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SCHOOL OF COMPUTING & INFORMATICS

AN ARTIFICIAL NEURAL NETWORK MODEL FOR FORECASTING INFLATION IN KENYA

BY

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A research project submitted in partial fulfillment for the Requirements for the award of the Degree of Masters of Science in Information Systems at the School of Computing and Informatics of the University of Nairobi

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DECLARATION

This research project is my original work and has not been presented for a degree in any other University.

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Approval

This research project has been submitted for examination with my approval as University Supervisor

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Eric Ayienga

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DEDICATION

This project is dedicated to my family

My Mother and Grand Mother though late, thank you for teaching me resilience

ACKNOWLEDGEMENT

I am thankful to God for giving me everything I needed to start and complete this project.
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ABSTRACT

The greatest priority of Monetary Authorities in an economy is price stability. Unstable prices result to inflation whose economic effects are undesirable. Price stability, calls for timely prediction of forecasting of inflation. This enables the Central Bank to take quick action by managing the situation causing persistent price changes. In Kenya, Inflation is forecasted using linear forecasting models which assume that economic data is linear in nature. Economic data is complex and nonlinear. Therefore, forecasts made using linear models may be inaccurate.

Nonlinear models have been applied with much success in forecasting in inflation. Artificial Neural Networks stand out as demonstrated by reviewed literature.

Different models of inflation forecasting were explored on their suitability to forecast inflation in Kenya. The viability of these models and performance was explored through literature review.

This project was realised by collecting inflation, GDP growth and oil prices from the Kenya National Bureau of Statistics, Energy Regulatory Commission and Petroleum Institute of East Africa. The data was obtained from publications and the websites.

Through experimentation, an ANN model of configuration 3: 12 was developed using 70% data for training, 20% percent data for testing and 10% for validation. This model had a RMSE of 9.52 against the ARIMA model whose RMSE was 19.49. Based on the RMSE values, was concluded that the Neural Network model is a better inflation forecasting model when compared to the ARIMA model.

This project describes the development, architecture and implementation of an ANN forecasting model for Kenya and its benchmarking with the ARIMA model.

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LIST OF ABBREVIATIONS

ACF- Autocorrelation Function

AIC- Akaike Information Criteria

ANN-Artificial Neural Networks

AR- Autoregressive

ARDL-Autoregressive Distributed Lag Model

ARIMA-Autoregressive Integrated Moving Average

BIC- Bayesian Information Criteria

BVAR-Bayesian Vector Autoregressive

CBK- Central Bank of Kenya

CBR- Central Bank Rate

CSV-Comma Separated Values

ERC-Energy Regulatory Commission

GB-Gigabytes

GDP-Gross Domestic Product

KNBS-Kenya National Bureau of Statistics

LL-Log Likelihood

MPC-Monetary Policy Committee

PACF-Partial Autocorrelation Function

PEIA-Petroleum Institute of East Africa

RAM-Random Access Memory

RMSE- Root Mean Square Error

SSE- Sum of Squared Errors

VAR-Vector Autoregressive

CHAPTER 1: INTRODUCTION

1.0 Background

Inflation is the continuous raise in price levels (la Bonte, 2011). Fewer goods are purchased when prices increase. Therefore, inflation results to the reduction of the purchasing power of the local currency. According to Bozkurt (2014), inflation impedes economic growth, financial sector development and affects the vulnerable members of the society. It increases economic uncertainty and decreases incomes.

To manage inflation, ensure economic stability and encourage long-term investments, monetary authorities need to maintain price stability. The total money in supply in a country influences the general price level and economic productivity of various sectors. Monetary authorities manage inflation by controlling the total money supply in an economy.

Over the past years, Kenya's monetary policy regime in the pursuit of price stability has evolved from direct controls to indirect monetary policy instruments regime. This shift ensures that the Economic policy makers are proactive in dealing with global economic shocks that has made the Kenya economy vulnerable.

The Constitution of Kenya 2010 and the CBK Act of 2015 created an independent Central Bank and set its primary objective as ensuring price stability or low inflation in Kenya. This objective is realised through the monetary policy which is formulated by the Monetary Policy Committee(MPC).

Linear models used to generate inflation forecasts in Kenya include: autoregressive (AR), error correction forecasting and calibrated macroeconomic models. Forecasts of the inflation are used in guiding policy decisions. These time-series econometric forecasting models are limited since they often assume linearity which is not consistent with the nonlinear nature of the real economic world.

To overcome the linear nature of autoregressive models, some institutions use Artificial Neural Networks (ANNS) to undertake inflation forecasting. This is because ANNs capture nonlinearities well, have the ability to mimic most functional dependencies, are immune to outliers and do not conform to any distribution. The predictive ability of the Neural Network models has been compared to that of linear models by some researchers. These studies found out that Neural Network based models are more precise in forecasting. For this reason, therefore, some central banks have used ANN models to forecast inflation, GDP growth among other macroeconomic indicators, HIĽOVSKÁ etal (2012).

In the review of relevant literature, it was observed that some studies on inflation forecasting have been conducted in Kenya; however, there is no study that has benchmarked the performance of ANN models to that of other models in inflation forecasting in Kenya. Therefore, this research project developed an ANN model which was used for inflation prediction in Kenya and benchmarked it with the Autoregressive Moving Average model.

1.1 Problem Statement

The CBK is mandated with monetary policy formulation and ensuring price stability. Stable prices ensure stable and predictable inflation. Inflation predictability creates confidence in the Economy resulting in more investments and sound economic growth.

To maintain price stability, monetary authorities need to forecast inflation accurately, timely and in a cost effective manner. Inflation can be forecasted using linear models or nonlinear models. In Kenya, inflation is forecasted using linear forecasting models

Using linear models to forecast inflation results to inaccurate forecasts. For linear models, data linearity is assumed, yet evidence indicates that macroeconomic series contain nonlinearities, Binner etal (2005). This assumption makes linear models inherently limited in forecasting macroeconomic series.

In their study of inflation forecasting, Haider etal (2007) observed that the root mean squared error of inflation forecasts based on nonlinear models is less than that of inflation forecasts based on linear models. Binner etal (2005), compared the inflation forecasting accuracy of the linear ARIMA and VAR models against the non-linear ANN model in the Euro area. The ARIMA and VAR models were used as linear models while ANNs were used as non-linear models. They concluded that nonlinear models give more accurate forecasts. Additionally, Binner et al (2006), compared performances of ANN model with linear models by using quarterly data of USA (1960: Q1-2003: Q1). The results indicated that the ANN model provided better forecasts.

1.2 Significance of Study

- They key outcome of this study was the development of an inflation forecasting model for Kenya
- Increased inflation forecasting ability for Kenya
- Comparing the forecasting performance of the ANN model with the ARIMA model will make it possible for inflation forecasters to choose the best model for Kenya.

1.3 Objectives of the Study

The main goal of this research was to develop an Artificial Intelligence model to forecast Inflation in Kenya and compare its performance with other forecasting models.

The specific aims are to:

i. Investigate existing forecasting models that have been used forecast to inflation
ii. Design an Artificial Intelligence model for predicting inflation in Kenya
iii. Develop a prototype based on the identified model using a suitable programming environment.
iv. Test and assess the performance of the Artificial Intelligence model in predicting Inflation in Kenya

1.4 Basic Assumptions and limitations of the study

Data was assumed to be valid and findings reliable. However, some errors may occur. These include:

i. The study will have relied on secondary data for information processing. This data could be faulty, leading to inaccurate results;
ii. There was no monthly GDP data, yet the project depended on monthly data from the input variables. Thus it is assumed the annual GDP data for a particular year is equal to the monthly GDP data.
iii. The research work was faced with financial, time and research materials constraints.

1.5 Scope of the Study

This study, focused on forecasting inflation in Kenya using an Artificial Intelligence model and benchmark it with an ARIMA model. The study examined the main forecasting techniques in economics, the concepts of the ANN model and its use in inflation forecasting. Inflation, theories of inflation and empirical studies on Inflation. The study was for the period January 2003 to January 2019. This period is chosen because of the availability of month to month year on year Inflation and oil prices data for Kenya. GDP data was available annually for this period.

1.6 Contributions of the research work

This research work contributed to the existing body of knowledge through the:

- Development of an inflation forecasting model for Kenya using ANN
- Establishment of the basis for choosing an inflation forecasting model appropriate for Kenya

1.7 Research Questions

The questions that guided the research project include: -

i. What are the current models for forecasting inflation in Kenya?
ii. How can we design an Artificial Intelligence model for predicting inflation in Kenya?
iii. How can we develop a prototype for predicting inflation?
iv. How do we test and assess the forecasting ability of the Artificial Intelligence model in predicting inflation in Kenya?

CHAPTER 2: LITERATURE REVIEW

2.0 Overview

The literature reviewed focused on inflation, forecasting models, inflation determinants forecasting of inflation and Artificial Neural Networks.

2.1 Inflation

This is the sustained increment of prices or continuous loss of value of the local currency (Labonte, 2011). In some instances, it is an economic state where there is a lot of money in circulation and very few goods to purchase. According to (Dragos etal, 2013), inflation can be controlled by controlling the amount of money in circulation.

Inflation is manifested by economic indicators like wages, interest rate, foreign exchange rate, and balance of trade. Negative effects of inflation include, loss of purchasing power of local currency, reduced investments, increase in lending rates, reduced savings, decline in economic growth, reduction in a country's competitiveness and economic uncertainty.

To manage inflation, economic policy makers in many countries aim at ensuring price stability. Stable prices support economic growth by allowing investors make better decisions on what and how to produce thus creating a more efficient environment for resource allocation. Also, stable prices make it possible for investors to concentrate on investing instead of using scarce resources to fight the effects of inflation. Moreover, stable prices ensure that investors would not demand for risk premiums to cater for long term investments and savings. Sustained increase in price levels are likely to make investors demand for risk premiums, thus discourage savings and investments (Central Bank of Sri Lanka, 2005).

2.1.1 Theories of Inflation

These theories are classified broadly as demand-side or the supply-side theories. They help in the understanding of the determinants of inflation.

The demand-side theories of inflation argue that inflation is mainly caused by very high demand for goods over supply in an economy. The Keynesian theory focuses on the short run demand pressures on the economy, while the Monetarist theory focuses only on money as a major long term inflation determinant (Totonchi, 2011).

The supply-side theories, comprise of Classical and the Structuralist theories of inflation. These theories dwell on factors that influence inflation from the supply-side of goods and services. Classical theorists believe that only supply shocks in an economy can influence the prices.

2.1.2 Determinants of Inflation

Alam etal (2016), sought to study inflation causes for India by co-integration method. From the study results: the total amount of money in circulation, currency depreciation and supply bottlenecks lead to an increase in price levels hence raise in inflation in the long term. Further analysis revealed that money growth and supply bottlenecks contribute to inflation more than any other. However, for short periods of time, supply bottlenecks are a major inflation factor.

