\partial Net_j / \partial \gamma_{ji} = X_i$

Substituting (i), (ii), and (iii) into ∇_{ji}, we have:

$$\nabla_{ji} = g'(Net_j)\, X_i \textstyle\sum_h \delta_h \beta_{hj} \qquad \mathbf{(2.15)}$$

The bias input in each unit of the hidden and the output layers is adjusted like other weights.

Although the gradient descent method is very popular, in training a multilayer network the method is very slow (Moshiri and Cameron, 2000). The Levenberg-Marquardt (LM) learning method which is an approximation of Gauss-Newton's optimization rule is however an improvement of the gradient descent method. It is given as:

$$\Delta W = (H'H + vI)^{-1} H'E \ldots \qquad \mathbf{(2.16)}$$

where (H) is the Jacobian matrix of derivatives of each error to each weight, (v) is the scalar, and (E) is an error vector. The LM update rule approximates gradient descent if (v) is very large, and is equivalent to the Gauss-Newton's method if (v) is small. In the LM method, (v) changes as the network trains. Since the Gauss-Newton method is faster and more accurate around the minimum error, the network shifts the learning rule from the gradient descent to Gauss-Newton by decreasing (v) when the error declines. The network iterates the process until the error fails to decrease further, then it stops.

2.4.5 Categories of Artificial Neural Networks

ANNs can be classified into dynamic and static categories. Unlike static networks, the dynamic networks are autoregressive and also generally more powerful at prediction (Matlab, 2011). Therefore, in this study, only dynamic networks are used to predict the inflation. Examples of dynamic networks which are also used in the study include the non-linear autoregressive (NAR) network model and the non-linear autoregressive with exogenous input (NARX) network model.

- **Non-Linear Autoregressive (NAR) Network Model**

The nonlinear autoregressive (NAR) network model is a feed-forward dynamic network, with feed-forward connections from input to hidden and to output layers of the network. The NAR model is based on the linear univariate time series model i.e. the autoregressive (AR) model. The defining equation for the NAR model is

$$y_t = f(y_{t-1}, y_{t-2}, \dots, y_{t-n}) \qquad \textbf{(2.17)}$$

where the future values of a time series $y(t)$ are predicted only from past values of that series.

- **Non-Linear Autoregressive with Exogenous Input (NARX) Network Model**

The nonlinear autoregressive with exogenous inputs (NARX) network model is also a feed-forward dynamic network. The NARX model is based on the linear time-series ARX model or VAR (p) model. The defining equation for the NARX model is

$$y_t = f(y_{t-1}, y_{t-2}, \dots, y_{t-n}, x_{t-1}, x_{t-2}, \dots, x_{t-n}) \qquad \textbf{(2.18)}$$

where future values of the dependent output series y_t are regressed on previous values of the output series and previous values of an independent (exogenous) input series.

Both the NAR and NARX networks are two-layer feed-forward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. The networks are trained in the feedback open-loop architecture as shown at the appendix; this is because training in the open-loop form is more efficient. The network, after training, is converted to close loop structure for the prediction.

2.4.6 Review of Empirical Studies Comparing ANN and Econometric Forecasting Models

Artificial Neural Network (ANN) is inspired by knowledge from neuroscience and has been developed in other fields such as mathematics, statistical physics, computer science, cognitive science and engineering (Hertz et al, 1991). ANNs have in recent times attracted much attention as forecasting tool in the field of economics and finance. The major reason is because the ANN model is nonlinear. Applications of the ANN in economics have mostly been in financial markets partly because of its performance and partly because of the availability of more data. In most cases, ANN models have outperformed the time series models in forecasting stock prices and exchange rates, or in classifying applications such as bond ratings (Ahmadi, 1993; Refenes, 1994; Lachtermacher and Fuller, 1995).

Some studies have also been conducted using the ANN method to forecast inflation in comparison with those of econometric models. These studies are reviewed in two parts. The first part is a review of studies conducted in the developed countries and the second part presents those done in developing economies.

2.4.6.1 Studies in Developed Economies

Moshiri (1997), Moshiri et al (1999) and Moshiri & Cameron (2000) compared the performance of back-propagation neural network (BPN) models with those of traditional econometric approaches to forecast inflation in Canada. Of the traditional econometric models, they used a structural reduced-form model, an ARIMA model, a VAR model, and a Bayesian VAR model. With ANN and econometric models using the same set of variables, the results showed that the hybrid BPN models were able to forecast as well as all the traditional econometric methods, and to outperform them in some cases. Swanson and White (1997) also applied an ANN model to forecast nine US macroeconomic series and compared their results with those from traditional econometric approaches. The results were mixed, but Swanson and White nevertheless concluded that ANN models were promising even where there is no explicit non-linearity.

Gazely and Binner (2000) investigated money-inflation link for USA, UK and Italian economies using ANN method. The results showed that the ANN model fits the money-inflation link well when a Divisia M2 measure of money is used. McNelis and McAdam (2004) also applied linear and ANN-based thick models for forecasting inflation based on Phillips curve formulations in the USA, Japan and the euro area. They concluded that the ANN-based thick models outperformed the best performing linear models in the prediction across a variety of countries. Binner (2005) too compared the inflation forecasting performance of linear and non-linear models for the Euro area. The univariate ARIMA and multivariate VAR models were used as linear forecasting models whereas ANNs were used as non-linear forecasting models. Results obtained suggested that non-linear models provide better within-sample and out-of-sample forecasts, and linear models are simply a subset of them.

Nakamura (2005, 2006) compared inflation forecast from the ANN model with the univariate autoregressive models by using USA data (1960:Q1 to 2003:Q3). She concludes that the ANN model performs well relative to AR models. Binner et al (2006), also compared performances of ANN model with AR model and MS-AR Model (Markov Switching Model) by using quarterly data of USA (1960:Q1-2003:Q1). Results obtained from the study put forward that ANN model has better forecasts. For the same US economy, Lee et al (2007) used ANN model and the autoregressive model to forecast inflation in comparative studies for the period 1975:M1 to 2003:M12. The results showed that the AR model was significantly outperformed by the ANN model for each horizon.

In a study to assess globalisation influences on inflation forecasting in an aggregate perspective using the Phillips curve for Hong Kong, Japan, Taiwan and the US, Hu et al (2007) adopted ANN-based thin and thick models. They found that the ANN-based thin and thick models showed significant superiority over the naive model in most cases and over the best linear model in some cases. Choudhary and Haider (2008) also assessed the power of ANN models as forecasting tools for monthly inflation rates for 28 OECD countries. For short out-of-sample forecasting horizons, they found that, on average, for 45% of the countries the ANN models were a superior predictor while the AR (1) model performed better for 21%. That is, they showed that overall ANN models performance dominate the simple AR (1) process for OECD countries especially for short to medium term forecasts. Wang and Wu (2010) in their study employed both the linear AS-AD model and nonlinear ANN technique to have a better understanding of the inflation behaviour in China from 1992: Q1 to 2010: Q1. Experimental results demonstrated the inflation model can be obtained via ANN technique with higher accuracy compared to AS-AD model.

2.4.6.2 Studies in Developing Economies

Some studies have also been conducted in the developing world using the ANN methodology. In her study in Jamaica, Serju (2002) forecasted Jamaica's core inflation using quarterly data between 1975 and 1998. She found that of the three models estimated (VEC, ARIMA and ANN); the ANN model was the most appropriate in making in-sample forecast of core inflation. Suhartono (2006) also applied ANN model for forecasting Indonesian inflation and compared the result with ARIMA and ARIMAX models. The results showed that the feed-forward neural network (FFNN) models outperform the traditional econometric time-series models. Haider and Hanif (2007) too used ANN to forecast inflation in Pakistan using the monthly data of 1993:M7 to 2007:M6. They also compared the forecast performance of the ANN model with conventional univariate time-series models such as AR

(1) and ARIMA models. They concluded that at least by the RMSE criterion forecast based on ANN are more precise.

In trying to capture nonlinear relationships among inflation and its determinants, Monge (2009) applied ANN to forecast Costa Rican inflation. He compared the forecasts with those obtained from "thick" models and traditional linear techniques. The evidence showed that linear techniques do not outperform ANN, and in the case of a Phillips curve, ANN forecasts statistically improve upon linear approaches especially for short run forecast horizons. Ibanez (2010) also used the ANN methodology to forecast monthly Paraguayan inflation time series. The results showed that of all the checks performed in the research ANN models remarkably outperformed ARMA specifications in 24-steps-ahead horizon forecasts.

In Turkey, several studies have been conducted using ANN methodology. Sahin et al (2004) applied an ANN model for the Turkish inflation using monthly data from 1994:M1 to 1998:M12. The results showed that the model performs well. Gungor and Berk (2006) also constructed the multilayer perceptron ANN model for the monthly data set from 1996:M2 to 2006:M1 for the Turkish economy and showed that the model predicts the level of inflation with a reasonable good degree of accuracy. Recently, Ozdemir and Taskin (2010) too used an ANN model to accurately forecast inflation in Turkey and to provide an important insight into inflation targeting. The results implied that it is possible to obtain successful inflation forecasts with ANNs. Again, Duzgun (2010) compared inflation forecasts from the generalized regression feed-forward neural networks (GRNN) with the traditional econometric method. The comparison results revealed that the ANN model is superior to ARIMA model in forecasting of CPI. For the same Turkish inflation forecast, Catik and Karacuka (2011) applied ARIMA, ARFIMA, FIGARCH (Fractionally Integrated GARCH), unobserved components models (UCM) and ANNs. They found that in terms of dynamic inflation forecasts UCM and ANN models turned out to have better forecasting accuracy than the other models.

In Pakistan, Noor-Ul-Amin (2011) in a case study compared forecasts from the ANN model to the Box-Jenkins methodology; ANN model were found to present much better out of sample forecasts as compared to the ARIMA model. Also in India, Pradhan (2011) presented an application of ANN to forecast inflation during the period 1994 to 2009. The study presented four different ANN models on the basis of inflation (WPI), economic growth (IIP), and money supply (MS). The paper finally concluded that the ANN models show better forecasting performance especially in their multivariate forms.

Studies conducted using the ANN model in Africa are very few. In a comparative study of ANN model with typical econometric methods in South Africa, Kabundi (2003) found that, initially, the ANNs were shown to outperform traditional econometric models in forecasting nonlinear behaviour. However, inflation forecasts from the ANN models were outperformed by those of vector error correcting models.

2.5 Conclusion

In this chapter we have reviewed inflation and the studies on the determinants of inflation. We found that among the various determinants, money supply and exchange rate are more important. The main techniques used to forecast macroeconomic variables like inflation were also reviewed. The time-series models were found to be more accurate at predictions. The AR and VAR models were among the popular time-series models used in forecasting. We also reviewed the studies that have used the ANN methodology to predict the inflation as compared with econometric models in both developed and developing economies. The consensus is that the ANN models outperform the econometric models in inflation prediction.

CHAPTER III

METHODOLOGY

3.0 Introduction

This chapter presents the way the study was conducted. It is in six parts. Part one presents the model specifications. Part two deals with the data type and sources. Part three presents the description of the variables. Part four presents how the ANN was designed and implemented. The forecast strategy is presented in part five and the final part presents the forecast evaluation method.

3.1 Model Specifications

In this study, four forecasting models are used to predict the inflation. Two of the models are time-series econometric models and the other two are ANN models. The models are specified as follows:

3.1.1 Time-series Econometric Models

The two time-series econometric models used to forecast the inflation are the autoregressive (AR) model and the vector autoregressive (VAR) model.

- **The AR (p) Model**

The AR (p) model predicts the inflation from past inflation values of lag length (p). The AR (p) model is specified as:

$$P_t = \varphi_0 + \sum_{i=1}^{\rho} \varphi_i P_{t-i} + \varepsilon_t \qquad \textbf{(3.1)}$$

where φ_is are the parameters of the model to be estimated, ρ is the lag length and P_{t-i} are lags of the inflation.

- **The VAR (p) Model**

The VAR (p) model predicts the inflation from past inflation values and past values of other predictor variables of the same lag length (p). In this study, the other predictor variables are the past values of broad money supply (M2+) growth rate and exchange rate depreciation. The VAR (p) model is specified as:

$$P_t = \alpha_{10} + \sum_{i=1}^{\rho} \beta_{1i} M_{t-i} + \sum_{i=1}^{\rho} \delta_{1i} P_{t-i} + \sum_{i=1}^{\rho} \nu_{1i} \mathcal{E}_{t-i} + \xi_{1t} \qquad \textbf{(3.2)}$$

$$M_t = \alpha_{20} + \sum_{i=1}^{\rho} \beta_{2i} M_{t-i} + \sum_{i=1}^{\rho} \delta_{2i} P_{t-i} + \sum_{i=1}^{\rho} \nu_{2i} \mathcal{E}_{t-i} + \xi_{2t}$$

$$\mathcal{E}_t = \alpha_{30} + \sum_{i=1}^{\rho} \beta_{3i} M_{t-i} + \sum_{i=1}^{\rho} \delta_{3i} P_{t-i} + \sum_{i=1}^{\rho} \nu_{3i} \mathcal{E}_{t-i} + \xi_{3t}$$

where M_{t-i}, $\mathcal{E}_{t-i}$, and P_{t-i} are past values of broad money supply growth rate, exchange rate depreciation and inflation rate respectively and α, β, δ, and ν are parameters to be estimated and ρ is the lag length.

3.1.2 The Artificial Neural Network (ANN) Models

The two ANN models used to predict the inflation in the study are the nonlinear autoregressive (NAR) network model and the nonlinear autoregressive with exogenous input (NARX) network model. The two ANN models are constructed based on the time-series econometric model specifications respectively i.e. in terms of lag lengths and variables used.

- **The NAR (p) Model**

The NAR (p) model like the AR (p) model predicts the inflation from past inflation values of lag length (p). The NAR model is constructed with twenty (20) hidden layer units and one (1) output layer. The hidden layer transfer function is the tan-sigmoid and that of the output unit is the linear transfer function. The NAR (p) model is specified as:

$$F_h = b_h + \sum \beta_{hj} \left(tansig \left(b_j + \sum \gamma_{ji}\, p_{t-i} \right) \right), \quad i = 1, \dots, p \quad j = 1, \dots, 20 \quad h = 1 \qquad \textbf{(3.3)}$$

where p_{t-i} are past values of the inflation, γs and βs are hidden and output layer weights respectively and the (**b**s) are the biases.

- **The NARX (p) Model**

The NARX (p) model similar to the VAR (p) model predicts the inflation from past inflation values and past values of other predictor variables of the same lag length (p). The other predictor variables are the past values of broad money supply (M2+) growth rate and exchange rate depreciation. The NARX model is constructed with the same hidden and output layer units and transfer functions as the NAR.

The NARX (p) model is specified as:

$$F_h = b_h + \sum \beta_{hj} \left(tansig\left(b_j + \sum \gamma_{ji}\, x_{t-i}\right)\right), \quad i = 1, \dots, p \quad j = 1, \dots, 20 \quad h = 1 \qquad \textbf{(3.4)}$$

where x_{t-i} are past values of the input and output variables, γs and βs are hidden and output layer weights respectively and the (**b**s) are the biases.

3.1.3 Statistical Tests

The Breusch-Godfrey Lagrangian Multiplier (LM) test statistic (Godfrey, 1978 and Breucsh, 1978) was used to test for the presence of serial autocorrelation in the VAR model. The Jarque-Bera (1987) asymptotic Lagrangian Multiplier normality test, which has X^2 distribution under the H_o is applied to the residuals of the AR and VAR. Also the Ljung-Box statistic for the autocorrelation (Q statistic) was test for serial autocorrelation problem in the specified AR model. The R^2 adjusted (Co-efficient of determination Adjusted) was also used to explain explicitly, the proportion of the behaviour of future inflation explained by the past inflation values and past values of independent variables.

3.2 Data Type and Sources

The study used mainly secondary data. The data are the inflation rates, broad money supply (M2+) growth rates and exchange rate depreciations. All the data were obtained from the Bank of Ghana website and quarterly economic bulletins. The data are monthly year-on-year series and cover the period January 1991 to December 2011.

The study relied purely on time series data. This was mainly because all the models used in the study are time series models.

3.2.1 Data Analysis and Interpretation

The data was analysed with the Gretl (2006), MatLab (2011) and Excel (2010) statistical packages. The Gretl package was used to aid the regression processes of the time-series econometric models. The Gretl was used because of its ability to handle time series analysis. The MatLab, on the other hand, was used to run the regression for the ANN models. The MatLab package was used because, for now, it is the only accessible package for neural network analysis. The Excel package was also used to aid in the tabular and graphical presentation of the results and analysis.

3.3 Variables Description

Several studies (Ozdemir & Taskin, 2010; Duzgun, 2010; Hu et al, 2007; Haider & Hanif, 2007; Lee et al, 2007; Gungor & Berk, 2006; Nakamura, 2005; Moshiri, 1997) forecasted the inflation macroeconomic variable. This study similarly forecasts the inflation in Ghana. Although some of these studies (Nakamura, 2005; Haider & Hanif, 2007) did only univariate analysis of the inflation, this study forecasts the inflation with both univariate and multivariate models. Therefore, independent variables are used. The variables in the models are described as follows:

- **Inflation Rate**

The inflation is the rate of change of the Consumer Price Index (CPI) series. The inflation rate is the monthly year-on-year i.e. the percentage change in the CPI between the current month and the same month in the past year.

- **Broad Money Supply (M2+) Growth Rate**

This refers to the rate of growth of currency in circulation and close substitutes for money like demand, time and savings deposits etc. The series is also monthly year-on-year percentage change in the broad money supply. The change is calculated as the percentage difference between the current month's money supply and the supply during the same month in the past year.

- **Exchange Rate Depreciation**

The exchange rate is the price of the foreign currency in domestic currency terms. The depreciation of the currency is the rate of change of the price of the foreign currency. The cedi is traded with many foreign currencies, but the dollar is the main currency used for foreign transaction. Therefore, the cedi-dollar exchange rate depreciation is used as a proxy for the exchange rate depreciation. The series are also monthly year-on-year percentage changes.

3.3.1 Time-series Data Properties

Time series forecasting requires abundant data especially in the case of ANNs. ANN learns by experience; therefore, the more the data supplied to it, the better the learning experience and subsequent predicting ability. If the data are few, there will not be sufficient degrees of freedom for statistical robustness. However, a long time series data could also contain a structural break which may necessitate only examining a sub-section of the entire data series or alternatively using intervention analysis or dummy variables. Meyler et al (1988) recommended that at least fifty observations should be used for univariate time series forecasting. Therefore, the range of data used in this study is based on this knowledge.

3.3.2 Time-series Data Tests

The variables used in the study are first checked for stationarity before estimating the equations. This is because if the variables are not stationary, the inferences derived from the estimation are not valid, leading to a spurious regression (Granger and Newbold, 1974). Using the augmented Dickey-Fuller (1979, 1981) test, the following equation was tested for each of the variables for integration order one:

$$\Delta x_t = \beta_0 + \beta_1 t + \beta_2 x_{t-1} + \sum_{i=1}^{n-1} \beta_{3i} \Delta x_{t-i} + \mu_t \qquad \textbf{(3.5)}$$

where Δ denotes the first order difference, t is the time trend, and n, the order of autoregression, is chosen so that the residual series is white noise. For the possibility of second-order integration, the equation below is also tested.

$$\Delta^2 x_t = \beta_0 + \beta_1 t + \beta_2 x_{t-1} + \sum_{i=1}^{n-1} \beta_{3i} \Delta^2 x_{t-i} + \nu_t \qquad \textbf{(3.6)}$$

where Δ^2 represents the second order difference.

Test for the cointegration is also performed before running the regression for the multivariable model since there may exist a long run relationship among the variables.

3.3.3 Lag Selection Tests

To estimate the AR (p) model requires the selection of the lag length that gives the best results. Therefore the autocorrelation and partial autocorrelation correlograms are used to aid in the choice of the lag length.

To estimate the VAR (p) model, the lag length (p) must be selected. The AIC (Akaike Information Criterion), BIC (Schwarz Bayesian criterion) and HQC (Hannan-Quinn criterion) are three criteria which are used to choose the number of lags in the model.

3.4 Implementation of the ANN Model

The design and implementation of the ANN model for time-series prediction using the MatLab (2011) neural network toolbox requires the following seven standard steps. These are data specification, creating and configuring the network, initialising weights and biases, and training, validating and using the network

I. Data Collection and Specification

In this study the variables used are the same as those used for the time-series econometric models.

II. Creating the Network

Dynamic ANN models are created based on the specification of the time-series econometric models. These are the NAR and NARX models. Both models have the tan-sigmoid transfer function in the hidden layer units and linear function in the output unit.

III. Configuring the Network

The nonlinearity of the ANN is due to the existence of the hidden layer units; and so, each network is configured with twenty (20) hidden neurons and one (1) output neuron as well as their respective lags (or delays). The network is then set to randomly divide the estimation data into three sets as follows: 70% are used for training the network, 15% to measure network generalization or to validate it and the last 15% to test the network's performance during and after training.

IV. Initialising the Weights and Biases

The weight and biases of the network are randomly initialised. A total of 281 weights (parameters) are estimated for the NAR network model and 881 for the NARX model. Hence, the ANNs are largely non-parametric models.

V. Training the Network

The Levenberg-Marquardt training algorithm, a standard procedure from the literature, is used this study. The training algorithm is run on the training set until the RMSE starts to increase on the validation set. The network is first created and trained in open loop form as shown in figures 3 and 5 at the appendix.

VI. Validating the Network

The training of the network continues until the validation error fails to decrease for six iterations. The validated network can then be used for the prediction. Otherwise, the network can be retrained with larger data or reconfigured to improve the results.

VII. Using the Network

The network is converted to close loop form after the training and used for the forecasting. Finally, the training function produce forecast results on the basis of RMSE minimisation criteria. The close loop networks used for the predictions are shown at the appendix as figure 4 and 5.

3.5 Forecasting Strategy

The data from January, 1991 to December 2011 (1, ..., T) is divided into two parts: 1 to T_1, and T_1+l to T, where $1 < T_1 < T$. First, the model is estimated using the data up to T_1 i.e. from

January, 1991 to December, 2010 and then the forecasting is done for the period T_1+ 1 to T, i.e. from January, 2011 to December, 2011. All four models are estimated using the first-difference data (i.e. the change in value of the variable between period *t-1* and period *t*) because the series are not stationary. Therefore, the models are first used to forecast the change in inflation for the period.

The forecasts of the inflation are dynamic forecasts rather than static forecasts. The difference between the static and dynamic forecasts is that the static forecast uses the actual values of the lags of the dependent variable for the forecasting periods, whereas the dynamic forecast uses the forecast values of the lags of the dependent variable each time. Therefore, in the dynamic forecasting, the errors made each time influence the forecast errors for the periods ahead. So, the forecast errors in dynamic forecasts are expected to be greater than those in static forecasts.

The predicted changes in the inflation are then used to compute the inflation forecasts. According to Stock and Watson (2007), when the initial prediction is in the first-difference, the predicted rate of inflation is the past rate of inflation plus its predicted change:

$$\hat{Inf}_{T+1|T} = Inf_T + d\_\hat{Inf}_{T+1|T} \qquad \textbf{(3.7)}$$

That is, the predicted first-difference of the inflation for period (t+1) is added to the inflation rate for the period (t) to generate the inflation forecast for the period (t+1).

The rate of inflation is predicted for one-period-ahead using each of the models. The forecast errors are then computed and compared.

3.6 Forecast Evaluation Method

The forecast error is the difference between the actual inflation rate and the predicted inflation rate. There are several measures of forecast errors. The measure adopted in the study was used by Moshiri (1997) and Haider & Hanif (2007).

The Root Mean Squared Forecast Error (RMSFE) is a measure of the size of the forecast error, that is, of a magnitude of typical mistakes made using a forecasting model (Stock & Watson, 2007). The RMSFE is computed as the measure of the forecast accuracy for each model; if for the forecast horizon i.e. Jan. 2011 to Dec. 2011, the RMSFE is lower for one model as compared with another, then, forecasts from the model are more accurate. The RMSFE is calculated as follows:

$$\text{RMSFE} = \sqrt{\frac{\sum_{i=0}^{T}(y_t - \hat{y}_t)^2}{T}} \qquad (\mathbf{3.8})$$

where y_t and $\hat{y}_t$ are the actual and the forecast values of the dependent variable, and T is the forecast sample size.

3.7 Conclusion

In this chapter we specified both the time-series econometric models and ANN models used in the study. The statistical tests conducted on the models have also been stated. The type and sources of the variables used as well as their descriptions have been presented. The forecast strategy and how the forecast performance of the models was evaluated have also been stated.

CHAPTER IV

RESULTS AND DISCUSSION

4.0 Introduction

This thesis is about inflation forecasting in Ghana using the ANN method and this chapter presents the results and discussions. The chapter is in four parts. Part one presents the test results on the time-series data used. Part two presents the results of the time-series econometric models. The third part also presents the results of the ANN models. Finally, part four compares the forecast results of the time-series econometric models and the ANN models.

4.1 Time-series Data Test Results

The times-series data test results consist of the unit root test results and the results for cointegration.

4.1.1 Unit Root Test Results

We tested for stationarity of the variables before using the data for the regression. Table 4.1 shows the Augmented Dickey-Fuller (ADF) unit root test results for all the variables between January, 1991 and December, 2010.

Table: 4.1 Augmented Dickey Fuller Unit Root Test Results

		Level		First Difference	
Variable	Lags	With Constant	With Constant & Trend	With Constant	With Constant & Trend
INF_YoY	1	-2.06768	-2.35699	-6.59709***	-6.59357***
M2+_YoY		-2.79842	-3.04654	-11.1362***	-11.1267***
EXC_YoY		-3.03277**	-3.27797	-6.56827***	-6.55761***

Note: From Mackinnon (1991), Dickey-Fuller unit-root critical values at the 5 percent level for T = 240 are: - 2.89 with constant but no trend and - 3.45 with constant and trend; critical values at the 1 percent level for T = 240 are: - 3.50 with constant but no trend and - 4.05 with constant and trend. ** and *** denote statistical significance at the 5 and 1 percent levels, respectively.

The results for the inflation series show that the tau values of -2.068 and -2.357 for the levels are both not significant at 5% level i.e. they are below the critical values of -2.89 with constant and -3.45 with constant and trend respectively. However, the tau values for the first difference of -6.597 with constant and -6.594 with constant and trend are significant at 1% level. Similar results are found for the other variables. Thus, the ADF unit root test results indicate that all the variables under consideration have unit root, implying that they are not stationary. The tests for the first differences of the variables, however, show that they are integrated of order one and therefore can be used for the estimation.

4.1.2 Results for Cointegration

We also tested for the possibility of a long run relationship among the variables using Engle-Granger cointegration before running the regression. Table 4.2 below shows the cointegration results.

Table 4.2 Engle Granger Cointegration Results

	coefficient	*std. error*	*t-ratio*	*p-value*
const	1.81177	2.66431	0.6800	0.4972
Ex_dep	0.0997929	0.0305739	3.264	0.0013 ***
M2__growth	0.515068	0.0760279	6.775	9.77e-011 ***

The t-statistics of 3.264 and 6.775 for the exchange rate depreciation and money supply growth rate respectively are both significant at 1% level. The Engle-Granger cointegration test results therefore imply that one cointegration equation exists at one (1) per cent significant level. That is, there exists a long run relationship among the variables.

4.2 Results for Time Series Econometric Models

The results for the time-series econometric models are presented for the AR and the VAR models respectively.

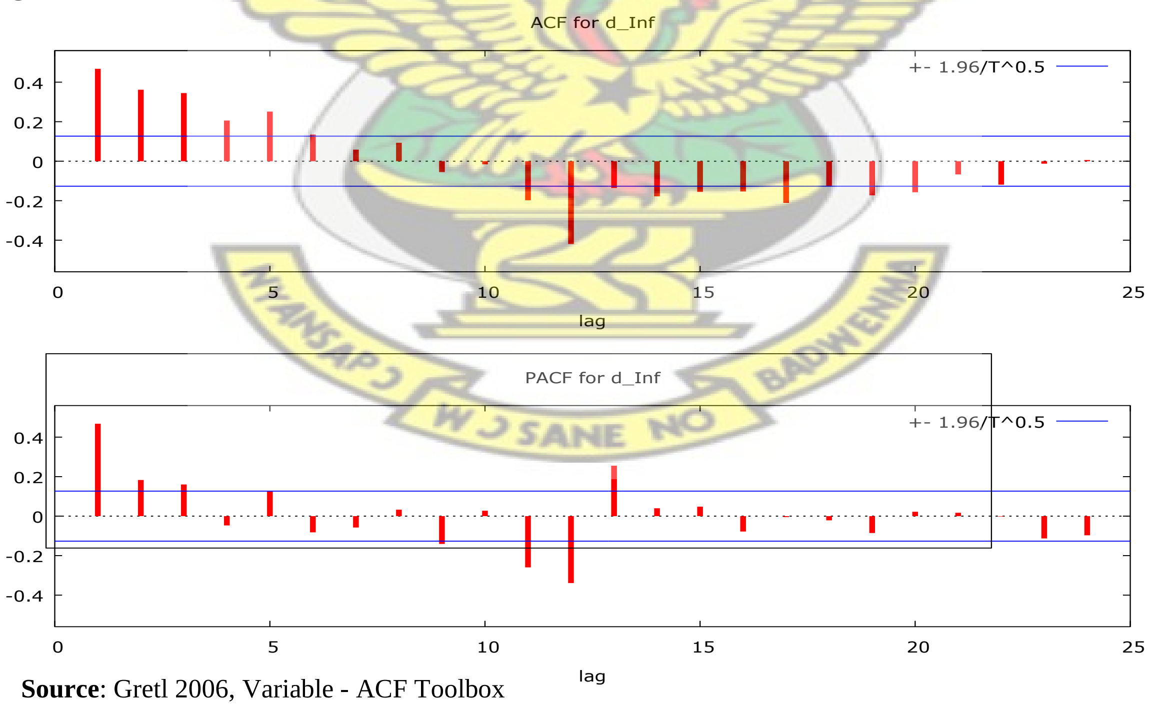
4.2.1 AR Model Results

The AR model results consist of the estimation results and forecast results.