Ayyoub etal (2011) examined how the growth of an economy is related to inflation and how Inflation impacts the growth of GDP. Further, they sought to determine whether inflation impacts economic growth uniformly or differently depending on the prevailing circumstances. The study findings indicated that inflation significantly influences the growth of the economy negatively. In addition, the study shows that the prevailing inflation harms GDP growth at a particular level of inflation.

Dibooglu etal (2004) studied economic output and inflation using quarterly data from1980: Q1 to 2002: Q3 for Turkey. From this study, trade terms, monetary policy and shocks from balance of payments emerged most prominent inflation contributing factors.

Inyiama (2013) examined how the rate of inflation and economic growth are related in Nigeria. In addition, the study examined how the rate of inflate and the rate of foreign currency exchange and interest rates were related between 1979 to 2010. The study results indicated that inflation and economic growth were negatively related while interest rates and foreign exchange rates were positively related to the inflation rate but not significantly.

Gathuu etal (2012) studied the impact of the amount of money in circulation, foreign exchange rate, oil prices and interest rates on inflation using VEC Model and monthly data. The study concluded that in Kenya inflation is triggered by demand and supply factors but crude oil prices and money supply are most critical.

Kirimi (2014) sought to study inflation determinants in Kenya between 1973 to 2013. From the study, it emerged that food prices were negatively related to inflation and CBR had 5% level of significance in causing inflation variations. The amount of money in circulation and foreign exchange rates were related positively to the inflation rate while the gross domestic product growth rate and the perception of corruption were related negatively to inflation. Wage demands and political instability impacted inflation insignificantly.

In their research to determine factors that influence inflation in Kenya, Ochieng etal (2016), realised that, price variations, lag inflation rates and GDP growth have significant effect on Inflation. Growth of money supply, interest and foreign exchange rates were insignificantly related to inflation. It was concluded that GDP growth, price variations and lag inflation rates are the ideal inflation factors for Kenya based on the study findings.

Akinboade etal (2004) conducted a study seeking to explain the determinants of inflation in South Africa. They managed to show that inflation to a large extent is structural in this economy. Labour costs, money supply and inflation are positively related over a short period of time. Rising labour costs have significant contributions to inflation in the long term.

Kavila etal (2016), explored inflation dynamics for Zimbabwe using ARDL model for the period 2009:1 to 2012:12. The currency in use then, foreign currency rates, prices of oil and previous inflation were identified as the major causes of inflation. When the Zimbabwean currency was in use, inflation dynamics was explained by increase in money in circulation and trade volumes.

Kabundi (2012), studied the underlying inflation factors in Uganda for long and short periods of time. Study results were used to conclude that inflation in Uganda can be explained by both internal and international factors. For the long term, the major inflation determinants were; the amount of money in circulation, local production and food costs. Food and energy prices influenced inflation in the short term.

2.2 Forecasting Techniques

A forecast is the prediction of the future. Forecasting is concerned with predicting various variables based on past and present data. The main methods for forecasting in economics are expert judgement, leading indicators, surveys, econometric equations and time-series models.

Expert Judgement

Expert judgement is an expression of forecasters' opinions in the prediction process based on experience or knowledge or both. According to Bolger (2004), expert judgement may be applied at various levels in economic forecasting which include, choice of variables, building equations, identification of variables, specifying economic indicators expectations and altering the model forecasts. Compared to econometric predictions, judgmental forecasts deal better with nominal variables, Wright (2011).

Leading Indicators

These are economic factors that indicate a change in economic direction and are used as short term predictors. They are used in predicting the future direction of variables like GDP and inflation in an economy.

Surveys

While studying inflation forecasting, Ang et al (2007) observed that inflation forecasts by survey were better than by other inflation forecasting methods. Additionally, non-professional participants in survey forecasts produce more accurate results than professionals using other methods.

Surveys provide quick and early information on the direction the economy is taking. Compared to quantitative data, surveys don't suffer from major revisions, making them useful and powerful tools for economic forecasting Lehman et al (2015).

Econometric equations

They are used for modelling the behavior of the economy.

Time-Series Models

Time series modeling aims at collecting and studying past data of a time series to develop a suitable model. This model is then used to make forecasts.

According to Clements etal (2002), econometric equations and models that are dependent on time are the major techniques for forecasting inflation. However, time-series models are better at prediction than the econometric systems of equations since they are free of parameter restrictions and model misspecification problems, Moshiri (2000).

2.3 Time-series Forecasting Models

These models assume that any data can be decomposed into a time trend, a cyclical element, a seasonal factor and an error term. The time series models can either be univariate or multivariate. The vector autoregressive (VAR) model is the most popular multivariate model. While the most popular univariate models are; autoregressive (AR) and autoregressive integrated moving averages (ARIMA) models.

Autoregressive (AR) Model

This is a one variable model that uses its past values to describe its behaviour. It is defined by equation 1 as:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \qquad (1)$$

φi are model parameters, c is not varying, ε_t is white noise.

ARIMA

It comprises the ARMA and Integrated parts. ARIMA model is either seasonal or non-seasonal. The non-seasonal model is denoted as ARIMA (p, d, q) while the seasonal model is denoted as

ARIMA (p, d, q)(P, D, Q)$_{m.}$ The parameters p, d, q are positive integers. P, D, Q represent the AR, differencing and MA terms for the seasonal part of the model. The number of periods in each season are represented by m.

2.3.1 Forecasting Inflation using Time-series Models

Several researchers have conducted studies on the predictive ability of these models in predicting macroeconomic variables such as inflation. In their research on core inflation in Nigeria, Kelikume I et al (2014) observed that the VAR model approximated current Nigerian inflation with minor errors in comparison to the ARIMA model.

Hanif etal (2015) compared the performance of forecasting inflation of various models over a two year period in Pakistani. They realized that forecasts from the autoregressive distributed lag model are better than forecasts of other linear models including structural Vector Autoregressive and Bayesian Vector Autoregressive models.

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. Marcellino (2006) also used the standard linear model to forecast inflation and GDP growth and compared them with the benchmark model. Generally, from the results, linear models were observed to forecast growth and inflation well as long as care is taken when they are specified.

In his research work Kotlowski (2008) compared the forecasting precision of dynamic factor models with that of the AR, VAR and the leading indicator model. The out-of-sample study was conducted using monthly data from the Polish and world economy. From the study, it was concluded that the dynamic factor model was more precise in predicting inflation.

Wright (2012) and Biswas et al (2010) compared the performance of Bayesian VAR model and the VAR model in a real-time forecasting exercise. They observed that the performance of the Bayesian VAR model was better.

2.4 Neural Networks

They process information by mimic the way biological neuron systems process information, especially the brain, Haider etal (2007). These models approximate functions that rely on many unknown inputs. Generally, these are interlinked neurons which exchange and process information.

The Artificial Neural Network theory grew out of the desire to design machines with cognitive ability, Haider etal (2007). Therefore, ANNs were created to imitate the processing and information learning abilities of the human brain. Based on the information it receives, the human brain recognises a pattern, generalises and predicts. ANN models mimic the human brain in processing information.

2.4.1 Biological Neural Networks

Refers to the system of interconnected neurons that work together. The interconnected units form the biological neural network.

Biological neurons comprise; cell body, dendrite, axon and synapse. The cell body processes inputs, dendrites accept inputs, axon turns the processed inputs into the outputs and synapses pass information between the neurons, Kohli etal (2014).

Dendrites facilitate the passing of signals between neurons. A signal strength that surpasses a certain magnitude will trigger a neuron to pass its own signal to the next neuron through the axon. The signal sent to other neurons through synapses trigger them, and this process continues, Kukreja etal (2016). As signals that are similar keep on surpassing the set magnitude, the signals path is recognised, a pattern is defined, and a deduction about the output based on the input signal is made by the network. Therefore, the network is capable of making predictions based on the received signals.

2.4.2 Artificial Neural

The processing units of ANNs imitate the structure and behaviour of the biological neurons. An artificial neuron comprises inputs(X_n) and an output. Additionally, it has an activation function, bias value and weights as shown in figure 1 below. The strength of the signal is the product of the weight and input value. A neuron has a single output and many inputs from various sources, Kukreja etal (2016).

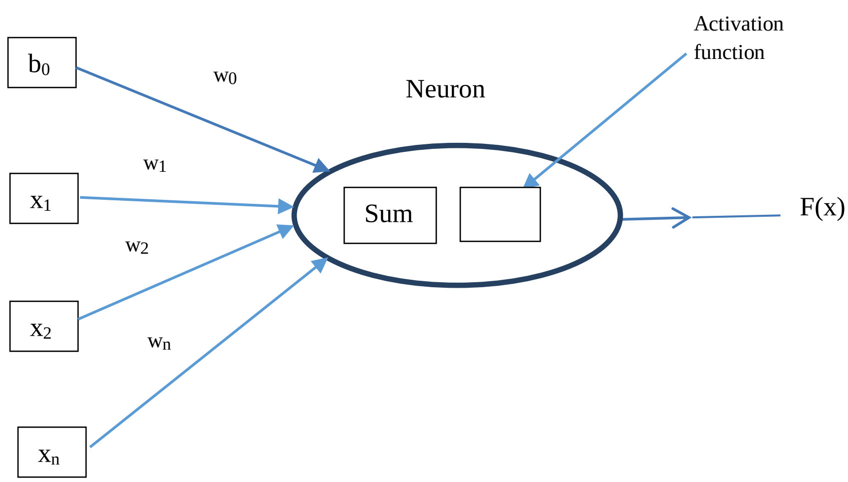


Figure 1 An Artificial Neuron Model (source: Kukreja etal (2016).

The Activation Function

It creates a neurons output signal out of the activation level. Activation functions include; sigmoid, step, linear, ramp and hyperbolic tangent. Hyperbolic tangent function resembles the sigmoid function, but its limits are from -1 to +1, unlike sigmoid which is from 0 to 1, Kukreja etal (2016).

The sigmoid function is very popular because it is relatively simple to calculate its first derivative during weight adjustment in back-propagation.

2.4.3 The Architecture ANN

This is the ordering of neurons into layers and the connections between the layers and the neurons, Suzuki (2013). The architecture can either be a feed forward network or a feedback network.

In feedforward architecture, the signal travels one in direction, while for feedback network the signal is bi-directional, Sharma (2012). Figure 2 below showing network flow processes in the multilayer architecture.