- **AR Model Estimation Results**

The autocorrelation and partial autocorrelation correlograms were applied to the first difference of the inflation series between the period January, 1991 and December, 2010 to aid in the choice of the lag length for the AR (p) model. The figure below shows the ACF results.

Figure 4.1 The ACF Results for the First Difference of the Inflation



Source: Gretl 2006, Variable - ACF Toolbox

The minimum ACF figure (-0.4912) for the first difference of the inflation series occurs at lag twelve (12) and thus the AR (12) model was chosen for the estimation. Table 4.3 shows the estimation results of the AR (12) model.

Table 4.3 The Estimation Results of the AR (12) Model

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	-0.0292129	0.0835857	-0.3495	0.72708	
d_Inf_1	0.375497	0.0675128	5.5619	<0.00001	***
d_Inf_2	0.121884	0.0709668	1.7175	0.08742	*
d_Inf_3	0.147836	0.0708391	2.0869	0.03815	**
d_Inf_4	-0.0224851	0.0713925	-0.3150	0.75312	
d_Inf_5	0.081797	0.0709263	1.1533	0.25016	
d_Inf_6	-0.00640781	0.0709522	-0.0903	0.92813	
d_Inf_7	-0.0645671	0.0708511	-0.9113	0.36322	
d_Inf_8	0.117674	0.0706859	1.6647	0.09751	*
d_Inf_9	-0.0836511	0.0711501	-1.1757	0.24110	
d_Inf_10	0.138857	0.0704456	1.9711	0.05008	*
d_Inf_11	-0.153022	0.0705855	-2.1679	0.03134	**
d_Inf_12	-0.0631246	0.0669839	-0.9424	0.34712	
u(-12)	-0.404864	0.0595331	-6.8007	<0.00001	***

Statistics based on the rho-differenced data:

Mean dependent var	-0.046346	S.D. dependent var	2.088276
Sum squared resid	598.7267	S.E. of regression	1.721625
R-squared	0.481417	Adjusted R-squared	0.450610
F(12, 202)	9.404677	P-value(F)	2.23e-14
rho	0.038034	Durbin-Watson	1.874359

The Lagrangian Multiplier normality test (with X^2 value 65.322) proved that the residuals of the AR model are normal. Also the Ljung-Box test for the autocorrelation showed that there is no serial autocorrelation problem in the specified model. The adjusted R-squared for the AR (12) model was 45%. This implies that past first differences of the inflation explain up to 45% of future changes in the inflation. The adjusted R^2 of the AR (12) model was however 98% when the levels of the inflation were used. This means that the use of the inflation first differences affected the explanatory power of the independent variables negatively. The AR (12) estimation which used the levels of the inflation are shown in table A.2 at the appendix.

- **AR (12) Model Forecast Results**

The estimated AR (12) model produced the dynamic out-of-sample forecasts for the twelve month period of January, 2011 to December, 2011. Table 4.4 shows the forecast results of the AR (12) model.

Table 4.4 The Forecast Results of the AR (12) Model

Year / Month	*Actual Inflation*	*Inflation Forecasts*	*Forecast Errors*	*Squared Errors*
2011:01	**9.08**	8.59	0.49	0.24
2011:02	**9.16**	8.78	0.38	0.14
2011:03	**9.13**	9.32	-0.19	0.04
2011:04	**9.02**	9.62	-0.60	0.36
2011:05	**8.9**	9.37	-0.47	0.22
2011:06	**8.59**	9.33	-0.74	0.55
2011:07	**8.39**	8.45	-0.06	0.004
2011:08	**8.41**	8.38	0.03	0.0007
2011:09	**8.4**	8.32	0.08	0.01
2011:10	**8.56**	8.30	0.26	0.07
2011:11	**8.55**	8.73	-0.18	0.03
2011:12	**8.58**	8.75	-0.17	0.03
Average	**8.73**	**8.83**		
			MSFE	0.1400
			RMSFE	**0.3742**

The AR (12) forecast results appear relatively close to the actuals for the forecast horizon. For instance for the month of August, the forecast is 8.38% as compared to the actual value of 8.41% (i.e. the forecast error is 0.03). The average forecast errors for the twelve months of 2011 are 0.14 and 0.3742 as measured by MSFE and RMSFE criteria respectively. The average of the inflation forecasts for the period is also 8.83%; this deviated from the actual average of 8.73% by 0.10 percentage point. The AR forecasts are thus fairly close to the actuals and are also consistent with those obtained by Haider and Hanif (2008) in Pakistan.

4.2.2 VAR Model Results

The VAR model results are also made up of both estimation and forecast results.

- **VAR Model Estimation Results**

The AIC (Akaike Information Criterion) produced the minimum figure of 15.2158 at the lag length fourteen (14) as compared to BIC (Schwarz Bayesian criterion) and HQC (Hannan-Quinn criterion). Therefore the VAR (14) model was estimated. Table 4.5 shows the VAR (14) estimation results:

Table 4.5 The Estimation Results of the VAR (14) Model

Variables	VAR Equation 1: d_Inf		VAR Equation 2: d_Ex_dep		VAR Equation 3: d_M2__growth	
	Coefficient	*t-ratio*	*Coefficient*	*t-ratio*	*Coefficient*	*t-ratio*
const	-0.0071924	-0.0605	-0.0058950	-0.0240	0.0311664	0.1290
d_Inf_1	0.328128	4.4422	-0.0761256	-0.5000	-0.22913	-1.5271
d_Inf_2	0.107932	1.4244	-0.16836	-1.0779	0.0173011	0.1124
d_Inf_3	0.109724	1.5582	-0.0829448	-0.5715	0.157332	1.1000
d_Inf_4	-0.0170405	-0.2470	0.235402	1.6555	-0.103758	-0.7405
d_Inf_5	0.0789787	1.1456	-0.05745	-0.4043	0.0120658	0.0862
d_Inf_6	0.0132001	0.1918	0.104667	0.7380	0.105052	0.7517
d_Inf_7	-0.0575264	-0.8363	-0.136337	-0.9615	-0.052758	-0.3776
d_Inf_8	0.101844	1.4807	0.0613971	0.4330	-0.0194197	-0.1390
d_Inf_9	-0.0751129	-1.0857	0.0253771	0.1779	-0.0008527	-0.0061
d_Inf_10	0.132468	1.9241	-0.0629892	-0.4439	0.0930182	0.6652
d_Inf_11	-0.156514	-2.2591	0.142491	0.9977	0.157862	1.1217
d_Inf_12	-0.392041	-5.5732	0.0632137	0.4360	-0.0711209	-0.4977
d_Inf_13	0.246952	3.2693	-0.118016	-0.7580	-0.0858295	-0.5594
d_Inf_14	0.0198067	0.2752	-0.268984	-1.8130	0.0762811	0.5217
d_Ex_dep_1	0.0401249	1.1358	0.599705	8.2355	0.150754	2.1009
d_Ex_dep_2	0.003026	0.0739	-0.0389984	-0.4622	-0.0415841	-0.5001
d_Ex_dep_3	0.0148507	0.3949	0.0448041	0.5780	-0.0060809	-0.0796
d_Ex_dep_4	-0.0088946	-0.2376	0.131271	1.7012	0.0113209	0.1489
d_Ex_dep_5	-0.0010365	-0.0276	-0.0387037	-0.4992	0.0441354	0.5777
d_Ex_dep_6	0.00100235	0.0268	0.144251	1.8684	0.0233914	0.3075
d_Ex_dep_7	-0.0327122	-0.8663	-0.135921	-1.7462	-0.0107191	-0.1397
d_Ex_dep_8	0.00329283	0.0871	0.0136892	0.1757	0.00845104	0.1100
d_Ex_dep_9	-0.0028185	-0.0755	0.0122359	0.1589	-0.0571793	-0.7538
d_Ex_dep_10	0.0318468	0.8561	-0.0628721	-0.8199	0.0082317	0.1089
d_Ex_dep_11	0.00497132	0.1345	0.0845401	1.1096	-0.0053461	-0.0712
d_Ex_dep_12	-0.035407	-0.9564	-0.473354	-6.2031	-0.0571739	-0.7603
d_Ex_dep_13	0.0956299	2.3959	0.163391	1.9859	0.0956217	1.1794
d_Ex_dep_14	-0.0893148	-2.5379	0.0513992	0.7085	-0.0725359	-1.0147
d_M2__growt_1	0.00950421	0.2567	-0.0226211	-0.2964	-0.114721	-1.5254
d_M2__growt_2	0.0449367	1.2025	-0.137185	-1.7809	0.0593049	0.7813
d_M2__growt_3	-0.0082778	-0.2324	0.133941	1.8240	-0.0668913	-0.9244
d_M2__growt_4	0.0286435	0.8068	-0.039019	-0.5332	-0.0193552	-0.2684
d_M2__growt_5	0.0375449	1.0659	-0.026166	-0.3604	0.129178	1.8055
d_M2__growt_6	0.0346308	0.9764	0.0776369	1.0619	0.148086	2.0555
d_M2__growt_7	0.051681	1.4547	-0.0065820	-0.0899	0.0644817	0.8936
d_M2__growt_8	0.0137917	0.3856	0.0475626	0.6451	0.00762342	0.1049
d_M2__growt_9	0.0372087	1.0511	-0.0762781	-1.0454	-0.0548918	-0.7634
d_M2__grow_10	0.025445	0.7192	0.0321756	0.4412	0.118672	1.6513
d_M2__grow_11	0.0540147	1.5222	0.086981	1.1891	0.00660434	0.0916
d_M2__grow_12	0.015244	0.4241	0.108804	1.4686	-0.457462	-6.2661
d_M2__grow_13	-0.0269891	-0.6815	-0.0037868	-0.0464	0.0435839	0.5418
d_M2__grow_14	-0.0035253	-0.0932	-0.136401	-1.7491	-0.100012	-1.3014
R^2	0.530756		0.596421		0.352910	
Adjusted R^2	0.422469		0.503288		0.203581	
P-value (F)	2.60e-14		2.81e-19		0.000049	
DW	1.945306		1.973659		1.971263	
SSR	1.780836		3.670852		3.617344	

Although the cointegration test results suggested the existence of a long run relationship among the variables, an error correction term, which captures long-run relationship among variables, was not included in the VAR model. This was to allow for equality in specification with the counterpart ANN model i.e. the NARX model.

The Lagrangian Multiplier normality test proved that the residuals of the VAR model are normal. Also the test for the autocorrelation showed that there is no serial autocorrelation problem in the specified VAR model. The adjusted R-squared for the VAR (14) model is 42%. This suggests that past first differences of the inflation, money supply and exchange rate depreciation explain up to 42% of future changes in the inflation. As shown at the appendix (i.e. table A.3), the adjusted R-squared of the VAR (14) model is however 98% when the levels of the variables were used. This means that the use of first differences of the variables negatively affected the explanatory power of the independent variables.

- **VAR (14) Model Forecast Results**

The VAR (14) forecast results for the same period of 2011 are also close to the actual figures but not as close as those of the AR. For the month of January for example, the inflation forecast is 9.13%; this is a little above the actual value of 9.08% (i.e. the forecast error is -0.05). The MSFE and RMSFE values for the forecast horizon are 1.69 and 1.30 respectively. The average value of the forecasts of 9.72% for the twelve months of 2011 is also significantly higher than the actual average of 8.73% by almost 1.00 percentage point. This implies that on average the VAR forecasts are not as accurate as the AR forecasts. This result is therefore consistent with those obtained by Moshiri (1997) for the case of Canada. Table 4.6 shows the forecast results of the VAR (14) model.

Table 4.6 The Forecast Results of the VAR (14) Model

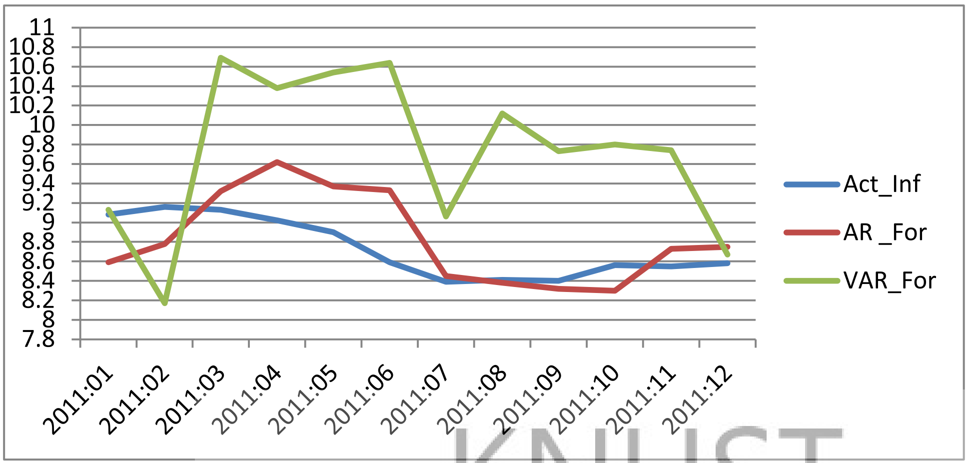
Year / Month	*Actual Inflation*	*Inflation Forecasts*	*Forecast Errors*	*Squared Errors*
2011:01	**9.08**	9.13	-0.05	0.003
2011:02	**9.16**	8.17	0.99	0.98
2011:03	**9.13**	10.69	-1.56	2.44
2011:04	**9.02**	10.38	-1.36	1.84
2011:05	**8.9**	10.54	-1.64	2.68
2011:06	**8.59**	10.64	-2.05	4.22
2011:07	**8.39**	9.06	-0.67	0.44
2011:08	**8.41**	10.12	-1.71	2.94
2011:09	**8.4**	9.73	-1.33	1.76
2011:10	**8.56**	9.80	-1.24	1.54
2011:11	**8.55**	9.74	-1.19	1.42
2011:12	**8.58**	8.67	-0.09	0.01
Average	**8.73**	**9.72**		
			MSFE	1.6896
			RMSFE	**1.2999**

Table 4.7 and figure 4.4 below compare the inflation forecast results of the two time-series econometric models i.e. the AR and VAR.

Table 4.7 Summary Forecast Results of the Econometric Models

Year / Month	*Actual Inflation*	*AR (12) Forecasts*	*VAR (14) Forecasts*
2011:01	**9.08**	8.59	9.13
2011:02	**9.16**	8.78	8.17
2011:03	**9.13**	9.32	10.69
2011:04	**9.02**	9.62	10.38
2011:05	**8.9**	9.37	10.54
2011:06	**8.59**	9.33	10.64
2011:07	**8.39**	8.45	9.06
2011:08	**8.41**	8.38	10.12
2011:09	**8.4**	8.32	9.73
2011:10	**8.56**	8.30	9.80
2011:11	**8.55**	8.73	9.74
2011:12	**8.58**	8.75	8.67
Average	**8.73**	**8.83**	**9.72**
	MSFE	0.1400	1.6896
	RMSFE	**0.3742**	**1.2999**

Figure 4.2 Charts of the Econometric Models Forecast Results



Source: Excel 2010, Spreadsheet Chart Display Toolbox

Table 4.7 indicates that the RMSFE value of 0.37 for the AR (12) model forecasts is smaller than that of the VAR (14) model forecasts of 1.30 for the twelve months of 2011. The averages of the inflation forecasts for the period also show the AR's average value of 8.83% is closer to the actual average of 8.73% than that of the VAR model of 9.72%. It is therefore clear that at least by the RMSFE criterion forecasts based on the AR (12) model are better than the VAR (14) forecasts. Figure 4.4 also provides the pictorial evidence of the findings.