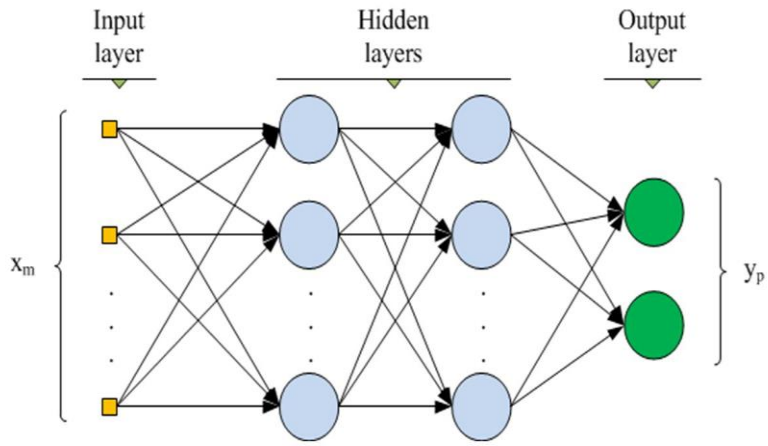


Figure 2 Multilayer Perceptron

2.4.4 Training of ANNs

Training an ANN entails providing it with input data that is known and requesting it to predict a known output, Kukreja etal (2016). The initial network weights are randomly set at the start of the training process, Maindi etal (2014). In artificial neural networks, training is either: supervised, unsupervised or reinforced,

Supervised learning

For this type of learning, the ANN is provided with inputs and an output that is desired. Thereafter, network operates on the inputs to get an output. The obtained and expected outputs are then compared. The variance between the outputs is an error. The resulting error is allowed to flow into the network, making the network change its weights thus controlling it. The act of taking the errors back into the system to adjust weights is repeated many times to continuously adjust the weights, Maindi etal (2014). The most common algorithm used during training of ANNS is the back-propagation algorithm.

Unsupervised learning

Only inputs are provided for this type of learning. The network makes a decision on what attributes it will utilise in classifying the input data, Maindi etal (2014).

Reinforced learning

For this type of training, the ANN acts on the environment which in return gives back a response to the ANN. Based on the response from the environment, the network classifies its actions as either good or bad.

2.4.5 Artificial Neural Networks Applications

Areas in which ANNs are applied include: computer vision, robot control, natural language processing, fraud detection, image processing, medical diagnosis and forecasting, Mishra etal (2018).

2.4.6 Strengths and Weaknesses of ANNs

Some strengths of neural networks include, Mishra etal (2018):

1. They are not linear
2. Mapping of inputs to outputs
3. adaptavity
4. Tolerance fault
5. Neurobiological analogy

According to Kumar etal (2014) some limitations of ANNs include:

1. unsuitable for solving ordinary life problems.

2. There is no methodologies or standards to guide development of ANNs.

4. uncertain quality outputs.

5. Most ANNs Systems don't describe how they solve problems.

6. Nature of Artificial Neural Networks is like a Black box. They do not provide explanations about their reasoning.

2.5 Designing Artificial Neural Networks

To design these networks, the designer needs to identify the network parameters and their appropriate values. The network parameters to be identified include: input variables, hidden layers, hidden layers nodes, learning rate, momentum rate and the amount of network training. Additionally, the network designer needs to consider the type of network to be designed, size of data used, epoch and activation function to be used. There are no set guidelines on how to choose the suitable parameter values, thus the trial and error method is used, Binner etal (2005).

a) Network Type:

The type of ANN to be developed will determine the type of training to be done and the training algorithm to be used.

b) Type of ANN Training:

Training of an ANN is done once the ANN design process is over. For training to begin, the initial weights are randomly chosen, Maind etal (2014). The type of training to be done is dependent on the nature of the problem being solved.

c) Proportion of Training and Testing sets:

When determining the proportion of data to be used as the training set, there is need to use as much as is possible of the available data, Russell et al. (2009). According to Ortiz-Rodriguez et al. (2013) the Robust Design of Artificial Neural Networks (RDANN) makes it possible to propose setting of the training data set at 80% and 20% of the data for testing.

d) Input, Hidden and Output units:

The application to be developed determines the inputs and output units. However, considerable effort is required to determine the hidden layer units. According to Binner etal (2005), few hidden nodes are used to guarantee a model that generalises well, yet such a model might not learn the data adequately. Consequently, some designers use experimentation in order to establish the number of hidden layer units.

In general, the design of a neural network should start with three layers before moving on to experiment with various network configurations.

e) Number of Repetitions during Training:

Training involves feeding the input pattern to the network in order to generate an output pattern, then comparing the generated output with the actual true output to determine the error. The next input value is fed to the ANN and neuron weights adjusted with a view of reducing the error. This is done repeatedly to the end of the dataset, then back to the start of dataset, until the error is significantly small. A run through a complete dataset is called an epoch.

f) Activation Function Choice:

This will be dependent on the type of ANN developed. The output expected from the network is the general guide to the choice of activation function. If there is need for a backpropagation algorithm, then the choice of the activation function must be a function that can be differentiated. This is because backpropagation employs the errors gradient of the in each repetition, to establish the magnitude of error in the learning process. Functions that can be differentiated include sigmoid function and hyperbolic tangent function. Even with this decision, the expected output values still determine whether the results of the function are positive numbers only.

g) Size of dataset:

The size of dataset to use on any ANN experiment is application dependent. General, Neural Networks work well with large volumes of data sets for better learning and good predictions.

h) Momentum and Learning rate:

These variables should be set during the design of the ANN. The learning rate is the magnitude of change for each node and the rate of improvement of the weights in the network. It is a value in the range of 0 to 1. A value close to 1 would mean faster learning, but this can lead to under-fitting.

According to Abraham (2005), the learning rate practically determines the magnitude of weight adjustments when each weight is altered. A very large learning rate may lead to constant overstepping of the local minima, leading to back and forth movements and reduced attainment of low error state. Very low learning rate may lead to a large number of iterations, leading to slow performance.

The momentum allows the adjusted weights of previous iteration to persist on the next iteration. A value greater than 0 means that the effect of the last weight adjustment is manifested in the current weight adjustment. It is practical to start training with high learning rate and low momentum and progressively switch the two as training progresses.

2.6 Applications of ANN Inflation Prediction

In their research work, Haider A etal (2007) used ANN methodology in forecasting Pakistan inflation using an ANN model that had 12 hidden neurons. The research used monthly inflation data to compare the inflation forecasting accuracy of the ANN model to that of the time series model. According to the study findings, the ANN model predicts inflation more accurately than the univariate time series forecasting model.

Nakamura E (2005), made the conclusion that ANN models outdo the AR model when forecasting inflation for one and two quarters horizons. The results obtained demonstrated that the predictive success of the ANN approach is to a large extent dependent on the early stopping procedure. Thus, the early stopping procedure should be included in experiments involving Artificial Neural Networks forecasting in the future.

Monge (2009), In his research paper on inflation forecasting, compared the prediction accuracy of the ANN model to that of the linear model. From the study, it was concluded that the ANN model outperforms the linear models in predicting inflation. In addition, systematically chosen ANNs performed better than thick ANN models.

Onimode etal (2015) examined the success of the ANNs in forecasting inflation. Using recent inflation data for Nigeria a simulated out of sample inflation forecasting was done. The ANN model did better than the linear model in forecasting inflation for short periods of time.

Pradhan etal (2011) presented a paper on the use of ANNs to forecast inflation in India. The research presented four different neural network models. For each of these models, the forecasting accomplishment was measured using mean squared error and mean absolute deviation. It was concluded from the research that the model with the most inputs gave the best forecasting results.

Hurtado etal (2013) used an ANN model to forecast inflation in Mexico which was very volatile at times. The researchers used different ANN models in this study by changing the hidden layer parameters. Consequently, the inflation forecast results were divided into, a volatile phase, transition phase, and a stability phase. The performance of the ANN model in forecasting inflation was then compared to inflation predictions done by the Bank of Mexico, thus demonstrating that ANNs forecast results were more accurate to the real inflation behavior.

Hadrat etal (2015) used the ANN model to forecast Ghanaian inflation. The research compared inflation forecasts from the ANN model to those of the time series models using the Root Mean Squared Forecast Error (RMSFE). The RMSFE value for the Neural Network was less than that of the linear models. Therefore, the ANN model is better at forecasting inflation.

2.8 Conceptual Framework

Review of the literature indicates that oil prices, GDP growth rate, lag inflation rates are the ideal inflation determinants for Kenya. These determinants will be used to forecast inflation using the ANN model in Kenya.

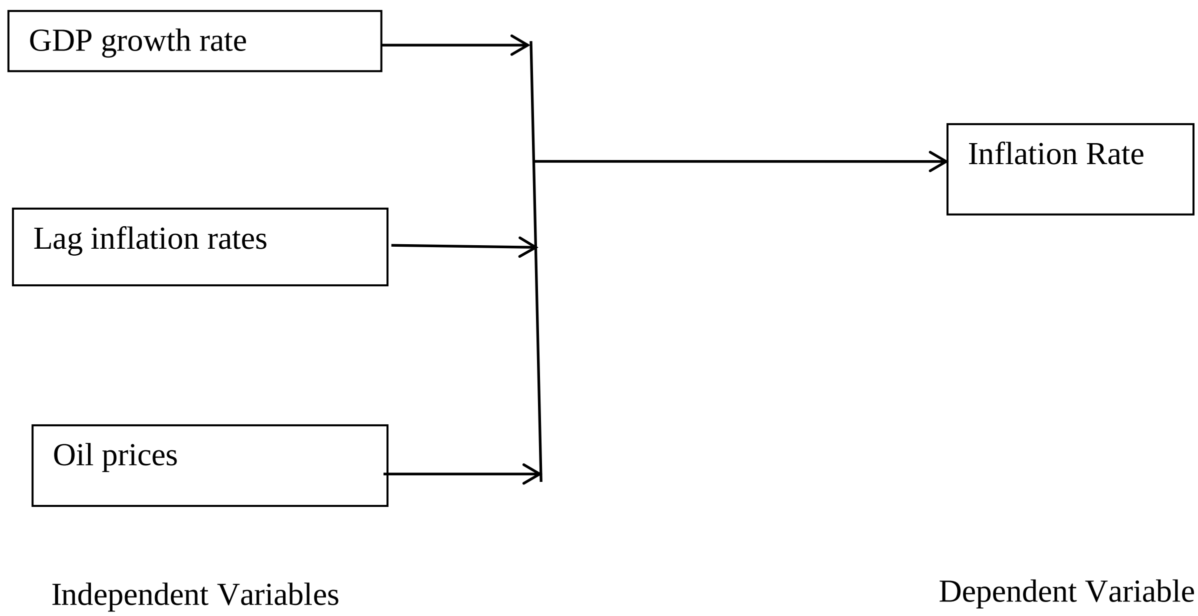


Figure 3 Conceptual framework

2.9 Literature Review Summary

This chapter looked at Inflation, Inflation determinants, Forecasting methods, a comparison of linear models and ANN models. From Literature, oil prices, lag inflation and GDP growth contribute significantly to inflation in Kenya. In Kenya no research had been undertaken to forecast Inflation using ANN and benchmark it with the ARIMA model. This research was undertaken to fill this gap.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter covered design of the research, data sources, analysis of data, methodologies for developing the forecasting models and comparison of the models.