4.3 Results for the ANN Models

The results for the ANN models are presented for the NAR and NARX models respectively.

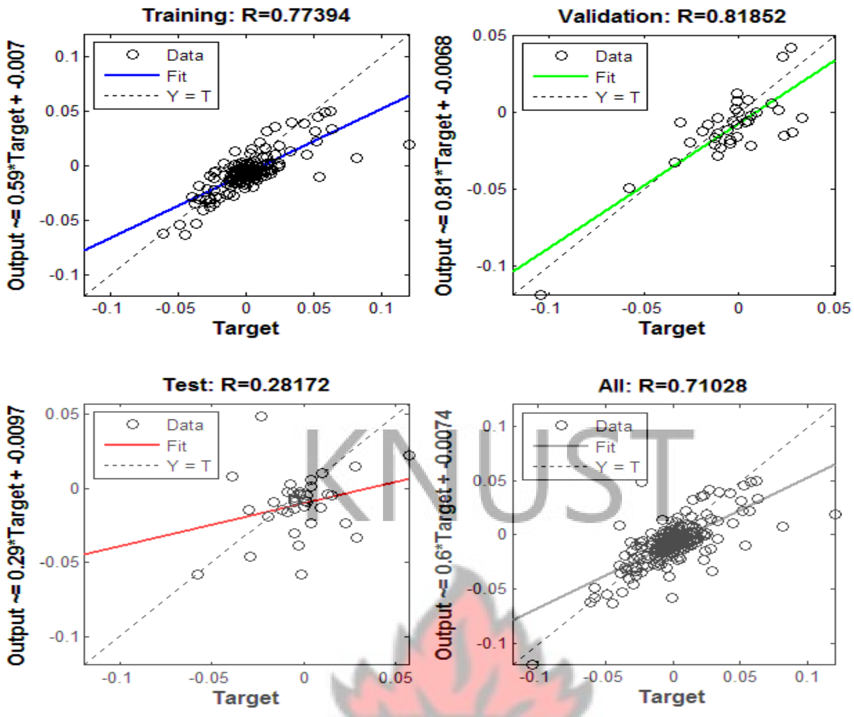
4.3.1 NAR Model Results

The NAR model results are made up of the estimation and forecast results.

- **NAR Model Estimation Results**

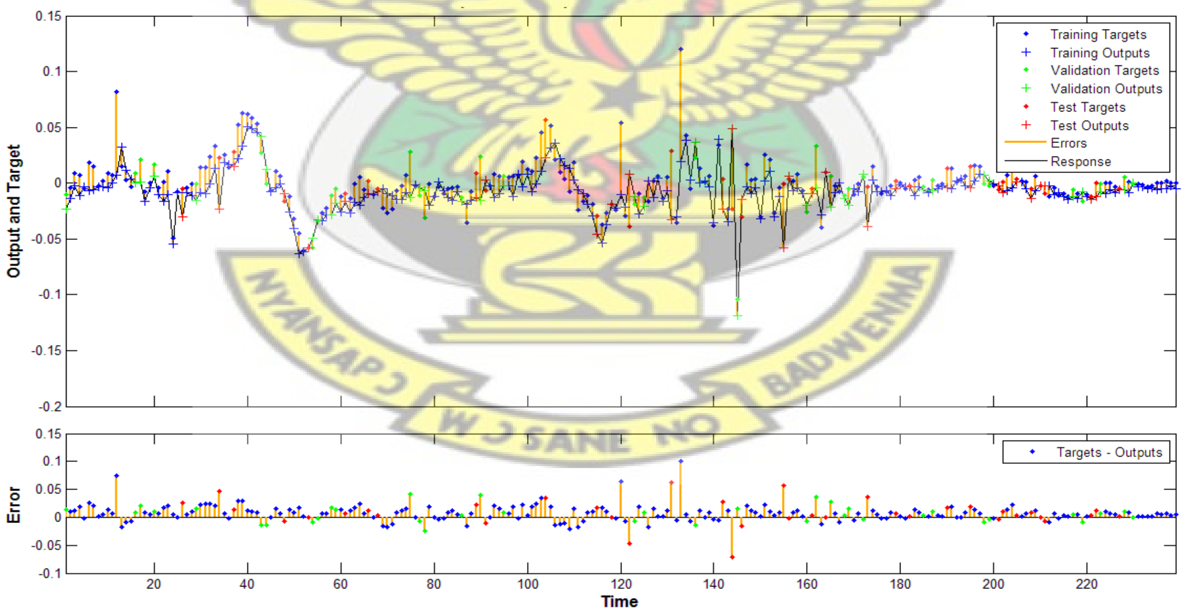
The NAR model used the lag length of twelve (12) and trained with the first-difference of the inflation like the AR model. Figure 4.6 below illustrates the regression results of the open loop NAR model for the estimation period of Jan. 1991 to Dec. 2010.

Figure 4.3 Training Regression Results of NAR (12) using the first-difference of the series



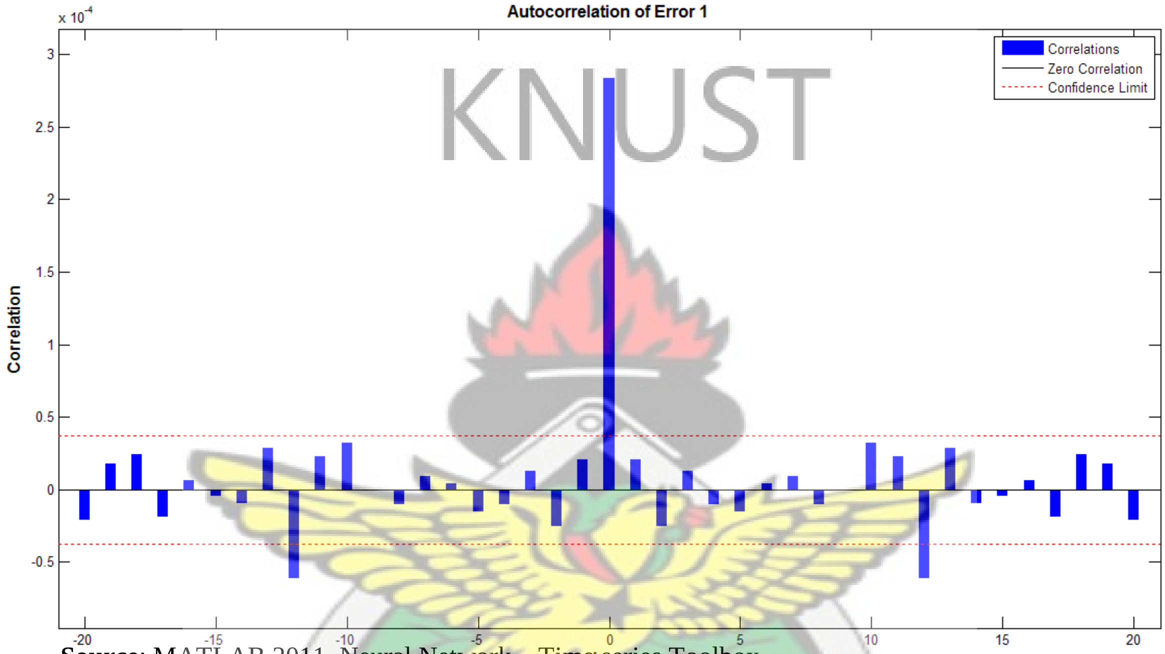
Source: MATLAB 2011, Neural Network – Time series Toolbox

Figure 4.4a NAR (12) Output, Actual and Error Response after Training



The NAR (12) model when the first-difference data was used produced training, validation and test regression (R) values of 77%, 82% and 28% respectively. The overall R value for the network training was 71%. The R values were however 99%, 99%, 98% and 99% respectively for the training, validation, test and the overall (R) when the levels of the inflation were used for the estimation as shown at the appendix (figure A.7). It must be noted here that the regression (R) values for the ANN models are not the same as the R^2 values for econometric estimations. The R values measure the correlation between the estimated and the actuals of the dependent variable for the estimation data. An R value of one (1) means a close relationship and zero (0) means a random relationship.

Figure 4.4b NAR (12) Error Graph



Source: MATLAB 2011, Neural Network – Time series Toolbox

The autocorrelation of error graph indicates that the errors are within the confidence interval (95%) and are therefore normal. The estimated parameters of the model are not displayed as there exist for the NAR (12) model with twenty (20) hidden units and one (1) output unit as many as 281 parameters. The open loop NAR (12) network model used for the training is shown as figure A.3 at the appendix.

- **NAR (12) Model Forecast Results**

The open loop NAR (12) model was converted to close loop for the prediction. The close loop NARX model forecasts for the forecast period of January, 2011 to December, 2011 are shown in table 4.8.

Table 4.8 **Forecast Results of the NAR (12) Model**

Year / Month	*Actual Inflation*	*Inflation Forecasts*	*Forecast Errors*	*Squared Errors*
2011:01	**9.08**	8.58	0.50	0.25
2011:02	**9.16**	9.08	0.08	0.01
2011:03	**9.13**	9.16	-0.03	0.0012
2011:04	**9.02**	9.14	-0.12	0.01
2011:05	**8.9**	9.03	-0.13	0.02
2011:06	**8.59**	8.91	-0.32	0.10
2011:07	**8.39**	8.59	-0.20	0.04
2011:08	**8.41**	8.39	0.02	0.0002
2011:09	**8.4**	8.42	-0.02	0.0002
2011:10	**8.56**	8.40	0.16	0.02
2011:11	**8.55**	8.57	-0.02	0.0003
2011:12	**8.58**	8.56	0.02	0.0005
Average	**8.73**	**8.74**		
			MSFE	0.0377
			RMSFE	**0.1943**

It can be observed from the table that the NAR (12) forecast are very close to the actual data for the forecast horizon. For example for the month of August, the forecast is 8.39%. This is marginally below the actual figure of 8.41% (i.e. having a forecast error of 0.02). The MSFE and RMSFE values of 0.038 and 0.194 respectively are also relatively low. The average of the inflation forecasts of 8.74% for the NAR model is also marginally above the actual average of 8.73% by 0.01 percentage point. This means that the NAR forecasts on average are very close to actual results for the period. The close loop network used for the NAR forecasting is shown as figure A.4 at the appendix.

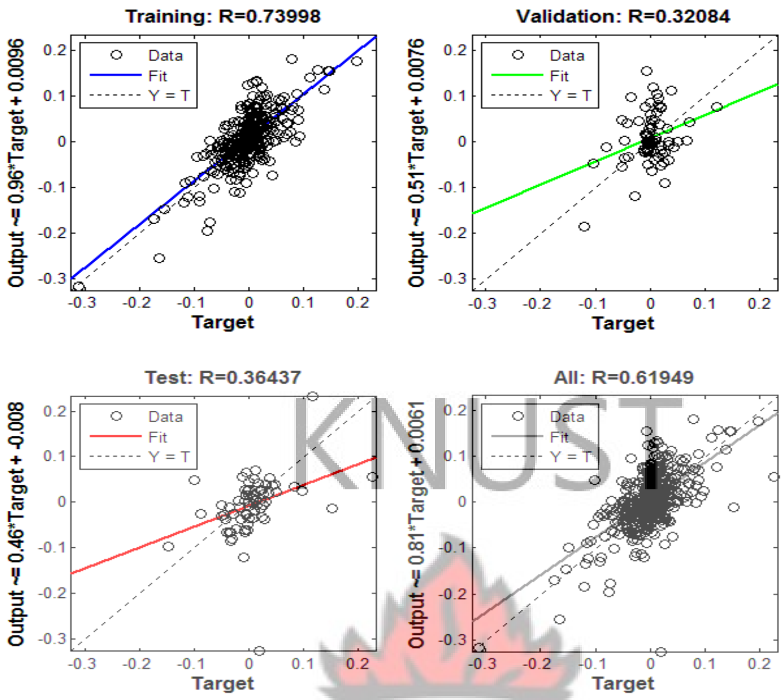
4.3.2 NARX Model Results

The NARX model results consist of the estimation and forecast results.

- **NARX Model Estimation Results**

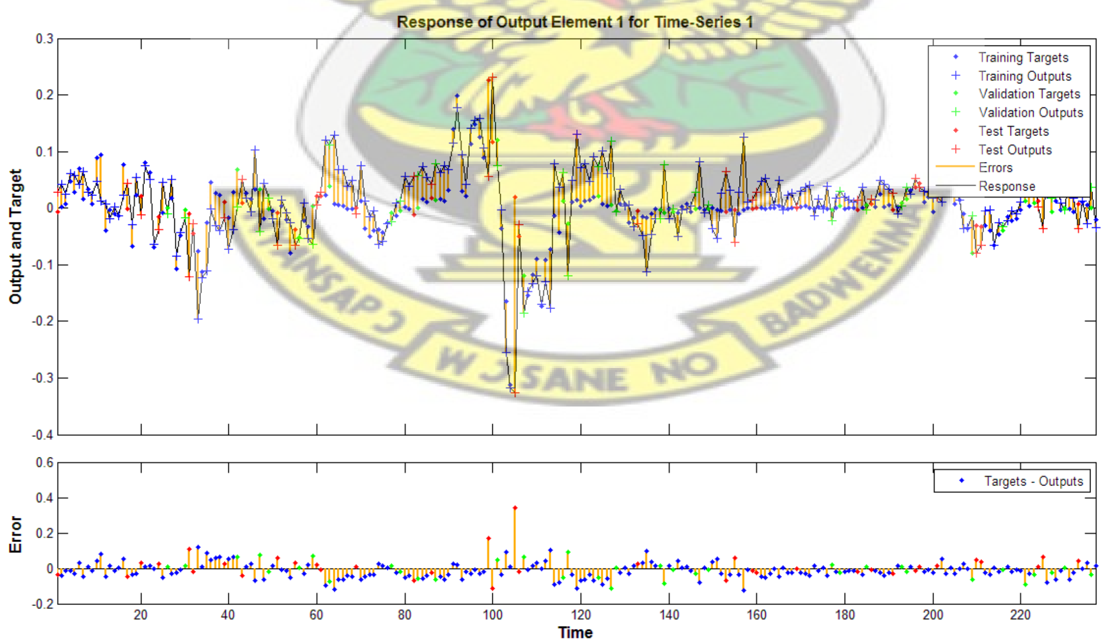
Like the VAR model, the NARX model used the lag length of twelve (14) and trained with the first-difference of all the series. Figure 4.6 below illustrates the regression results of the open loop NARX model for the estimation period of January, 1991 to December, 2010.