3.1 Research Design

This project used quantitative techniques and applied research to create an ANN forecasting model, test the model performance and benchmark it with other forecasting models. According to (Kothari, 2004), applied research aims at solving a 'societal or business' problem.

A prototype was developed out of the ANN model for purposes of testing and forecasting inflation. The study used monthly year on year inflation data and GDP growth data from the KNBS. Oil prices data was obtained from Energy Regulatory Commission and Petroleum Institute of East Africa websites. The study employed mainly quantitative approach using existing data to generating new data. The results were subjected to accuracy tests by checking the forecast errors.

The data that was used in evaluating the performance of the prototype was for the period July 2017 to January 2019. Currency of the data enabled the research to relate as much as possible to the current economic situation, making it possible for the model to apply its prediction ability to the current situation. Secondary data was used for this study. This was desirable since the research aimed at demonstrating the applicability of a particular tool to a practical business problem. The data that was used in this research project was readily available. By using publicly available data, the research experiments described in this project, can be conducted independently by anyone accessing the data. The data itself can also be authenticated independently.

The basis for comparison of the two models was the Root Mean Squared Error (RMSE). The magnitude of error between two data sets is measured using the RMSE. A comparatively lower RMSE value would imply a better prediction, hence a better model.

The formula for RMSE is:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}$$

Where

N= number of observations

Pi= predicted value

Oi= actual value (2)

The ANN model was benchmarked against the linear model by computing and comparing the RMSE values. The model with the smallest RMSE was considered the most suitable for inflation forecasting in Kenya.

3.2 Research Data

In order to design and evaluate the models, the research needed data that can be used to model inflation. The research therefore compiled data on inflation, oil prices, GDP growth rate from KNBS publications. Some data was obtained from the KNBS, Energy regulatory commission and Petroleum Institute of East Africa websites. In compiling the data, there was need to give some thought on the source, volume and suitability of data.

3.2.1 Sources of Data

This research project obtained its data from the KNBS publications, Energy regulatory commission and Petroleum Institute of East Africa websites. Economic Survey Publications for various years helped in validating data from the websites. These sources were selected because they are public institutions that are mandated to collect and publish statistics. Therefore, data in their custody is authentic.

3.2.2 Volume of Data

The data was for month to month year-on-year inflation rates for Kenya, oil prices, GDP growth rate cover the period January 2003 to January 2019. This period is chosen because there is data consistency throughout this period.

3.2.3 Compiling the Data

Inflation and GDP growth data were downloaded from the KNBS website as excel spreadsheets, while oil prices data was obtained from the Energy regulatory commission website and captured into excel spreadsheet. Some GDP data was captured from the Economic Survey publications into an excel spreadsheet.

The collected data was checked for errors, outliers, anomalies and gaps using MS Excel. The data was then organized, presented and interpreted using statistical tools

3.3 Building the ANN Model

The Neural Network model was built using Cross-Industry Standard Process for Data Mining (CRISP-DM), a structured robust approach to data mining. This methodology is dynamic and flexible. It allows the developer to work iteratively, by moving back and forth from one stage to the other, hence resolving problems before a full fledge prototype is built. This methodology comprises understanding the business and its data, preparation of data, model building, model evaluation and model implementation.

3.3.1 Business Understanding

This was done by reviewing various Economic Survey and leading Economic Indicators publications from the KNBS website. The intention was to understand inflation in Kenya and factors that influence it. In addition, the publications were reviewed in order to understand the major causes of inflation in Kenya. An initial assessment of tools and techniques that are used to forecast inflation was done at this juncture.

3.3.2 Data understanding

In this stage, the researcher extracted data from KNBS website and library from the identified sources. The data was downloaded as excel files from the KNBS website and checked for consistence by comparing data collected from different sources. Data found in publications only, was capture into an excel sheet. Oil prices data was obtained from Energy Regulatory commission website. All data was subjected to statistical analysis to generate its mean, variance, range. This analysis helped in understanding the nature of data available for the project.

3.3.3 Data Preparation

Identified data at this stage was captured in a spreadsheet in columns and rows so as to identify and correct anomalies, blanks, outliers and errors. Adjustments where necessary were made to accommodate the research objectives. A line graph was drawn using a spreadsheet to establish trends and seasonality in the data and thus help the researcher understand the data better.

Data for use in ANNs was normalized using the equation below

$$\text{Normalised }(x) = \frac{\text{Real}(x)-\text{Min}(x)}{\text{Max}((x)-\text{Min}(x)}$$

Normalised (x) = normalized x value.

Real(x) = actual value to be normalised

Min(x) = minimum data value

Max((x) = maximum data value

3.3.4 Modelling the Prototype

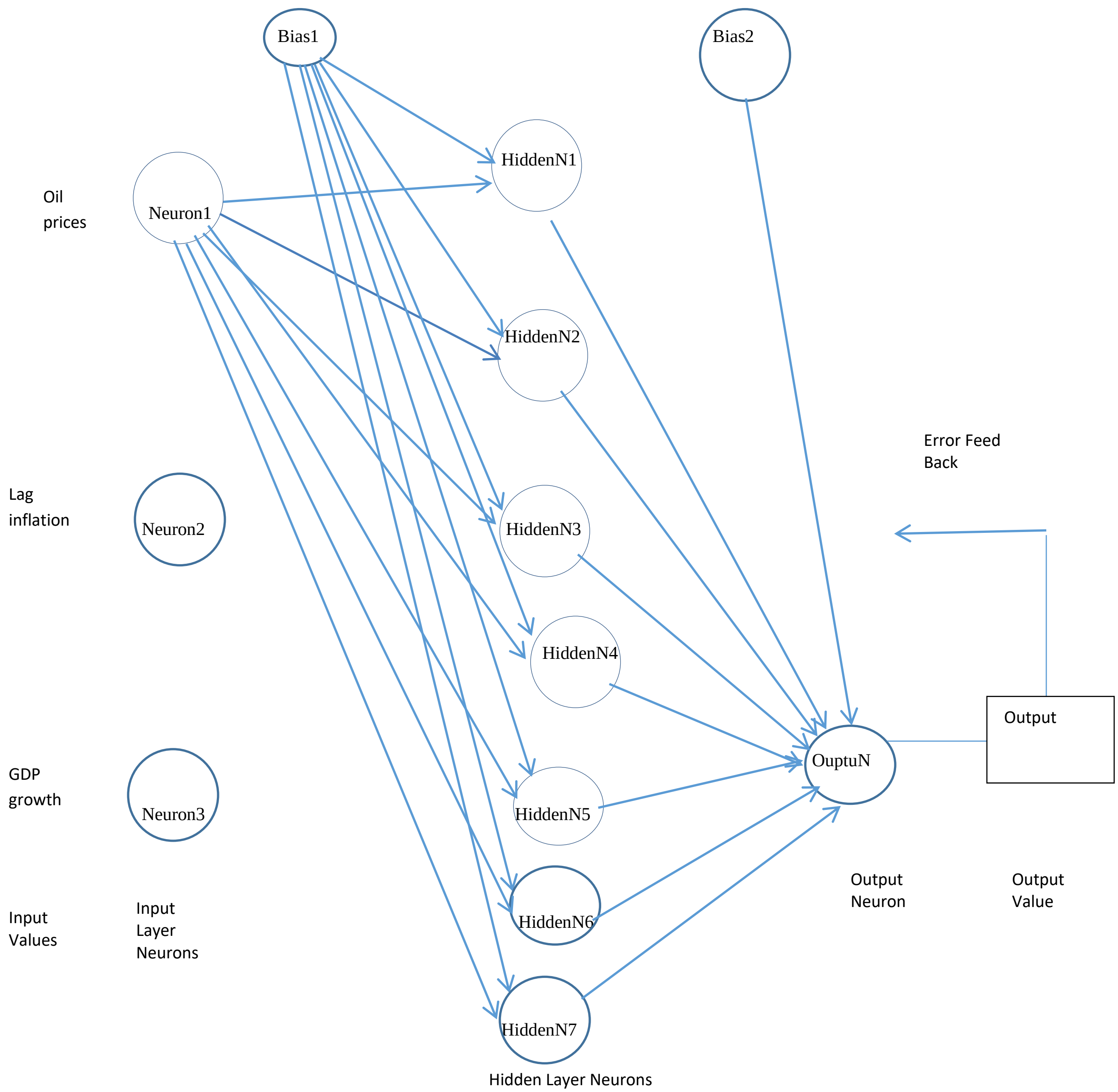
The initial model was developed with an architecture of three layers. The number of inflation determinants in Kenya were assumed to be equal to the number of input neurons. The initial model was formulated with the configuration below and represented by Figure 4 Below:

(i). Number of inputs = 3

(ii) Number of hidden layers = 1

(iii) Number of neurons per hidden layer = 7 i.e. 2N + 1

(iv) Bias per layer = 1



Neuron to neuron connections is shown only for Neuron1, outputN, Bias1 and Bias2. The other neurons connect to each other in the same manner

Figure 4 - ANN baseline model

3.3.4.1 Determining Parameters of the new model

Hidden layer Neurons

The initial model was initiated with a setting of 3:7. The data was split as follows; 70 % of the data set for training, 30% of the data set for testing and 10% of the data for model validation. The hidden layer neurons were altered, for each number of neurons, the total mean squared error was recorded. The number of hidden neurons with the least mean squared error value were selected for final configuration of the model. 12 hidden neurons were selected because they resulted to a model with the least total mean squared error.

Table 1: Number of Hidden Neurons

Architecture	Number of neurons in the hidden layer	Hidden layers	Total mean square error
3:7	7	1	0.2730
3:10	10	1	0.0334
3:12	12	1	0.0071
3:14	14	1	0.1824
3:16	16	1	0.1086
3:7:14	7:14	2	0.1824
3:7:21	7:21	2	0.0216
3:21:21	21:21	2	0.0849

Determining the proportion of training set

The new model was exposed to 70 % and 60% training data respectively. In each case, the model was trained and tested and the total mean squared error was recorded. The training data percentage that resulted to the least total mean squared error was selected. 70% training data was selected because it had the least error.

Table 2: Training data proportion

Training data	Total Mean squared error
70%	0.4114
60%	0.9333

Training cycles Determination

The model was further subjected to varying training iterations. The training iterations and the corresponding network error were recorded. The training cycles with the least number of errors were chosen for this research project.