Figure 4.5 Training Regression Results of NARX (14) using the first-difference of the series



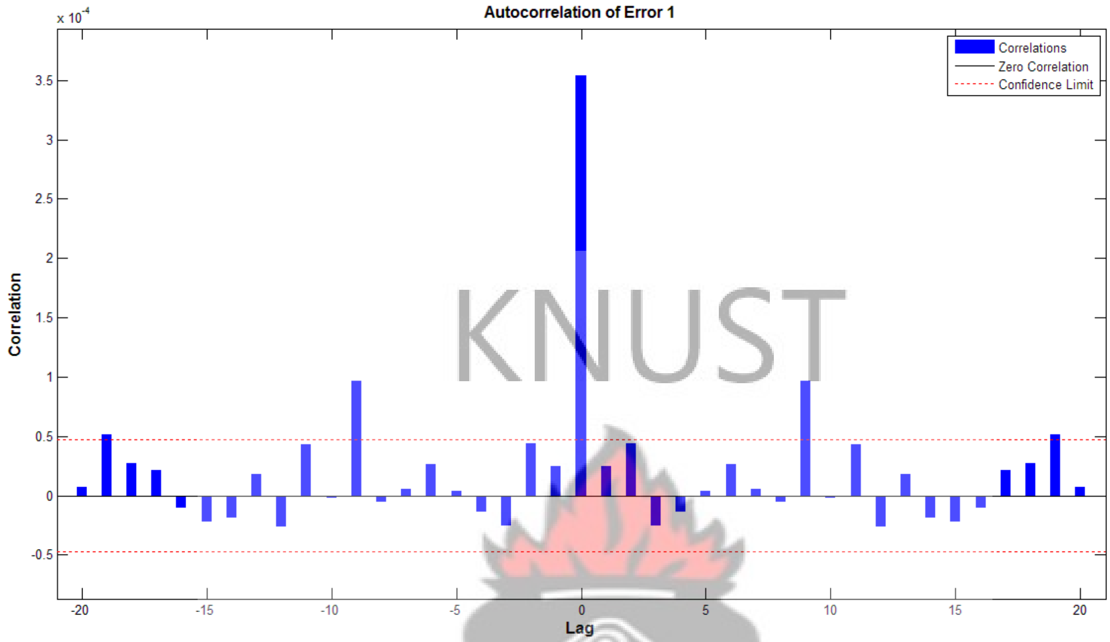
Source: MATLAB 2011, Neural Network – Time series Toolbox

Figure 4.6a NARX (14) Output, Actual and Error Response after Training



The trained NARX (14) model produced training, validation and test R values of 74%, 32% and 36% respectively and the overall R is 62%. The overall R of the estimation when the levels of the series were used is however 99%. This implies that the use of the levels of the series produce better correlation results than the use of the first-differences.

Figure 4.6b NARX (14) Error Graph



Source: MATLAB 2011, Neural Network – Time series Toolbox

The error graph shows that the errors are normal. There exist also a total of 881 estimated parameters for the NARX (14) model with two (2) exogenous inputs, twenty (20) hidden layer units and one (1) output unit. As a result, the parameters are not displayed. The open loop NARX model used for the training is shown as figure A.5 at the appendix.

- **NARX (14) Model Forecast Results**

The forecasts of the NARX (14) model using the close loop configuration for the period January, 2011 to December, 2011 are shown in table 4.9.

Table 4.9 Forecast Results of the NARX (14) Network Model

Year / Month	*Actual Inflation*	*Inflation Forecasts*	*Forecast Errors*	*Squared Errors*
2011:01	**9.08**	8.57	0.51	0.26
2011:02	**9.16**	9.08	0.08	0.01
2011:03	**9.13**	9.17	-0.04	0.0013
2011:04	**9.02**	9.14	-0.12	0.01
2011:05	**8.9**	9.04	-0.14	0.02
2011:06	**8.59**	8.88	-0.29	0.09
2011:07	**8.39**	8.58	-0.19	0.04
2011:08	**8.41**	8.38	0.03	0.0007
2011:09	**8.4**	8.41	-0.01	0.0001
2011:10	**8.56**	8.39	0.17	0.03
2011:11	**8.55**	8.55	0.00	0.00001
2011:12	**8.58**	8.55	0.03	0.0009
Average	8.73	**8.73**		
			MSFE	0.0376
			RMSFE	**0.1938**

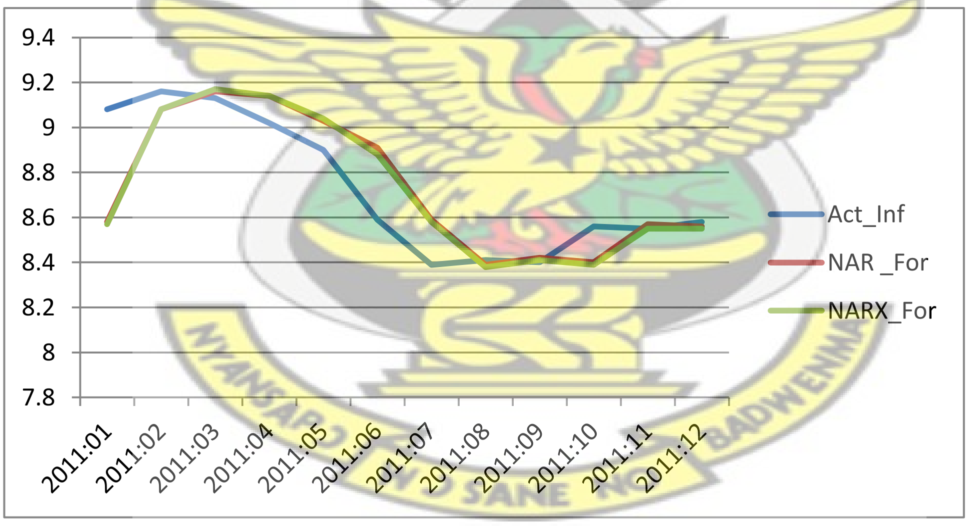
The table shows that the NARX (14) forecasts are also very close to the actual data for the forecast horizon. For the month of November for example, the forecast is 8.55%. This is approximately the same as the actual figure of 8.55% (i.e. having a forecast error of 0.00). The MSFE and RMSFE for the twelve months period are 0.0376 and 0.1938 respectively. The average of the NARX forecasts for the period of 2011 of 8.73% is just the same as the actual average although the monthly individual forecasts differ slightly from the actuals. This means that the NARX forecast results have the lowest error and are thus the most accurate of all the models.

The results of the NAR and NARX models are summarised in table 4.10 and figure 4.14.

Table 4.10 The Summary Forecast Results of the ANN Models

Year / Month	*Actual Inflation*	*NAR (12) Forecasts*	*NARX (14) Forecasts*
2011:01	**9.08**	8.58	8.57
2011:02	**9.16**	9.08	9.08
2011:03	**9.13**	9.16	9.17
2011:04	**9.02**	9.14	9.14
2011:05	**8.9**	9.03	9.04
2011:06	**8.59**	8.91	8.88
2011:07	**8.39**	8.59	8.58
2011:08	**8.41**	8.39	8.38
2011:09	**8.4**	8.42	8.41
2011:10	**8.56**	8.40	8.39
2011:11	**8.55**	8.57	8.55
2011:12	**8.58**	8.56	8.55
Average	**8.73**	**8.74**	**8.73**
	MSFE	0.0377	0.0376
	RMSFE	**0.1943**	**0.1938**

Figure 4.7 Charts of the ANN Models Forecast Results



Source: Excel 2010, Spreadsheet Chart Display Toolbox

From both the table and figure above, it is clear that the two ANN models produce forecasts that follow closely with the actual inflation data for the forecast period of 2011. Moreover, the NARX forecast RMSFE of 0.1938 is marginally below the RMSFE of the NAR which is 0.1943. Thus, the NARX model performs slightly better than the NAR in the prediction.

4.4 Comparison of Forecast Results

The main objective of this part is to compare the forecast results of the NAR with the AR and the NARX forecasts with the VAR in order to evaluate the forecast performance of the ANNs. Table 4.11 shows the summary forecast results of the time-series econometric and ANN models.

Table 4.11 Summary Forecast Results of the Econometric and ANN Models

Year / Month	*Actual Inflation*	*AR (12) Forecasts*	*VAR (14) Forecasts*	*NAR (12) Forecasts*	*NARX (14) Forecasts*
2011:01	**9.08**	8.59	9.13	8.58	8.57
2011:02	**9.16**	8.78	8.17	9.08	9.08
2011:03	**9.13**	9.32	10.69	9.16	9.17
2011:04	**9.02**	9.62	10.38	9.14	9.14
2011:05	**8.9**	9.37	10.54	9.03	9.04
2011:06	**8.59**	9.33	10.64	8.91	8.88
2011:07	**8.39**	8.45	9.06	8.59	8.58
2011:08	**8.41**	8.38	10.12	8.39	8.38
2011:09	**8.4**	8.32	9.73	8.42	8.41
2011:10	**8.56**	8.30	9.80	8.40	8.39
2011:11	**8.55**	8.73	9.74	8.57	8.55
2011:12	**8.58**	8.75	8.67	8.56	8.55
Average	**8.73**	**8.83**	**9.72**	**8.74**	**8.73**
	MSFE	0.1400	1.6896	0.0377	0.0376
	RMSFE	**0.3742**	**1.2999**	**0.1943**	**0.1938**

Table 4.11 clearly shows that forecasts based on the ANN methods are more precise for both the univariate and multivariate models. For example for the month of February, 2011 the NAR forecast of 9.08% deviated from the actual inflation rate of 9.16% by 0.08 percentage point. However, its econometric counterpart, AR, produced a forecast of 8.78% with a high forecast error of 0.38. The NARX model produced a forecast of 9.08% with an error of 0.08 for the same month; however, the VAR model predicted 8.17% with an error as high as -0.99.

The actual value of inflation in November was 8.55%, so the AR forecast of 8.73% is high by 0.18 percentage point. However, the NAR model produced a forecast of 8.57% with a lower error of 0.02. The NARX forecast is the same as the actual for the month; but, the VAR forecast of 9.74% is high by 1.19 percentage points.

The MSFE and RMSFE for the forecast period of 2011 are 0.0377 and 0.1943 respectively for the NAR model. These are far lower than those of the AR model which are 0.14 and 0.3742 respectively. The errors of the NARX model are 0.376 and 0.1938 which are also far below those of the VAR of 1.6896 and 1.299 respectively.

Therefore, the ANN models have lower forecast errors than the econometric models for the one-period-ahead dynamic forecasts for the forecast period of Jan. 2011 to Dec. 2011. Precisely, the univariate NAR model has lower forecast error as compared with its econometric counterpart AR with the same specification. Similarly, the NARX model also records the lower forecast error when compared with the VAR econometric counterpart of the same specification. The average of the forecasts for the 2011 period of 8.74% and 8.73% for the NAR and NARX respectively are also closer to the actual average of 8.73% than those of AR and VAR which are 8.83% and 9.72% respectively.

The multivariate ANN model (NARX) slightly outperforms the univariate model (NAR) in the contest. This may be due to the inclusion of the exogenous inputs which may contain additional information to predict the inflation. However, the same cannot be said about the econometric models; the AR model performs relatively better than the VAR model.

The summary forecast results therefore reveals that at least by the RMSFE criterion forecast based on the ANN models are more accurate. In all, the NARX model has the lowest RMSFE and thus is much more accurate. This forecast comparison result based on the Ghanaian data is also consistent with earlier findings; Moshiri (1997) for the case of Canada, Nakamura (2006) for US case, Haider & Hanif (2008) for the case of Pakistan and Choudhary & Haider (2008) for the case of 28 OECD countries.

CHAPTER IV

SUMMARY OF FINDINGS, RECOMMENDATIONS AND CONCLUSION

5.0 Introduction

The thesis is about inflation forecasting in Ghana using the ANN model and the goal was to evaluate the forecast performance of the ANN by comparing the results with those of time-series econometric models. In this chapter, we present summary of findings, recommendation and concluding remarks.

5.1 Summary of Findings

The study applied four models to forecast inflation using the Ghanaian data. Two of the models were time-series econometric models i.e. AR and VAR and the other two were ANN models i.e. NAR and NARX models. The following are the summary of findings.

i. It was found in the study that inflation forecasts from the AR (12) model were close to the actual figures. For the twelve months of 2011, August had the closest forecast results i.e. 8.38% compared to the actual rate of 8.41% with only a forecast error of 0.03. The MSFE and RMSFE measures for the forecast horizon of 0.14 and 0.3742 respectively were also relatively better than those of the VAR (14) model. The mean of the AR forecasts for 2011 of 8.83% was also fairly close to the mean of the actual inflation rates of 8.73% with a deviation 0.10 percentage points.

ii. The study also found that the VAR (14) forecast results for the same forecast period were close to the actuals but not as close as the AR forecasts. The best forecast result for the VAR was 9.13% for the month of January, 2011; this is above the actual rate of 9.08% by 0.05 percentage points. Of the four models used for the prediction, the VAR produced the highest forecast errors for the forecast horizon of 2011. These are 1.69 and 1.30 as per the MSFE and RMSFE criteria respectively. The average of the VAR forecasts of 9.72% also deviated significantly from the mean of the actuals by approximately 1.00 percentage points.

iii. In comparing the two time-series econometric models i.e. AR and VAR, it was found that the AR model produced the lower RMSFE of 0.3742 and the closer mean forecast value of 8.83% to the mean of the actuals. This result implies that, of the two econometric models, forecasts based on AR model are more accurate. It follows therefore that the multivariate vector autoregressive model does not improve the forecast results on the data used. The findings' is thus consistent with those obtained by Moshiri (1997).

iv. The study revealed that the NAR (12) forecasts were relatively close to the actual data for the forecast horizon. The closest forecast of 8.39% as against actual rate of 8.41% (i.e. having a forecast error of 0.02) was achieved in August. The average total forecast errors for the twelve months of 2011 were 0.038 and 0.194 for the MSFE and RMSFE respectively. The average inflation forecast for the NAR was also 8.74% as against the actual average of 8.73%.

v. The study found that forecasts from the NARX (14) were very close to the actual data. For the month of November for example, the forecast rate of 8.55% was the same as the actual rate. The MSFE and RMSFE for the period were 0.0376 and 0.1938 respectively and the mean of the forecasts of 8.73% was the same as the mean of the actuals.

vi. The study also revealed that between the two ANN models i.e. NAR and NARX, the multivariate NARX model produced slightly lower RMSFE (i.e. 0.1938) than the univariate NAR model (i.e. 0.194). The mean of the NARX forecasts was also closer to the mean of the actuals than the NAR. Therefore, the NARX outperformed the NAR implying that the inclusion of the exogenous inputs marginally improved the forecast results.

vii. More importantly, the study found that between the NAR and AR models, the NAR model produced the lower forecast error and between the VAR and the NARX models, the forecast error of the NARX was the lower. That is, it was observed that both the univariate (i.e. NAR) and multivariate (i.e. NARX) ANN models significantly outperformed the times-series econometric models (i.e. AR and VAR) in the inflation prediction. The result therefore highlights the fact that the monthly y-o-y inflation data used for the study are more consistent with the non-linear behaviour assumed by the ANN models.