Table 3: Number of Iterations

Number of iterations	Total mean squared error
Model 3:7	
5000	0.4114
20000	0.4114
50000	0.4114
10000	0.4114
Model 3:12	
10000	0.01209

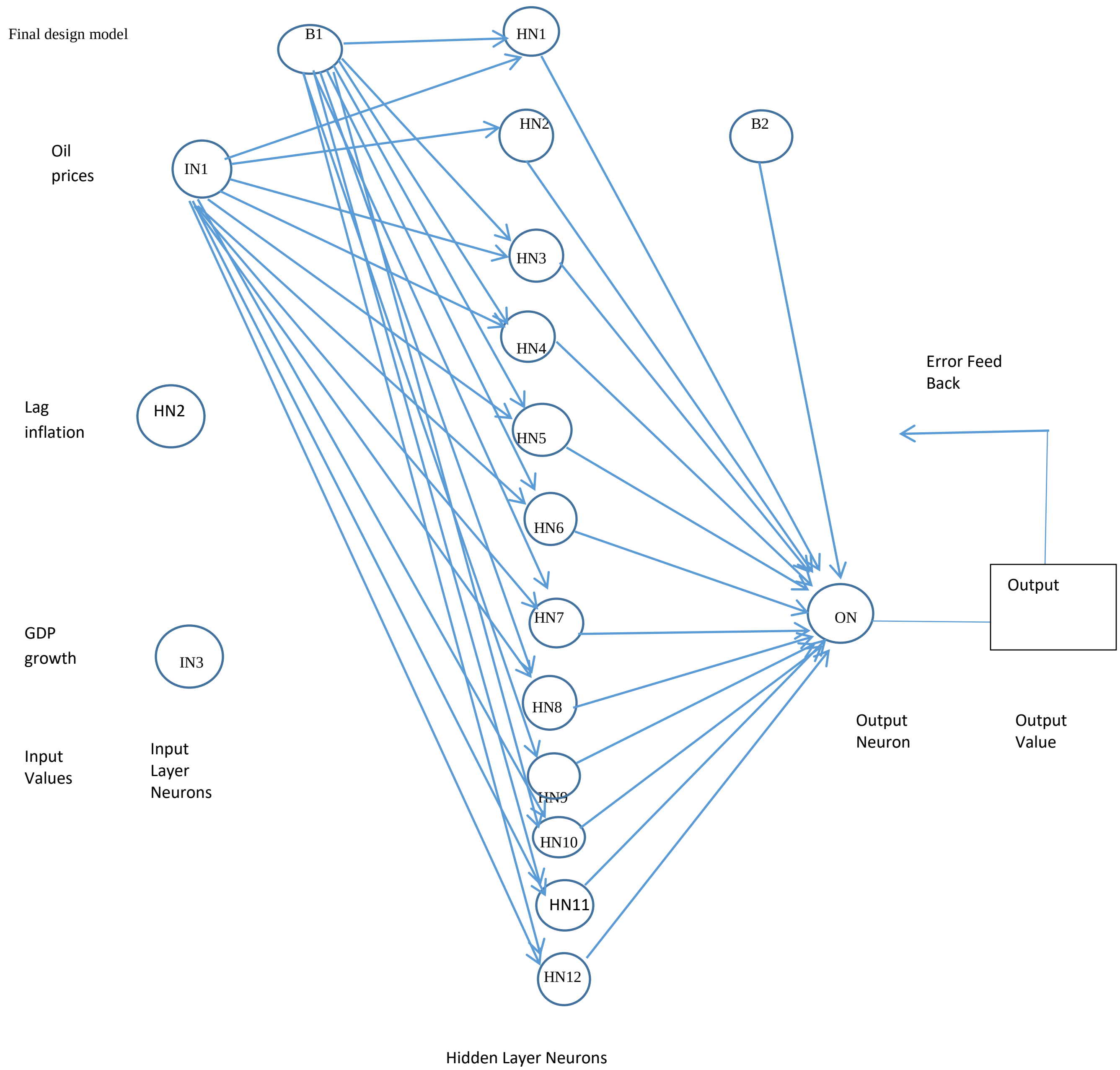
Under the same conditions, the total mean square error was constant at 0.4114. For different number of iterations for model 3:7. Thus for the final model, number of iterations will be dependent on the hidden neurons. For the chosen model, model 3:12 the number of iterations is 10000.

The **Initial weights** and Momentum values were set randomly. The **Learning rate** was randomly set with values ranging between 0 and 1.

3.3.4.2 The Final Proposed Model

The final model, as determine by experimentation was of configuration of 3:21, using 70 % of the available data (January 2003 to March 2014) for training, with at least 10,000 Repetitions during training. The testing was done with 20% of the data (April 2014 to June 2017).

The new developed model is shown in Figure 5 below.



Neuron to neuron connection is shown only IN1 and ON and biases B1, B2. The other neurons connect to each other in the same manner.

Figure 5 - ANN Design model

3.3.4.3 Designing the Prototype

The model configuration of 3:12:1, using 70% of the available data for training and 10,000 iterations was used to develop the prototype. The model layout is multilayer with feedforward connectivity, adjustment of weights is by error backpropagation and training is by supervised learning. The design tools used were pseudocode and flow charts, Wanjawa (2014).

The pseudocode for creating, training and testing the prototype is as detailed:

1. Create the network with 3 input neuron and 1 output
    - 1.1 Set hidden layers = 1
    - 1.2 Set hidden layer neurons = 12
    - 1.3 Create Bias neurons = 2
    - 1.4 Set the bias weight = 1
2. Create activation function
3. Generate random weights for each neuron
4. Set the learning rate and momentum
5. Prepare the input data file
    - 5.1 Normalize the research data
    - 5.2 Format the input data file as a comma separated (CSV)
    - 5.3 Determine the number of records in the file
6. Network training

```
Open the training data file
    Load the first data line
    Repeat
        Feed the data line forward through the network
        Calculate the sum of inputs, weights and activation for each layer up to the
        output neuron
        Obtain final output value
        Read the expected result   from the data line
        Calculate error = expected value- output value
        Change weights feeding output neuron in order to reduce its error based on
        the input data
        Do back propagation
```

Change weights associated with each hidden neuron, so that their error contribution to input data is reduced

Load the next data line

Until end of file

Until error is significantly small

close the training data file

7. Test the network

Ask user for to load test data file

Use trained network to calculate an output value

Display the result

User ends testing

The design of the training algorithm is illustrated by the flowchart below

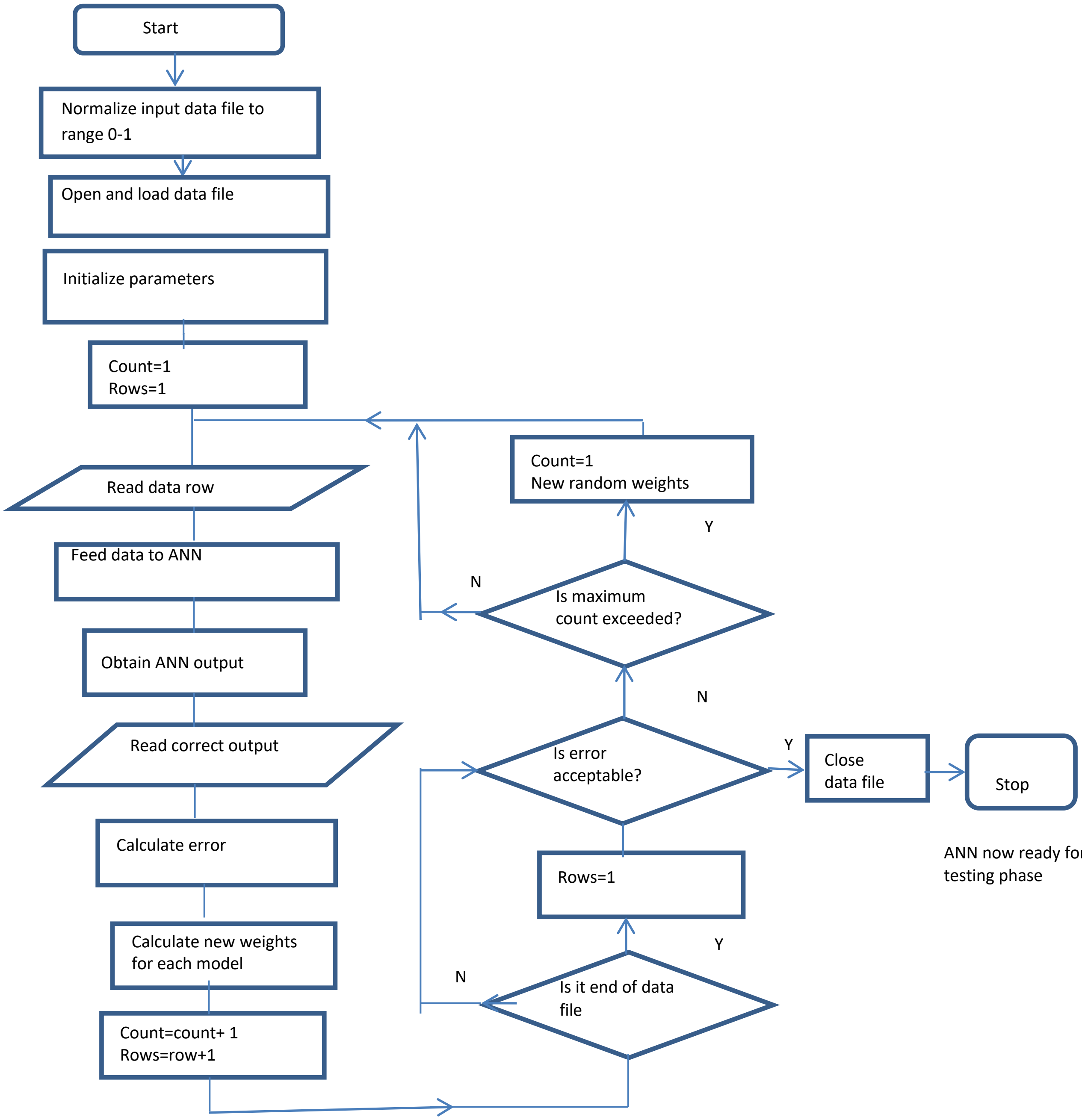


Figure 6: Flow Chart for training ANN (Source: Wanjawa (2014)

The design of the testing algorithm is illustrated by the flowchart in the figure below