5.2 Recommendations

On the basis of the findings in Chapter Four, the following recommendations are made.

i. The results of the study have shown that the ANN models perform better than the econometric models in inflation prediction. It is therefore recommended that the Bank of Ghana uses the ANN model in their forecasting toolkit to predict the inflation as some central banks (e.g. The State Bank of Pakistan, CZECH National Bank, Bank of Canada and Bank of Jamaica) are doing.

ii. The study further recommends for the Bank of Ghana to use the ANN model in addition to the econometric models to predict other macroeconomic variables such as the exchange rate and GDP.

iii. The ANN methodology is new to economics literature, but the results of the study indicate that the model can be a useful research tool for economists. The study therefore recommends for further studies to use the ANN model to predict economic variables.

iv. The study also recommends that the other types of ANN models such as the generalised regression neural network (GRNN) and the multilayer perceptron (MLP) neural network should be explored for prediction by future studies so as to expose the full potentials of the ANN models.

v. In this study the dataset is not large and so the study recommends for further studies to use more data in the modelling and forecasting of the inflation. This may perhaps improve the forecast results as suggested by some researchers.

vi. The ANN model is not only good at time-series predictions but can solve very complex and nonlinear problems such as maximisation or optimisation problems. Therefore, it is also recommended for further studies to explore all the possible uses to which the ANN models can be put in economics.

5.3 Practical Limitations of the Study

i. The ANN model mimics the human brain and so learns by experience. The model therefore learns and predicts well with more data. Although the ANN prediction was good, the results may improve with more data. Data availability was thus a limitation on the study.

ii. The ANN methodology is a physical science model and as such new to the social sciences such as economics. Therefore, the workload in finding both theoretical and empirical literature on the model delayed the progress of the work.

5.4 Concluding Remarks

Bank of Ghana is mandated to pursue a primary objective of achieving and maintaining price stability since the enactment of the Bank of Ghana Act in 2002 (BoG Act 612). To achieve this objective the BoG has adopted inflation targeting as its monetary policy framework (BoG, 2002). Inflation targeting requires the BoG to be able to predict the inflation with much more precision to guide policy discussions at the Monetary Policy Committee (MPC).

Two methods i.e. econometric and ANN models have been used to predict macroeconomic variables such as the inflation by some central banks and researchers. However, the BoG and researchers in Ghana have used only the econometric models to predict the inflation.

The purpose of the study was to evaluate the performance of the ANN model by comparing forecasts from the ANN with those of time-series econometric models. The criterion for forecast accuracy was the out-of-sample RMSFE. The study used monthly time-series data from January, 1991 to December, 2011 i.e. the y-o-y inflation rate, y-o-y broad money supply (M2+) growth rate and y-o-y exchange rate depreciation from BoG. The ANN models (i.e. NAR and NARX) and the econometric models (i.e. AR and VAR) were applied to the data from Jan., 1991 to Dec., 2010 so as to forecast for the period from Jan., 2011 to Dec., 2011.

The RMSFEs were compared for the ANN and time-series econometric models. The results showed that the ANN models have lower RMSFEs than the econometric models. Thus, at least by the RMSFE criterion forecast based on ANN models are more accurate. The study therefore recommends that monetary policymakers should include the ANN model in their forecasting toolkit. The use of the ANN methodology in economic studies to predict other macroeconomic variables such as GDP and exchange rate is also recommended so that the entire potential of the model will be exposed.

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APPENDIX

Monetary Time Series Data, Bank of Ghana

No.	Year	Month	GH ¢ / $ Exchange Rate	Yr-on-Yr Inflation Rate	Broad Money (M2+) Suppy (GH¢'m)	YoY Inf Rate	Exch Rate Depn	M2+ Growth Rate
1	1990	Jan	0.0306	33	26.2			
2	1990	Feb	0.0308	35.9	24.5			
3	1990	Mar	0.0312	36.1	23.7			
4	1990	Apr	0.0317	36	24.1			
5	1990	May	0.0326	35.6	23.6			
6	1990	Jun	0.0329	36.5	24.5			
7	1990	Jul	0.0332	39	24.5			
8	1990	Aug	0.0336	40.2	23.3			
9	1990	Sep	0.0338	41.4	25.8			
10	1990	Oct	0.0342	39.3	26.6			
11	1990	Nov	0.0344	37.2	28.4			
12	1990	Dec	0.0345	35.9	29.5			
13	1991	Jan	0.0346	30.4	29.7	30.4	13.07	13.36
14	1991	Feb	0.0354	26.6	29.4	26.6	14.94	20.00
15	1991	Mar	0.0361	24.9	28.9	24.9	15.71	21.94
16	1991	Apr	0.0364	22.3	29.3	22.3	14.83	21.58
17	1991	May	0.0366	19.8	29.3	19.8	12.27	24.15
18	1991	Jun	0.0367	17.3	29.1	17.3	11.55	18.78
19	1991	Jul	0.037	15.3	29.2	15.3	11.45	19.18
20	1991	Aug	0.0373	14.6	29	14.6	11.01	24.46
21	1991	Sep	0.0376	13.2	30.8	13.2	11.24	19.38
22	1991	Oct	0.0379	13.9	32	13.9	10.82	20.30
23	1991	Nov	0.0386	13	34.3	13	12.21	20.77
24	1991	Dec	0.039	10.3	37.2	10.3	13.04	26.10
25	1992	Jan	0.039	8.7	36	8.7	12.72	21.21
26	1992	Feb	0.0393	7.7	37.6	7.7	11.02	27.89
27	1992	Mar	0.0407	7.3	38.8	7.3	12.74	34.26
28	1992	Apr	0.0408	8.2	39.7	8.2	12.09	35.49
29	1992	May	0.0411	8.9	39.7	8.9	12.30	35.49
30	1992	Jun	0.0415	8.4	41.9	8.4	13.08	43.99
31	1992	Jul	0.0436	10.2	43.1	10.2	17.84	47.60
32	1992	Aug	0.045	11.7	44	11.7	20.64	51.72
33	1992	Sep	0.048	11.5	44.8	11.5	27.66	45.45
34	1992	Oct	0.049	11.7	46.9	11.7	29.29	46.56
35	1992	Nov	0.0512	12.6	52	12.6	32.64	51.60

36	1992	Dec	0.052	13.3	56.9	13.3	33.33	52.96
37	1993	Jan	0.0555	21.5	60.3	21.5	42.31	67.50
38	1993	Feb	0.0596	23	58.6	23	51.65	55.85
39	1993	Mar	0.0601	23.3	58.8	23.3	47.67	51.55
40	1993	Apr	0.0601	23	59.3	23	47.30	49.37
41	1993	May	0.0601	23.9	59.1	23.9	46.23	48.87
42	1993	Jun	0.0601	26	61	26	44.82	45.58
43	1993	Jul	0.0665	25.2	62.6	25.2	52.52	45.24
44	1993	Aug	0.0686	25.2	64.2	25.2	52.44	45.91
45	1993	Sep	0.0699	26.9	64.5	26.9	45.63	43.97
46	1993	Oct	0.0725	26.5	66	26.5	47.96	40.72
47	1993	Nov	0.0768	26.6	67.9	26.6	50.00	30.58
48	1993	Dec	0.0822	27.7	76.6	27.7	58.08	34.62
49	1994	Jan	0.0912	22.8	76.2	22.8	64.32	26.37
50	1994	Feb	0.0938	22	79.3	22	57.38	35.32
51	1994	Mar	0.0937	21.5	79.2	21.5	55.91	34.69
52	1994	Apr	0.0932	21.1	80.8	21.1	55.07	36.26
53	1994	May	0.0932	21	82.5	21	55.07	39.59
54	1994	Jun	0.0943	20.9	86.6	20.9	56.91	41.97
55	1994	Jul	0.0972	22.3	89.3	22.3	46.17	42.65
56	1994	Aug	0.0969	23.7	93.2	23.7	41.25	45.17
57	1994	Sep	0.0985	26.1	95.4	26.1	40.92	47.91
58	1994	Oct	0.1014	29.4	104.1	29.4	39.86	57.73
59	1994	Nov	0.104	31.7	107.9	31.7	35.42	58.91
60	1994	Dec	0.1051	34.2	117.3	34.2	27.86	53.13
61	1995	Jan	0.1063	35.6	122	35.6	16.56	60.10
62	1995	Feb	0.1069	38.4	120.3	38.4	13.97	51.70
63	1995	Mar	0.1111	43.6	121.1	43.6	18.57	52.90
64	1995	Apr	0.113	49.9	123.1	49.9	21.24	52.35
65	1995	May	0.1151	56.1	126	56.1	23.50	52.73
66	1995	Jun	0.1174	61.9	130.8	61.9	24.50	51.04
67	1995	Jul	0.1193	67.2	129.7	67.2	22.74	45.24
68	1995	Aug	0.1216	69.9	134.7	69.9	25.49	44.53
69	1995	Sep	0.1303	69.8	138.4	69.8	32.28	45.07
70	1995	Oct	0.1351	69.1	148.1	69.1	33.23	42.27
71	1995	Nov	0.1414	70.2	157.1	70.2	35.96	45.60
72	1995	Dec	0.1446	70.8	165	70.8	37.58	40.66
73	1996	Jan	0.1498	69.2	168	69.2	40.92	37.70
74	1996	Feb	0.1542	68	174.4	68	44.25	44.97
75	1996	Mar	0.1582	64.8	178.6	64.8	42.39	47.48
76	1996	Apr	0.1607	60.3	187	60.3	42.21	51.91
77	1996	May	0.1631	54.2	187.8	54.2	41.70	49.05

78	1996	Jun	0.1654	48.4	192.3	48.4	40.89	47.02
79	1996	Jul	0.1686	42.6	199.5	42.6	41.32	53.82
80	1996	Aug	0.1693	39.2	205.5	39.2	39.23	52.56
81	1996	Sep	0.1711	36.5	209.3	36.5	31.31	51.23
82	1996	Oct	0.1724	34.3	226.1	34.3	27.61	52.67
83	1996	Nov	0.1732	33.2	223.4	33.2	22.49	42.20
84	1996	Dec	0.174	32.7	235.7	32.7	20.33	42.85
85	1997	Jan	0.1754	31.5	239.7	31.5	17.09	42.68
86	1997	Feb	0.1812	30.6	249	30.6	17.51	42.78
87	1997	Mar	0.1893	29.2	248.5	29.2	19.66	39.14
88	1997	Apr	0.1956	29.1	254	29.1	21.72	35.83
89	1997	May	0.2023	29.6	264.6	29.6	24.03	40.89
90	1997	Jun	0.2116	29	272.9	29	27.93	41.91
91	1997	Jul	0.2169	29.2	281.3	29.2	28.65	41.00
92	1997	Aug	0.2187	28.2	283	28.2	29.18	37.71
93	1997	Sep	0.2216	27.7	287	27.7	29.51	37.12
94	1997	Oct	0.2231	25.5	300.3	25.5	29.41	32.82
95	1997	Nov	0.2239	22.8	309	22.8	29.27	38.32
96	1997	Dec	0.225	20.5	331.9	20.5	29.31	40.81
97	1998	Jan	0.2289	19.8	337.5	19.8	30.50	40.80
98	1998	Feb	0.2298	19.6	334.3	19.6	26.82	34.26
99	1998	Mar	0.2306	20.3	331.9	20.3	21.82	33.56
100	1998	Apr	0.2307	23.1	337	23.1	17.94	32.68
101	1998	May	0.2308	22.9	338	22.9	14.09	27.74
102	1998	Jun	0.2323	21.8	349.6	21.8	9.78	28.11
103	1998	Jul	0.2325	18.7	353.8	18.7	7.19	25.77
104	1998	Aug	0.2325	18.6	352.5	18.6	6.31	24.56
105	1998	Sep	0.2324	17.4	352.9	17.4	4.87	22.96
106	1998	Oct	0.2327	17.1	362.9	17.1	4.30	20.85
107	1998	Nov	0.2339	16.2	376.6	16.2	4.47	21.88
108	1998	Dec	0.2346	15.7	390.3	15.7	4.27	17.60
109	1999	Jan	0.2358	15.3	395.8	15.3	3.01	17.27
110	1999	Feb	0.237	15	392.7	15	3.13	17.47
111	1999	Mar	0.2416	13.7	392.7	13.7	4.77	18.32
112	1999	Apr	0.244	10.2	394.8	10.2	5.77	17.15
113	1999	May	0.2481	9.4	402.8	9.4	7.50	19.17
114	1999	Jun	0.253	10.3	412.8	10.3	8.91	18.08
115	1999	Jul	0.2571	12.7	420.3	12.7	10.58	18.80
116	1999	Aug	0.2599	12	424.6	12	11.78	20.45
117	1999	Sep	0.267	11.8	419.6	11.8	14.89	18.90
118	1999	Oct	0.2997	12.6	434.5	12.6	28.79	19.73
119	1999	Nov	0.3475	13.2	459.1	13.2	48.57	21.91

120	1999	Dec	0.3557	13.8	494.7	13.8	51.62	26.75
121	2000	Jan	0.3626	14.3	492.9	14.3	53.77	24.53
122	2000	Feb	0.3911	14.9	496.6	14.9	65.02	26.46
123	2000	Mar	0.4344	15.6	514.7	15.6	79.80	31.07
124	2000	Apr	0.4693	17.5	528.9	17.5	92.34	33.97
125	2000	May	0.4991	18.7	544.5	18.7	101.17	35.18
126	2000	Jun	0.5664	19.8	564.7	19.8	123.87	36.80
127	2000	Jul	0.6056	22.1	588	22.1	135.55	39.90
128	2000	Aug	0.6436	26.6	600.7	26.6	147.63	41.47
129	2000	Sep	0.6515	32.3	627	32.3	144.01	49.43
130	2000	Oct	0.6817	37.4	641.8	37.4	127.46	47.71
131	2000	Nov	0.682	39.5	692.7	39.5	96.26	50.88
132	2000	Dec	0.7048	40.5	724.8	40.5	98.14	46.51
133	2001	Jan	0.7006	40.9	747.1	40.9	93.22	51.57
134	2001	Feb	0.709	40.1	751.5	40.1	81.28	51.33
135	2001	Mar	0.7205	41.9	756.2	41.9	65.86	46.92
136	2001	Apr	0.7228	39.5	762.1	39.5	54.02	44.09
137	2001	May	0.7236	37.9	765.8	37.9	44.98	40.64
138	2001	Jun	0.7227	36.8	771.1	36.8	27.60	36.55
139	2001	Jul	0.7177	34.9	796.3	34.9	18.51	35.43
140	2001	Aug	0.7159	32	807.7	32	11.23	34.46
141	2001	Sep	0.7157	28.3	848.5	28.3	9.85	35.33
142	2001	Oct	0.7195	25.6	898.5	25.6	5.54	40.00
143	2001	Nov	0.7278	23.7	966.2	23.7	6.72	39.48
144	2001	Dec	0.7322	21.3	1024.8	21.3	3.89	41.39
145	2002	Jan	0.7357	26.7	1043.6	26.7	5.01	39.69
146	2002	Feb	0.7545	23.8	1057.8	23.8	6.42	40.76
147	2002	Mar	0.769	19.9	1074.5	19.9	6.73	42.09
148	2002	Apr	0.7803	18	1079.2	18	7.96	41.61
149	2002	May	0.791	17.1	1102.9	17.1	9.31	44.02
150	2002	Jun	0.8043	15.8	1126	15.8	11.29	46.03
151	2002	Jul	0.8136	14.2	1165	14.2	13.36	46.30
152	2002	Aug	0.8164	14.4	1181.5	14.4	14.04	46.28
153	2002	Sep	0.8188	15	1213.6	15	14.41	43.03
154	2002	Oct	0.8275	13.6	1302.5	13.6	15.01	44.96
155	2002	Nov	0.8339	14.1	1432.6	14.1	14.58	48.27
156	2002	Dec	0.8439	17	1536.8	17	15.26	49.96
157	2003	Jan	0.8537	13.5	1540.8	13.5	16.04	47.64
158	2003	Feb	0.856	25.5	1561.5	25.5	13.45	47.62
159	2003	Mar	0.86	29.8	1521	29.8	11.83	41.55
160	2003	Apr	0.869	29.3	1513.5	29.3	11.37	40.24
161	2003	May	0.8684	31.6	1580.8	31.6	9.79	43.33