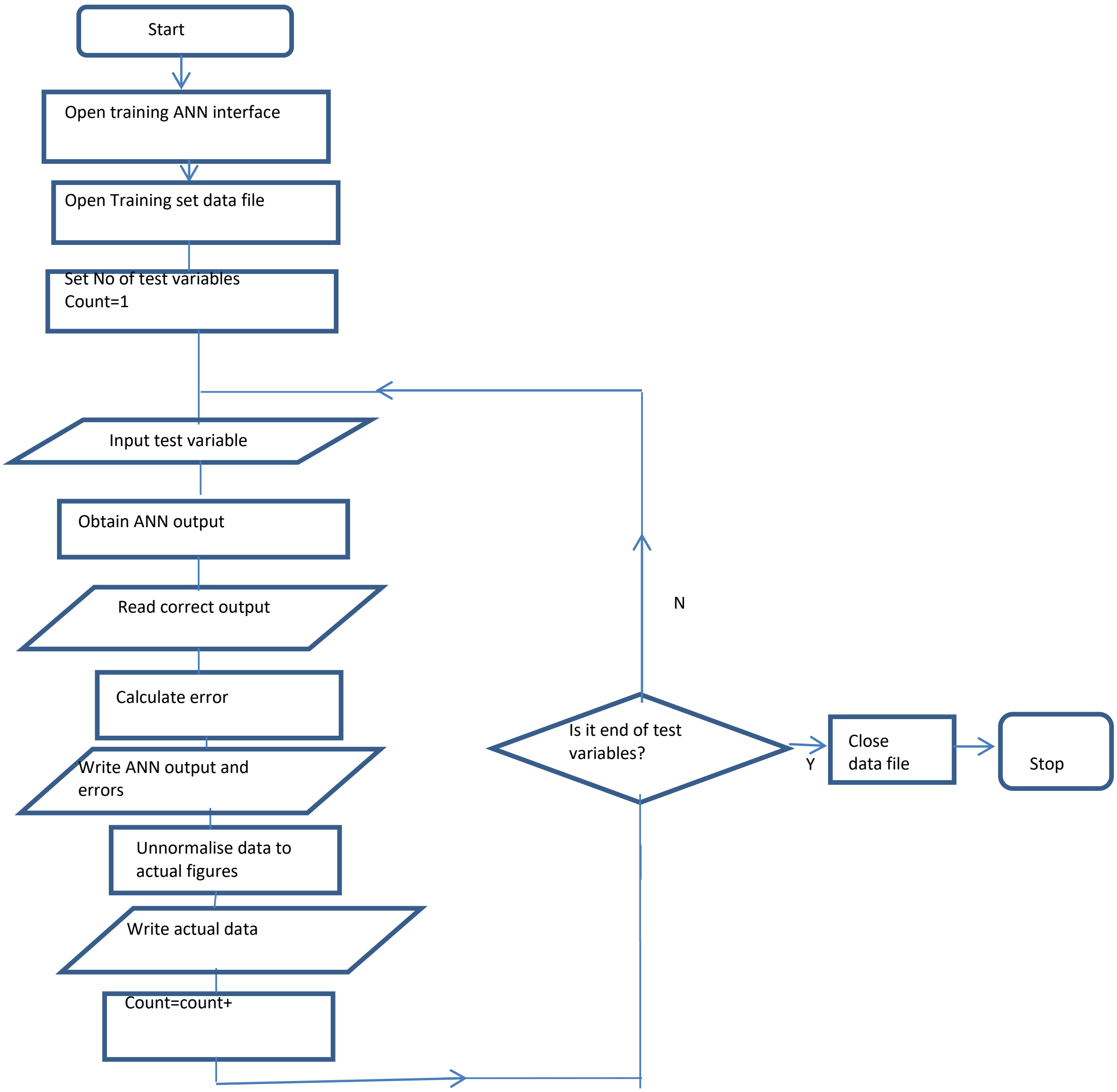


Figure 7 Flow Chart for Testing ANN (Source: Wanjawa (2014)

3.3.4.4 Developing the ANN Prototype

The equipments, tools and materials listed below were used for developing the prototype:

1. Laptop computer, with specifications: at least PIV, 1GB RAM, 1GB free disk space

2. Operating System on the computer – Windows 10

4. Monthly Inflation data, monthly oil prices and GDP growth rate data collected and formatted as Comma Separated Values (CSV) format, stored on the computer

6. Open source program (Neuroph) downloaded, as availed by the developers (Neuroph) and installed on the computer

The prototype was developed using Neuroph studio. This is a graphical Artificial Neural Network framework, easy to learn and with an appealing user interface.

3.3.4.5 Implementation phase

The prototype was installed on a laptop. CSV data necessary for the running of the prototype was stored in the laptop too.

Once the ANN porotype was developed, it was used in forecasting inflation in Kenya from July 2017 to January 2019.

The inflation forecasts obtained were recorded and saved in an excel sheet.

3.3.5 Evaluating the ANN prototype

The t-test was used to evaluate the forecasting ability of the ANN prototype. The t-test was done using the steps below using a function in Ms. Excel:

- The null hypothesis denoted H_0, for the *t*-test for this test would be that the mean for the forecasted inflation values is equal to the mean of actual inflation.
- The mean of the actual inflation and the mean of forecasted inflation will be calculated
- Then Variance(var) for each data sample will be calculated
- the t-test will be computed using the equation

$$t = \frac{\bar{X}_T - \bar{X}_C}{\sqrt{\frac{var_T}{n_T} + \frac{var_C}{n_C}}} \qquad (3)$$

Where $\bar{X}_T$ = actual inflation value, $\bar{X}_c$ = forecasted inflation value, var_T = variance of actual inflation data, var_C = variance of forecasted inflation data, n_T = number of actual inflation data values, n_C = number of forecasted inflation data values

- The tabulated t value at significance level of p=0.05 and $n_T + n_C$ degrees of freedom will be read from the *t-table*
- The calculated t-value will then be compared against the tabulated t-value to test the hypothesis and thus find out if the two sets of data have the same mean.

Results of the students t-test

t-Test: Paired Two Sample for Means		
	Variable 1	*Variable 2*
Mean	5.187361684	6.997413
Variance	1.50245682	0.002122
Observations	19	19
Pearson Correlation	-0.641161339	
Hypothesized Mean Difference	0	
Df	18	
t Stat	-6.282819188	
P(T<=t) one-tail	3.174E-06	
t Critical one-tail	1.734063607	
P(T<=t) two-tail	6.34801E-06	
t Critical two-tail	2.10092204	
The hypothesis that the two means are the same was rejected. This because the P value is greater than the Alpha value		
therefore the two means are not equal		

Table 4: Table for student's t-test

3.4 Linear Model Development

This model was developed using Box-Jenkins methodology This methodology is appropriate since its forecasts are dependent only on past data values. The methodology was used in determining a suitable inflation forecasting model. This methodology comprises model identification and selection, parameter estimation, model checking and forecasting.

3.4.1 Model identification and selection

Data preparation: This was done by checking the data for consistence, gaps and anomalies using an excel sheet table.

Model Identification:

a) **determining inflation data stationarity**

Inflation data was plotted against time using a line graph in MS Excel in order to identify inflation trends and data stationarity. The plotted data was not stationary, thus the differencing technique was used to transform the data, using the equation

$Y_i = Z_i - Z_{i-1}$

Where Z_i is the original Inflation data and Y_i is the transformed Inflation data.

Differenced inflation values were plotted against time to check for data stationarity and trends. The process of differencing was repeated until the data exhibited no more trends when plotted in a graph. In ARIMA modeling, the number of times the data undergoes differencing is represented by d.

b) **Computation of the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF)**

ACF

It is a plot of ACF coefficients against the time lag. The Autocorrelation coefficient at lag h will be calculated using the equation,

$$r_h = c_h / c_0 \qquad (4)$$

where c_h is the autocovariance function and c_0 is the variance function

The autocovariance function was calculated using the equation

$$c_h = \frac{1}{N}\sum_{t=1}^{N-h}\left(Y_t - \bar{Y}\right)\left(Y_{t+h} - \bar{Y}\right) \qquad (5)$$

The variance function was calculated using the equation

$$c_0 = \frac{1}{N}\sum_{t=1}^{N}\left(Y_t - \bar{Y}\right)^2 \qquad (6)$$

Where N= sample size, Y= inflation data, $\bar{Y}$ = the inflation mean value, t= time value, h=the lag value

PACF

It is a plot of the PACF coefficients against time lag t of a time series. Plotting the partial autocorrelative functions will help in determining the suitable lags in an Autoregressive model or in an ARIMA represented by **p**.

Equation 7 below, was used to calculate partial autocorrelation coefficient lag at t

$$\Pi t = \frac{pt - \Sigma_{j=1} \Pi_{t-1}. P_{t-j}}{1- \Sigma_{j=1} \Pi_{t-1}. P_{t-j}} \qquad (7)$$

where Π= partial autocorrelation coefficient, t=lag, p=autocorrelation coefficient, j=number of data values

c) **Identifying q and p**

When the PACFs cut off after a few lags, the last lag with a large value is the estimated value of p. In case the PACFs does not cut off, this is indicative of an MA model with p=0 or an ARIMA model with positive values of p and q.

When the ACFs cut off after a few lags, the last lag with a large value is the estimated value of q. In case the ACFs does not cut off, this is indicative of an AR model with q=0 or an ARIMA model with positive values of p and q.

When both ACFs and PACFs cut off, the model is an ARIMA (p, d, q). Identifying the p and q values directly is not an easy task, thus the trial and error method is used.

d) **ARIMA model determination**

The shapes of the ACF and the PACF plots as summarised in table 5 below were used to guide in determining the model

Possible Model	Shape of ACF Plot	Shape of PACF Plot
ARIMA(p,d,0)	Decay is exponential or sinusoidal	Large spike at lag p and none beyond lag p
ARIMA(0,d,q)	Large spike at lag p and none beyond lag p	Decay is exponential or sinusoidal

Table 5: Table for model identification

3.4.2 Parameter Estimation

This involved approximating the variables of the identified models using the non-linear least squares method. This was done by fitting the model to inflation data by reducing the sum of errors between the actual inflation and the predictions. The initial model parameters were provided to give an initial model. The parameters were refined iteratively until the squared sum of errors was minimum.

The sum of errors were calculated using the equation below:

$$S = \sum_{i=1}^{m} r_i^2 \qquad (8)$$

Where $r_i = y_i - f(x_i, \boldsymbol{\beta})$ represents the errors, S = is the sum of errors, yi=inflation data, β = model parameters and *f*(xi, β) = model predictions

3.4.3 Model Checking

The identified model for inflation forecasting was checked for adequacy by checking whether residuals of the actual values minus those estimated through the model are random. This was done by plotting the correlograms of the residuals.

3.4.4 Forecasting

The selected model was used to forecast inflation from January 2017 to January 2019.

3.8. Comparative Evaluation of the ANN forecasting Model with other forecasting model

The RMSE values for the developed ANN model and the ARIMA model, were calculated and compared. The RMSE value for each model was calculated based on the same time period. The lower the RMSE, the better the model is at forecasting.

4.0 CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1 ANN prototype Evaluation

Evaluation of the ANN model was done using experimental methods. The tests were done using the developed prototype, based on a configuration of 3:21 with 70% data for training and 30% data for testing, with the number of repetitions was set to 10,000.

From the student t test, the actual inflation and the predicted inflation are not equal. Therefore, the developed ANN model is not very accurate.

4.2 Testing the Prototype

This was done using the developed prototype by invoking a training operation, followed by a Testing operation as shown by table 6 below.

4.2.1ANN Model Forecasting Results

Month-Year	Predicted inflation	Actual Inflation	Error
July -2017	6.924388	7.470164	-0.545776
August -2017	6.913756	8.040748	-1.126992
September -2017	6.94388	7.060832	-0.116952
October -2017	6.945652	5.719428	1.226224
November -2017	6.958056	4.730652	2.227404
December -2017	6.956284	4.500292	2.455992
January -2018	7.01476	4.829884	2.184876
February -2018	7.004128	4.459536	2.544592
March -2018	7.000584	4.17956	2.821024
April -2018	7.021848	3.729472	3.292376
May -2018	7.043112	3.9492	3.093912
June -2018	7.039568	4.280564	2.759004
July -2018	7.039568	4.349672	2.689896
August -2018	7.034252	4.039572	2.99468

September -2018	7.051972	5.699936	1.352036
October -2018	7.071464	5.529824	1.54164
November -2018	7.016532	5.57944	1.437092
December -2018	6.982864	5.710568	1.272296
January -2019	6.98818	4.700528	2.287652

Table 6: Table for evaluating ANN model performance

Table 6 shows that the predicted values are not equal to the actual inflation. In most instances the predicted values are greater than the actual values. The prediction tended to be more erroneous with time. This indicates that the Neural Network makes better predictions for short term predictions.

4.3 ARIMA Modeling process

4.3.1 Data Description

The table below shows the inflation descriptive statistics. The inflation data has a non-normal distribution according to the measure of skewness as shown in the table below.

Mean	8.356862229
Standard Error	0.315158829
Median	7.01
Mode	5.53
Standard Deviation	4.366968836
Sample Variance	19.07041681
Kurtosis	-0.106793154
Skewness	0.964081284
Range	17.71440967
Minimum	2.001323798
Maximum	19.71573347
Sum	1604.517548
Count	192

Table 7: Descriptive Statistics for the inflation series

4.3.2 Model identification and selection

4. 3.2.1 Data preparation

An excel sheet table that contained a column on the months and a column on actual inflation was created. Actual inflation data was checked for anomalies and gaps by subjecting it to mathematical operations. One value was identified as causing erroneous calculations. The data type for this data value was identified as text, consequently it was changed to numeric data value.

4. 3.2.2 Determining if inflation data is stationary

A line graph as indicated in the chart below was plotted. Monthly inflation values from January 2003 to January 2019 were plotted against time in months. The graph shows inflation fluctuations throughout the forecasting period. This indicates that the variance and mean values for this data are not constant. Therefore, this inflation data is not stationery.

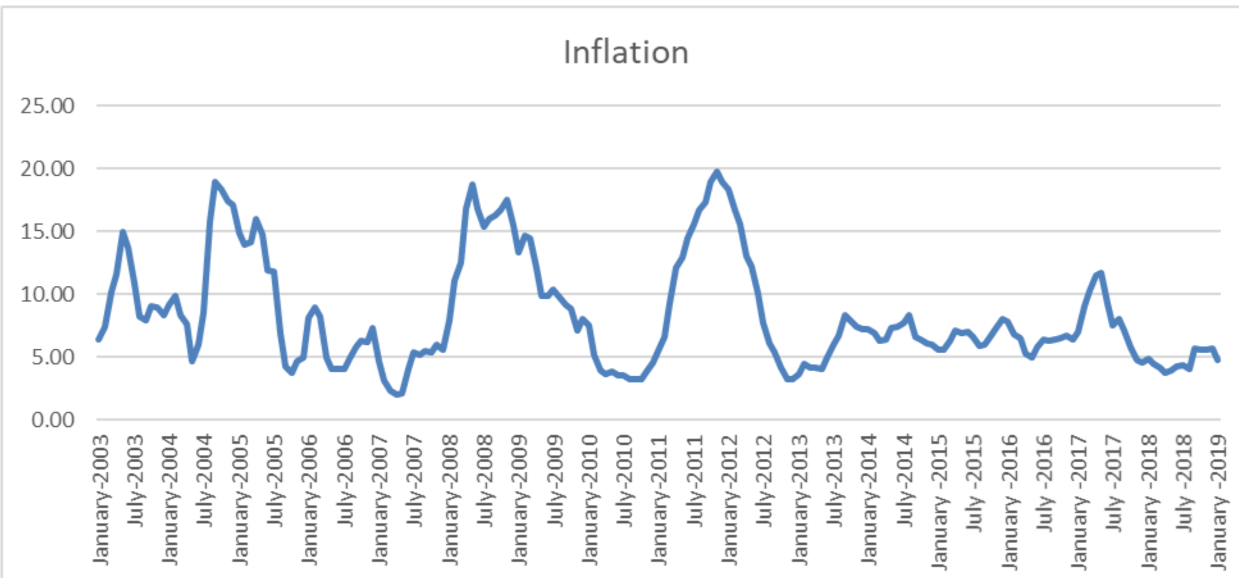


Figure 8: Graph of original inflation data against time in months

4. 3.2.3 Inflation data differencing

The original inflation data was transformed into stationery data using the differencing procedure as indicated by the formula below

$Y_i=Z_i-Z_{i-1}$

Where Z_i is the original inflation values and Y_i is the transformed

A graph of the differenced data was plotted against time in months to identify trends and stationarity in the data. The transformed inflation data displayed no trends and inflation oscillation was within zero. This is indicative of constant mean and variance, meaning the data had been transformed into a stationary data series.

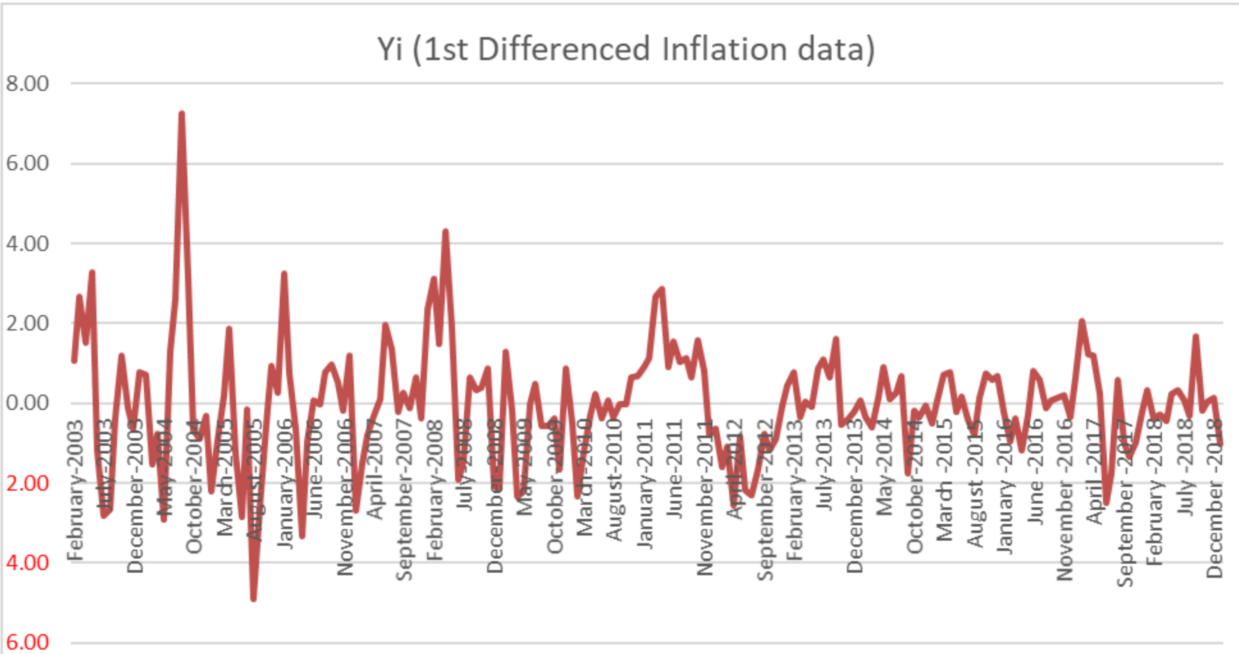


Figure 9: Graph of differenced inflation data against time in months

Augmented Dickey Fuller (ADF) test

This was done using the test function of the real statistics add on in excel. The test indicated that the data had been transformed into stationary data series.

ADF	
Test	
criteria	schwert
drift	no
trend	no
lag	14
alpha	0.05
tau-stat	-4.46459
tau-crit	-1.94249
stationary	yes
aic	2.994224
bic	3.264435
lags	14
coeff	-0.83567
p-value	< .01

ADF test for the differenced data.

Thus the value of d in the model is 1.

4. 3.2.4 The ACF and PACF correlograms

They were determined using the SPSS software. The correlograms are as indicated below.

ACF (Autocorrelation Function)

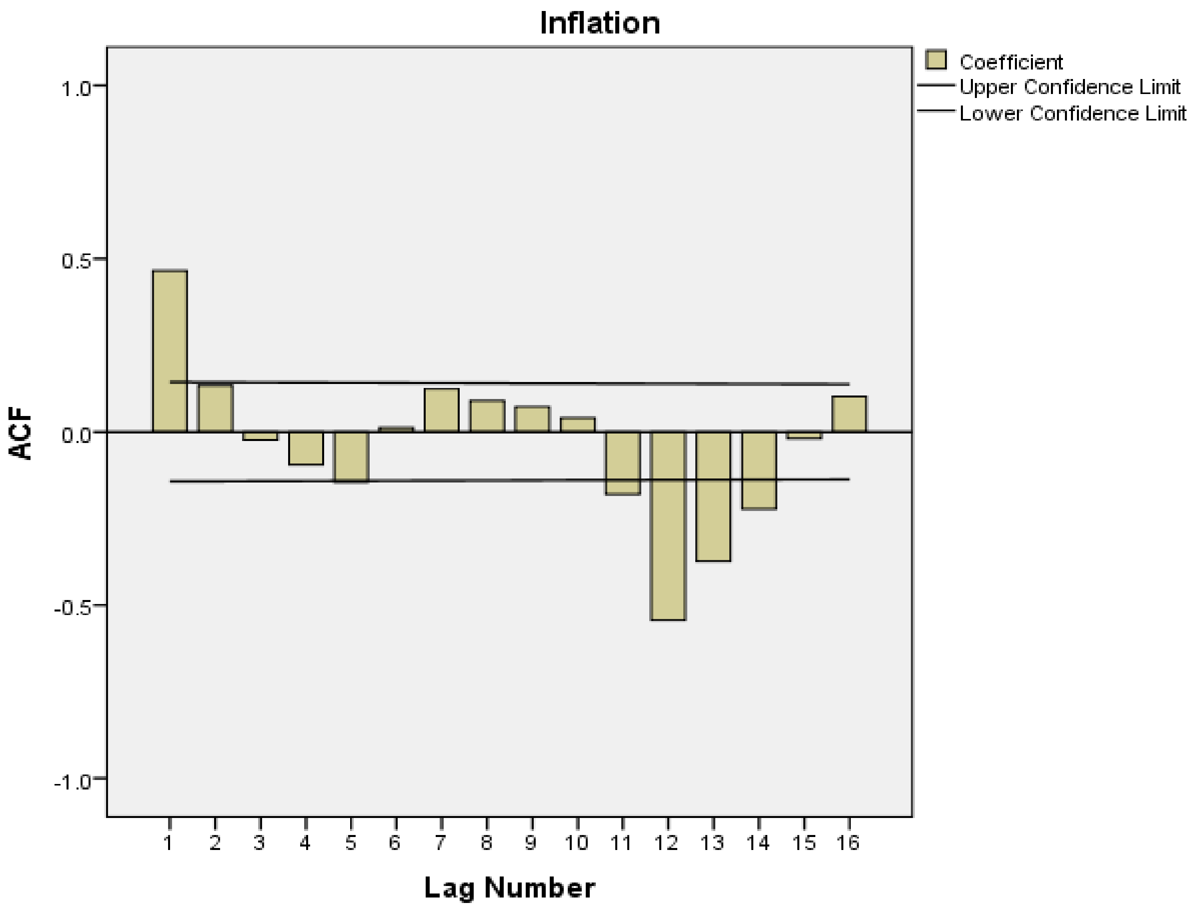


Figure 10: ACF correlogram, ACF values against lags

Significant ACF values are observed at lag 1,12,13,14. Therefore values of q for the model are 1,12,13,14.