162	2003	Jun	0.87	32.9	1604.3	32.9	8.17	42.48
163	2003	Jul	0.8722	33	1625.4	33	7.20	39.52
164	2003	Aug	0.8736	33.6	1651.1	33.6	7.01	39.75
165	2003	Sep	0.8732	29.8	1644.6	29.8	6.64	35.51
166	2003	Oct	0.8754	33.2	1799.7	33.2	5.79	38.17
167	2003	Nov	0.8805	33.6	1927.8	33.6	5.59	34.57
168	2003	Dec	0.8852	31.3	2117.4	31.3	4.89	37.78
169	2004	Jan	0.888	29	2147.1	29	4.02	39.35
170	2004	Feb	0.8915	18.6	2116.4	18.6	4.15	35.54
171	2004	Mar	0.9018	15.6	2124.8	15.6	4.86	39.70
172	2004	Apr	0.9049	17.3	2145.5	17.3	4.13	41.76
173	2004	May	0.9029	17.6	2187.5	17.6	3.97	38.38
174	2004	Jun	0.9047	18	2249	18	3.99	40.19
175	2004	Jul	0.9042	15	2248.7	15	3.67	38.35
176	2004	Aug	0.9046	17.5	2277.9	17.5	3.55	37.96
177	2004	Sep	0.9052	19.6	2328.5	19.6	3.66	41.58
178	2004	Oct	0.9049	16.9	2467.9	16.9	3.37	37.13
179	2004	Nov	0.9055	16.5	2600.8	16.5	2.84	34.91
180	2004	Dec	0.9051	16.4	2668.6	16.4	2.25	26.03
181	2005	Jan	0.905	16.8	2587.3	16.8	1.91	20.50
182	2005	Feb	0.9058	17	2605.4	17	1.60	23.11
183	2005	Mar	0.9075	17.8	2633.7	17.8	0.63	23.95
184	2005	Apr	0.9081	17.1	2689.8	17.1	0.35	25.37
185	2005	May	0.9066	14.5	2689.8	14.5	0.41	22.96
186	2005	Jun	0.9075	14	2710.8	14	0.31	20.53
187	2005	Jul	0.9077	17.3	2711.2	17.3	0.39	20.57
188	2005	Aug	0.9086	13.3	2801	13.3	0.44	22.96
189	2005	Sep	0.9086	14.3	2700.6	14.3	0.38	15.98
190	2005	Oct	0.9084	14.9	2870.2	14.9	0.39	16.30
191	2005	Nov	0.9099	14.7	2876.8	14.7	0.49	10.61
192	2005	Dec	0.9131	13.9	3041.8	13.9	0.88	13.98
193	2006	Jan	0.9129	12.8	3067.3	12.8	0.87	18.55
194	2006	Feb	0.9119	12.3	3137.9	12.3	0.67	20.44
195	2006	Mar	0.9139	11.3	3150.1	11.3	0.71	19.61
196	2006	Apr	0.9141	11.2	3283.5	11.2	0.66	22.07
197	2006	May	0.9145	11.7	3337.2	11.7	0.87	24.07
198	2006	Jun	0.9191	11.4	3407.9	11.4	1.28	25.72
199	2006	Jul	0.9198	12.9	3462.1	12.9	1.33	27.70
200	2006	Aug	0.9198	12.6	3523.6	12.6	1.23	25.80
201	2006	Sep	0.921	11.7	3608.3	11.7	1.36	33.61
202	2006	Oct	0.9224	10.9	3745.7	10.9	1.54	30.50
203	2006	Nov	0.9229	10.7	3940.2	10.7	1.43	36.96

204	2006	Dec	0.9235	10.9	4230.2	10.9	1.14	39.07
205	2007	Jan	0.9235	10.9	4276.1	10.9	1.16	39.41
206	2007	Feb	0.9256	10.4	4229.1	10.4	1.50	34.77
207	2007	Mar	0.9269	10.2	4282.4	10.2	1.42	35.94
208	2007	Apr	0.9274	10.5	4470.6	10.5	1.45	36.15
209	2007	May	0.9274	11	4594.7	11	1.41	37.68
210	2007	Jun	0.9285	10.7	4524.8	10.7	1.02	32.77
211	2007	Jul	0.93	10.1	4678.4	10.1	1.11	35.13
212	2007	Aug	0.9355	10.4	4827.4	10.4	1.71	37.00
213	2007	Sep	0.9428	10.2	5000	10.2	2.37	38.57
214	2007	Oct	0.9455	10.1	5200	10.1	2.50	38.83
215	2007	Nov	0.968	11.4	5300	11.4	4.89	34.51
216	2007	Dec	0.9704	12.7	5593	12.7	5.08	32.22
217	2008	Jan	0.9759	12.8	5710.3	12.8	5.67	33.54
218	2008	Feb	0.9751	13.2	5772.9	13.2	5.35	36.50
219	2008	Mar	0.978	13.8	5959.2	13.8	5.51	39.16
220	2008	Apr	0.9872	15.3	6010.6	15.3	6.45	34.45
221	2008	May	1.0024	16.9	6251.2	16.9	8.09	36.05
222	2008	Jun	1.0325	18.4	6197	18.4	11.20	36.96
223	2008	Jul	1.0692	18.3	6518.2	18.3	14.97	39.33
224	2008	Aug	1.1161	18.1	6694.8	18.1	19.31	38.68
225	2008	Sep	1.1345	17.9	6934.4	17.9	20.33	38.69
226	2008	Oct	1.1565	17.3	7059.3	17.3	22.32	35.76
227	2008	Nov	1.1777	17.4	7194.4	17.4	21.66	35.74
228	2008	Dec	1.2141	18.1	8061.1	18.1	25.11	44.13
229	2009	Jan	1.2828	19.9	7823.8	19.9	31.45	37.01
230	2009	Feb	1.3402	20.3	7846.7	20.3	37.44	35.92
231	2009	Mar	1.3832	20.5	8211.9	20.5	41.43	37.80
232	2009	Apr	1.4042	20.6	8200.3	20.6	42.24	36.43
233	2009	May	1.4396	20.1	8350.1	20.1	43.62	33.58
234	2009	Jun	1.4725	20.7	8659.7	20.7	42.62	39.74
235	2009	Jul	1.4858	20.5	8793.3	20.5	38.96	34.90
236	2009	Aug	1.4619	19.6	8694.5	19.6	30.98	29.87
237	2009	Sep	1.4514	18.4	8728.8	18.4	27.93	25.88
238	2009	Oct	1.4416	18	9214.5	18	24.65	30.53
239	2009	Nov	1.4322	16.9	8711.3	16.9	21.61	21.08
240	2009	Dec	1.4287	16	10233.3	16	17.68	26.95
241	2010	Jan	1.4257	14.8	10222.33	14.8	11.14	30.66
242	2010	Feb	1.4266	14.2	10094.059	14.2	6.45	28.64
243	2010	Mar	1.4168	13.3	10538.017	13.3	2.43	28.33
244	2010	Apr	1.417	11.7	10408.2	11.7	0.91	26.92
245	2010	May	1.4206	10.7	10467.06	10.7	-1.32	25.35

246	2010	Jun	1.4267	9.5	10846.035		9.5	-3.11	25.25
247	2010	Jul	1.4353	9.5	10770.761		9.5	-3.40	22.49
248	2010	Aug	1.4307	9.4	10829.997		9.4	-2.13	24.56
249	2010	Sep	1.4269	9.4	11170.8		9.4	-1.69	27.98
250	2010	Oct	1.4293	9.38	12259.59		9.38	-0.85	33.05
251	2010	Nov	1.4367	9.08	12924.817		9.08	0.31	48.37
252	2010	Dec	1.4738	8.58	13662.997		8.58	3.16	33.52
253	2011	Jan	1.5013	9.08	13644.88		9.08	5.30	33.48
254	2011	Feb	1.4937	9.16	13719.92		9.16	4.70	35.92
255	2011	Mar	1.5021	9.13	14334.48		9.13	6.02	36.03
256	2011	Apr	1.4972	9.02	14728.9		9.02	5.66	41.51
257	2011	May	1.5018	8.9	14727.88		8.9	5.72	40.71
258	2011	Jun	1.5064	8.59	15202.1		8.59	5.59	40.16
259	2011	Jul	1.5055	8.39	15353.82		8.39	4.89	42.55
260	2011	Aug	1.5104	8.41	15388.72		8.41	5.57	42.09
261	2011	Sep	1.5224	8.4	15851.23		8.4	6.69	41.90
262	2011	Oct	1.5328	8.56	16929.136		8.56	7.24	38.09
263	2011	Nov	1.5412	8.55	-		8.55	7.27	
264	2011	Dec	1.5505	8.58	-		8.58	5.20	
265	2012	Jan	1.6475	8.73	-				
266	2012	Feb	1.6735	8.6	-				
267	2012	Mar	1.6888	8.8	-				

Table A.2 AR (12) Model Estimation Results using the levels of the series

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	0.396707	0.207364	1.9131	0.05714	*
Inf_1	1.35472	0.0691844	19.5812	<0.00001	***
Inf_2	-0.242598	0.115396	-2.1023	0.03676	**
Inf_3	0.0292122	0.115692	0.2525	0.80091	
Inf_4	-0.191772	0.114855	-1.6697	0.09652	*
Inf_5	0.137395	0.114532	1.1996	0.23168	
Inf_6	-0.0853265	0.11476	-0.7435	0.45803	
Inf_7	-0.0989576	0.114479	-0.8644	0.38838	
Inf_8	0.207835	0.114231	1.8194	0.07032	*
Inf_9	-0.191807	0.114284	-1.6783	0.09482	*
Inf_10	0.209489	0.115032	1.8211	0.07006	*
Inf_11	-0.311879	0.114571	-2.7222	0.00705	***
Inf_12	0.166612	0.0686827	2.4258	0.01615	**
u(-12)	-0.452857	0.0605661	-7.4771	<0.00001	***

Statistics based on the rho-differenced data:

Mean dependent var	34.25331	S.D. dependent var	17.05175
Sum squared resid	634.9495	S.E. of regression	1.768567
R-squared	0.984535	Adjusted R-squared	0.983621
F(12, 203)	1648.611	P-value(F)	4.8e-195
rho	0.026288	Durbin-Watson	1.767766

Table A.3 VAR (14) Model Estimation Results using the levels of the series

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	-0.48517	0.640985	-0.7569	0.45007	
Inf_1	1.28431	0.0718665	17.8708	<0.00001	***
Inf_2	-0.211091	0.11135	-1.8957	0.05957	*
Inf_3	-0.00199624	0.112074	-0.0178	0.98581	
Inf_4	-0.108024	0.109516	-0.9864	0.32525	
Inf_5	0.0884971	0.109603	0.8074	0.42047	
Inf_6	-0.0614011	0.10968	-0.5598	0.57629	
Inf_7	-0.0562859	0.109682	-0.5132	0.60845	
Inf_8	0.139731	0.109876	1.2717	0.20509	
Inf_9	-0.160353	0.110276	-1.4541	0.14763	
Inf_10	0.182725	0.1105	1.6536	0.09992	*
Inf_11	-0.269166	0.111021	-2.4245	0.01630	**
Inf_12	-0.256003	0.113065	-2.2642	0.02473	**
Inf_13	0.632261	0.112872	5.6016	<0.00001	***
Inf_14	-0.241536	0.0700688	-3.4471	0.00070	***
Ex_dep_1	0.0263516	0.0352479	0.7476	0.45566	
Ex_dep_2	0.0220953	0.0627643	0.3520	0.72522	
Ex_dep_3	-0.0368287	0.064018	-0.5753	0.56580	
Ex_dep_4	-0.00967917	0.0638577	-0.1516	0.87969	
Ex_dep_5	0.00165585	0.0636673	0.0260	0.97928	
Ex_dep_6	0.00214887	0.0636899	0.0337	0.97312	
Ex_dep_7	-0.0231817	0.0637803	-0.3635	0.71668	
Ex_dep_8	0.0109184	0.0636868	0.1714	0.86407	
Ex_dep_9	0.0102788	0.0632326	0.1626	0.87105	
Ex_dep_10	0.0207359	0.0627364	0.3305	0.74138	
Ex_dep_11	-0.0211044	0.0624913	-0.3377	0.73596	
Ex_dep_12	-0.0244344	0.0621905	-0.3929	0.69485	
Ex_dep_13	0.0675512	0.0607048	1.1128	0.26726	
Ex_dep_14	-0.0371549	0.0355488	-1.0452	0.29732	
M2__growth_1	0.00844926	0.0375153	0.2252	0.82206	
M2__growth_2	0.0404691	0.0479388	0.8442	0.39967	
M2__growth_3	-0.0361297	0.0453769	-0.7962	0.42694	
M2__growth_4	0.0273333	0.0460727	0.5933	0.55374	
M2__growth_5	0.0125691	0.0458322	0.2742	0.78421	
M2__growth_6	0.00560219	0.0459843	0.1218	0.90317	
M2__growth_7	0.00876372	0.0454007	0.1930	0.84715	
M2__growth_8	-0.040804	0.0454009	-0.8987	0.36997	
M2__growth_9	0.0151354	0.0453023	0.3341	0.73869	
M2__growth_10	-0.00991184	0.0452307	-0.2191	0.82679	
M2__growth_11	0.0405675	0.0457994	0.8858	0.37691	
M2__growth_12	-0.0384989	0.0460123	-0.8367	0.40385	
M2__growth_13	-0.0519998	0.0477136	-1.0898	0.27722	
M2__growth_14	0.0496013	0.0381212	1.3011	0.19484	

Statistics based on the rho-differenced data:

Mean dependent var	23.00549	S.D. dependent var	13.78628
Sum squared resid	578.6957	S.E. of regression	1.778278
R-squared	0.986468	Adjusted R-squared	0.983362
F(42, 183)	317.6225	P-value (F)	4.7e-150
rho	0.006295	Durbin-Watson	1.981398

Figure A.1

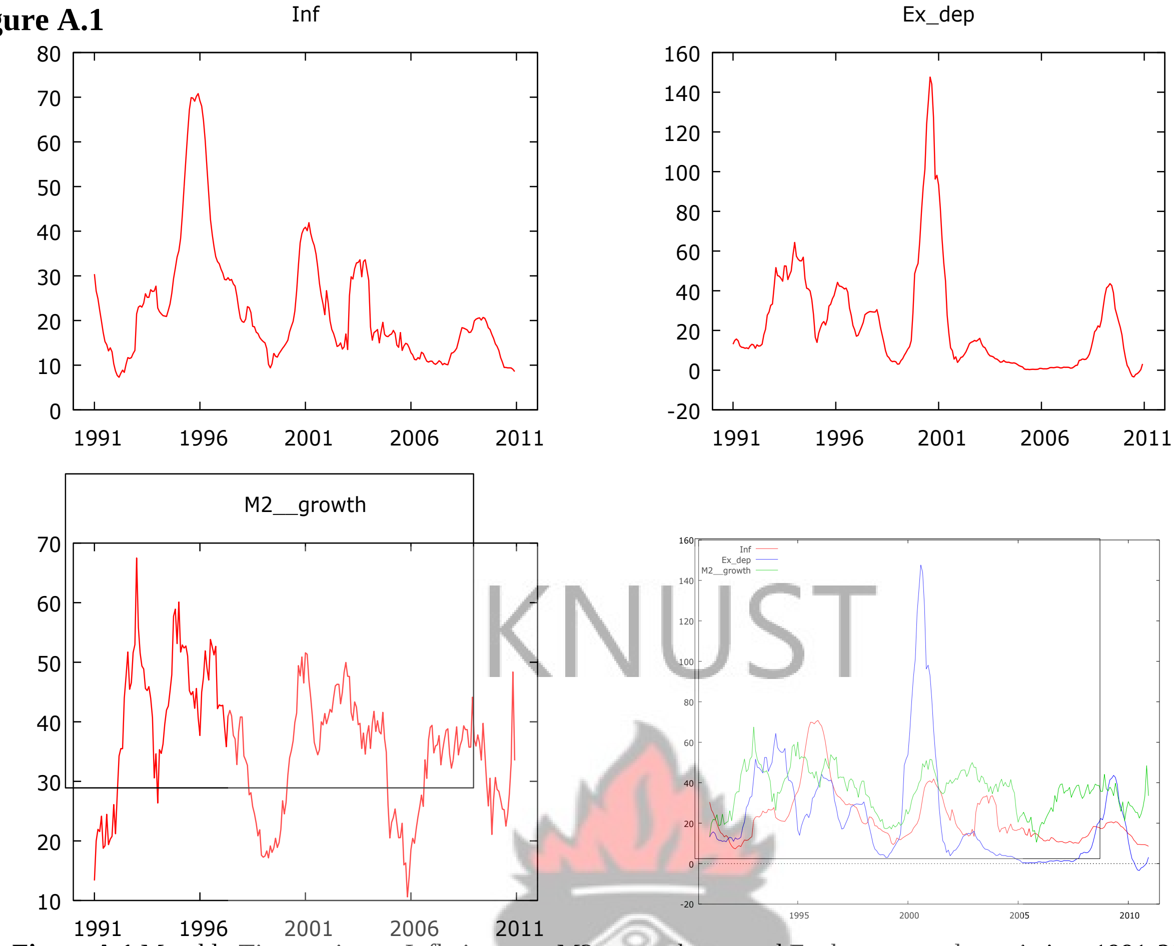

Figure A.1 Monthly Time-series on Inflation rate, M2+ growth rate and Exchange rate depreciation: 1991-2010

Source: Gretl 2006, Time-series data - Display levels Toolbox

Figure A.2

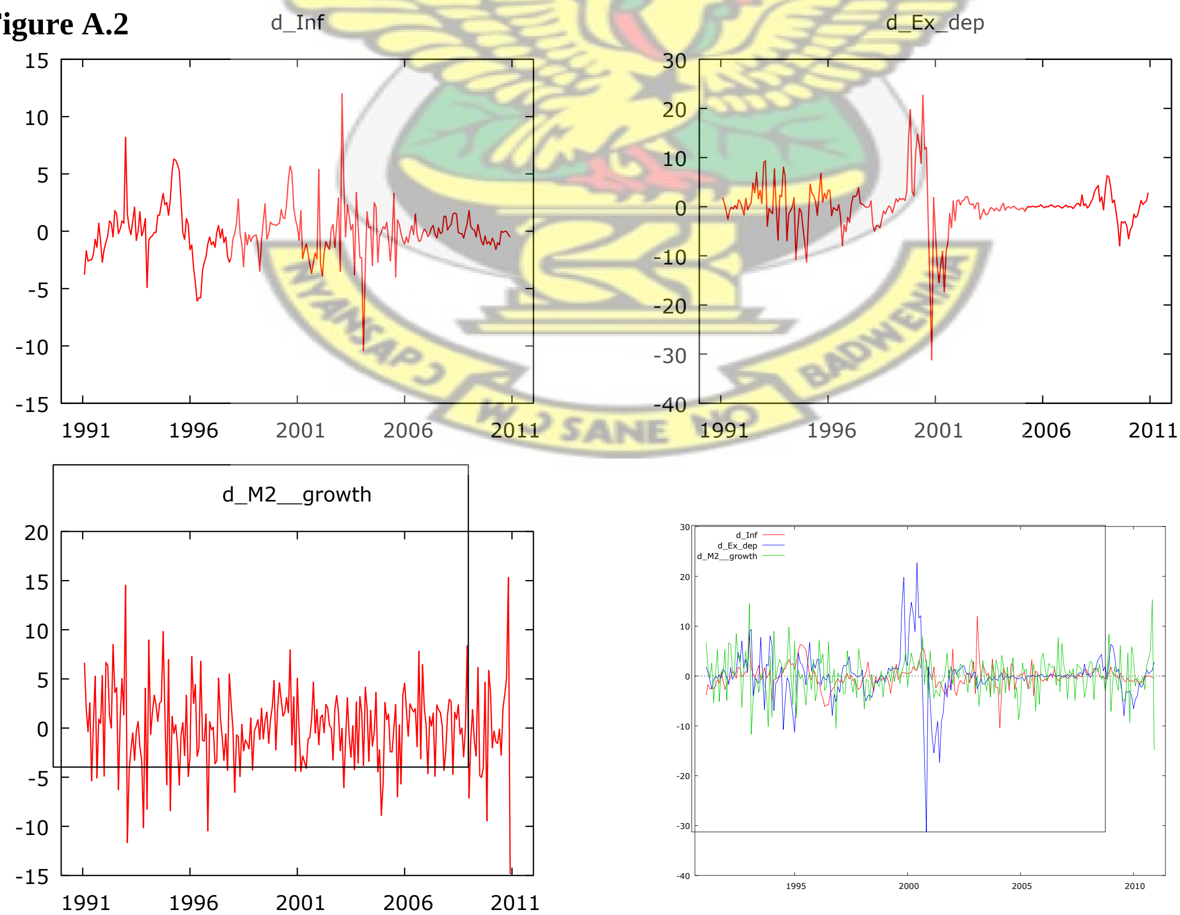

Figure A.2 First Differences of the Monthly Time series data: 1991-2010

Source: Gretl 2006, Time-series data - Display First-differences Toolbox

Figure A.3 NAR Training Model in Open Loop Architecture

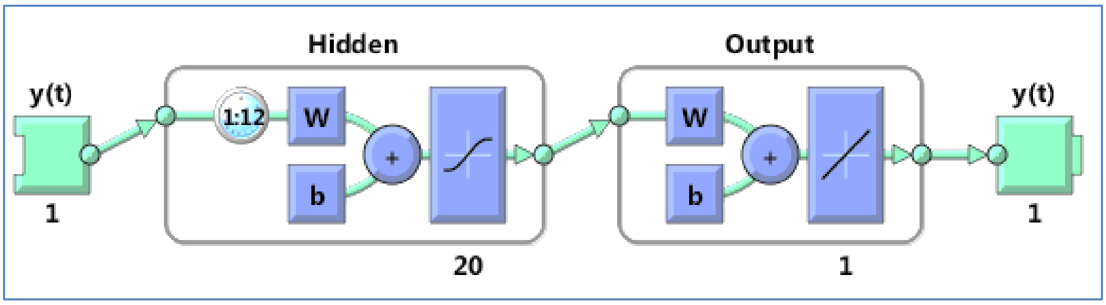

Figure A.3 A NAR Training model with one input unit, twenty hidden units, one output unit and twelve lags

Figure A.4 NAR Forecasting Model in Close Loop Architecture

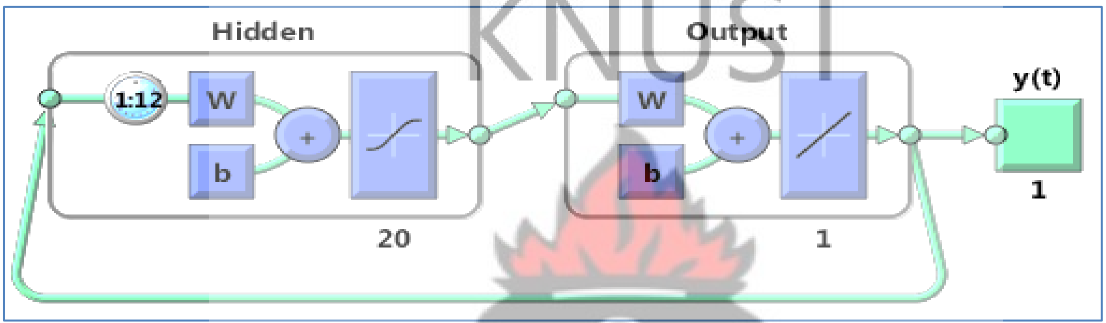

Figure A.4 A NAR Forecasting model with feedback input, twenty hidden units, one output unit and twelve lags

Figure A.5 NARX Training Model in Open Loop Architecture

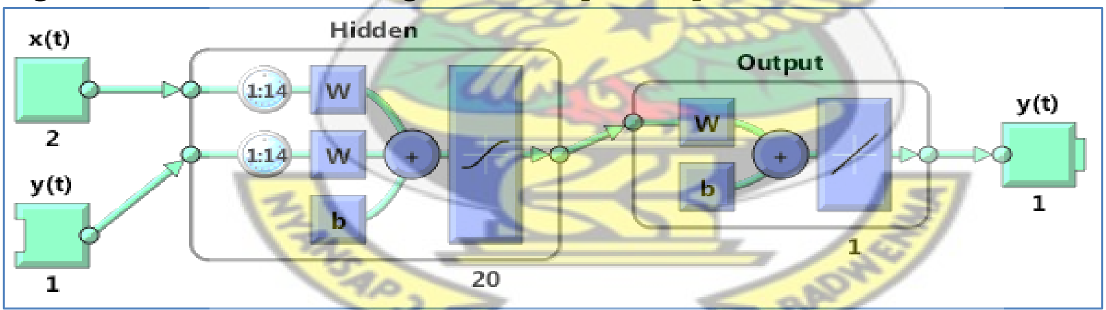

Figure A.5 A NARX Training model with three input units, twenty hidden units, one output unit, and fourteen lags

Figure A.6 NARX Forecasting Model in Close Loop Architecture

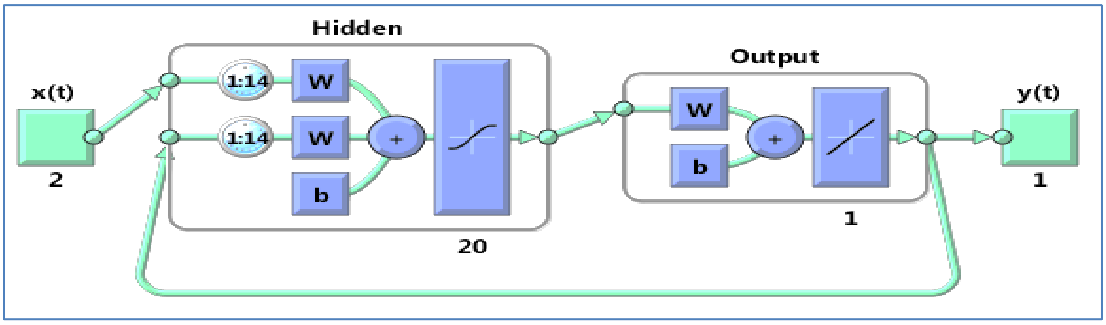

Figure A.5 A NARX Forecasting model with two input units and feedback input, twenty hidden units, one output unit, and fourteen lags

Source: MatLab (2011) Neural Network Toolbox

Figure A.7 Training Regression results of NAR (12) using the levels of the series

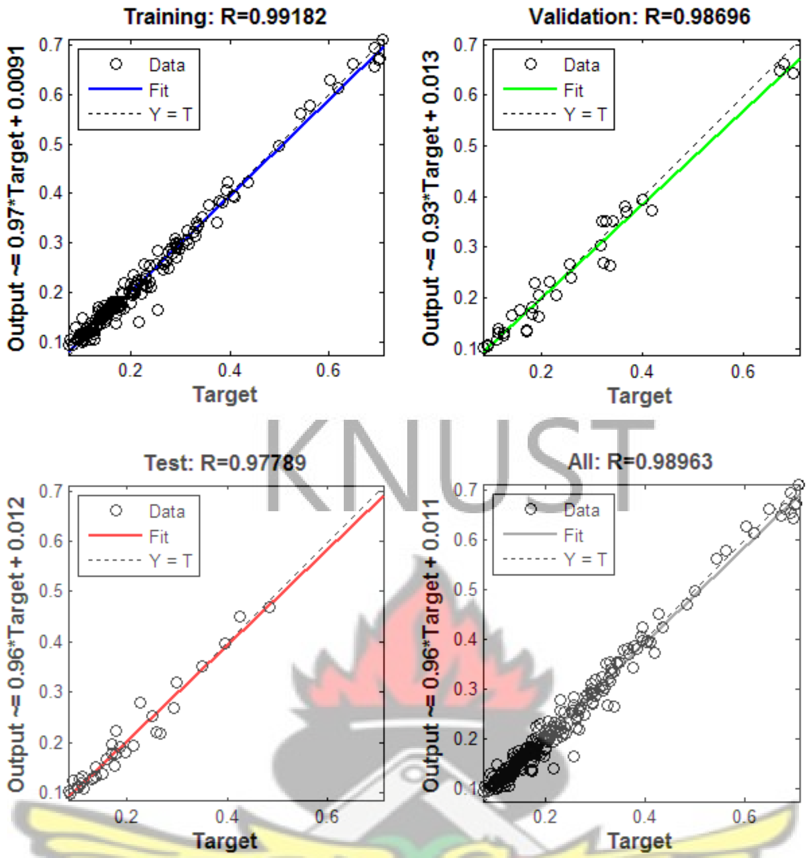

Figure A.8 Training Regression Results of NARX (14) using the levels of the series