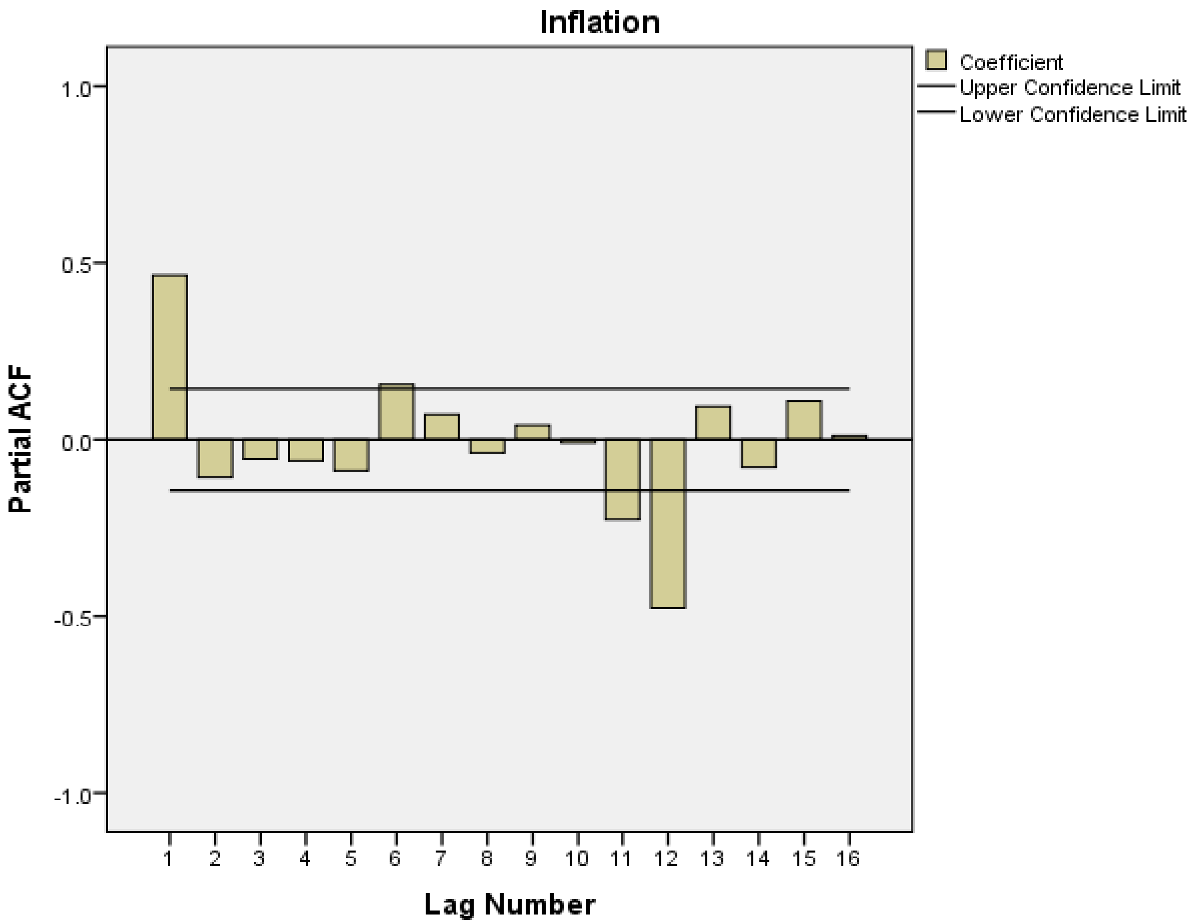


Figure 11: PACF correlogram, PACF values against lags

Significant PACF values are observed at lag 1, 11, 12. Therefore values of p for the model are 1 11, 12.

4. 3.2.5 The values of q and p

The shapes of the correlograms indicate possible ARIMA (p, d, 0) and ARIMA (0, d, q) models. In addition, the shapes of the correlograms indicate a model that has both AR and MA terms in it. Therefore, this is possibly an ARIMA (p, 1, d) model.

4.3.3 ARIMA model determination

Significant ACF values are observed at lag 1,12,13,14. Therefore the q values of the model are 1,12,13,14. Also, Significant PACF values are observed at lag 1, 11, 12. Therefore the p values of the model (p, d, q) are 1, 11, 12. In addition, there exists other models where the p and q values are equal to zero.

Therefore, the possible models derived from the significant ACF (q) and PACF (p) values will be: (0,1,1), (0,1,12), (0,1,13), (0,1,14), (11,1,0), (11,1,1), (11,1,12), (11,1,13), (11,1,14), (12,1,0), (12,1,1), (12,1,12), (12,1,13), (12,1,14).

4.3.4 Parameter Estimation

Table 8 below gives a list of models and their sum of squared errors (SSE), log likelihood (LL), Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC) values. These values were generated when each model was fitted against inflation values.

Model(p,d,q)	SSE	LL	AIC	BIC
0,1,1	317.467	-320.717	645.434	651.949
0,1,12	216.917	-284.156	594.313	636.66
1,1,0	311.436	-318.875	641.751	648.266
1,1,1	308.739	-318.046	642.092	651.865
1,1,12	181.035	-266.792	561.583	607.188

Table 8: Models and their SSE, LL, AIC, BIC values

The smallest SSE value was used to identify the most appropriate model for forecasting inflation. This is the model ARIMA (1, 1, 12) with SSE=181.

The parameters of the identified model ARIMA (1, 1, 12) were estimated and recorded in the table below

Lags		Estimates
1	AR1	0.593
1	MA1	-0.186
2	MA2	-0.132
3	MA3	-0.089
4	MA4	-0.016
5	MA5	-0.039
6	MA6	-0.022
7	MA7	-0.0084
8	MA8	-0.174
9	MA9	0.087
10	MA10	0.043
11	MA11	-0.0031
12	MA12	-0.877
Constant		0.045

Table 9: Estimated model parameters

4.3.5 Model Checking

This was done by checking whether residuals of the actuals values minus those estimated by the model are random. This was achieved by creating the ACF and PACF based on the residuals.

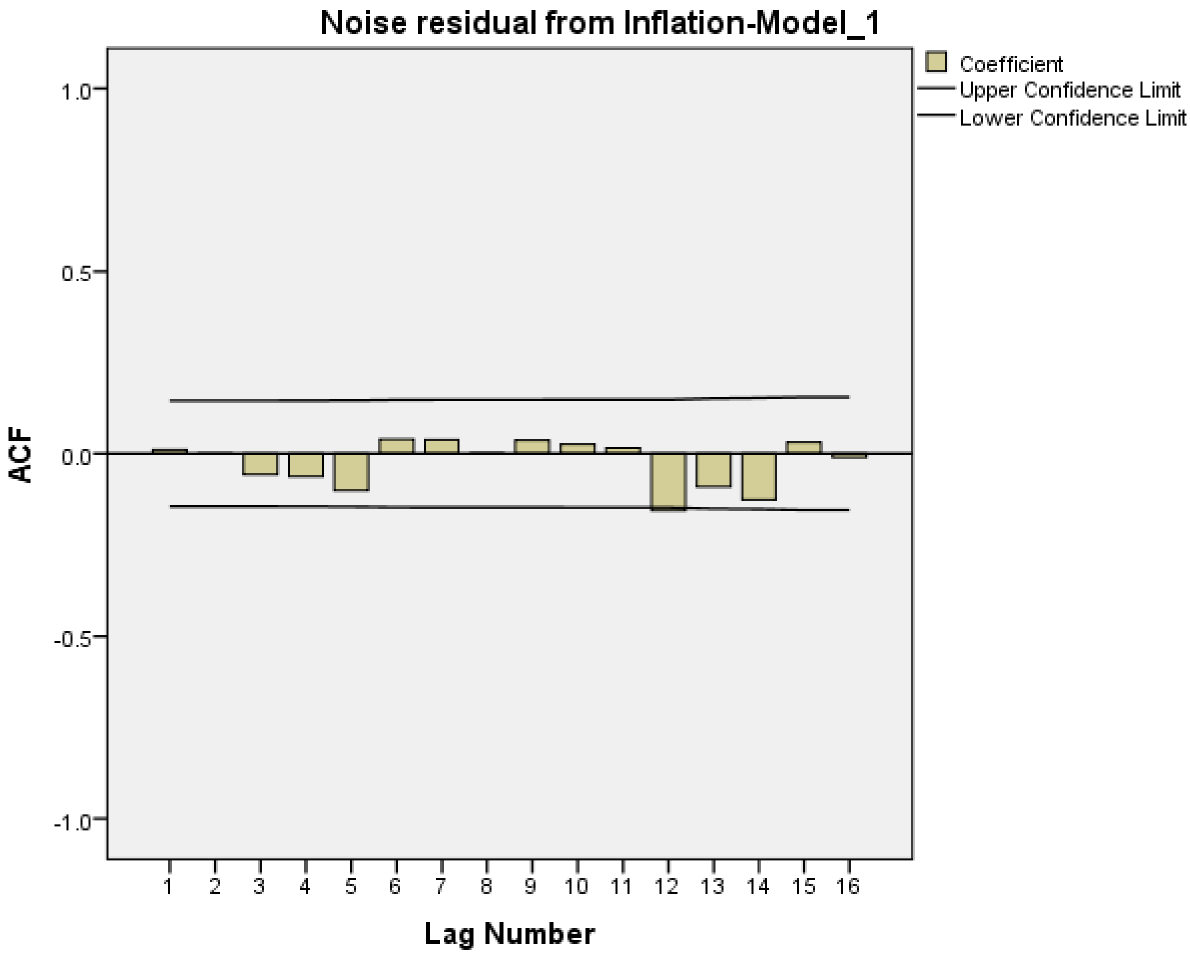


Figure 12: Model Residuals ACF

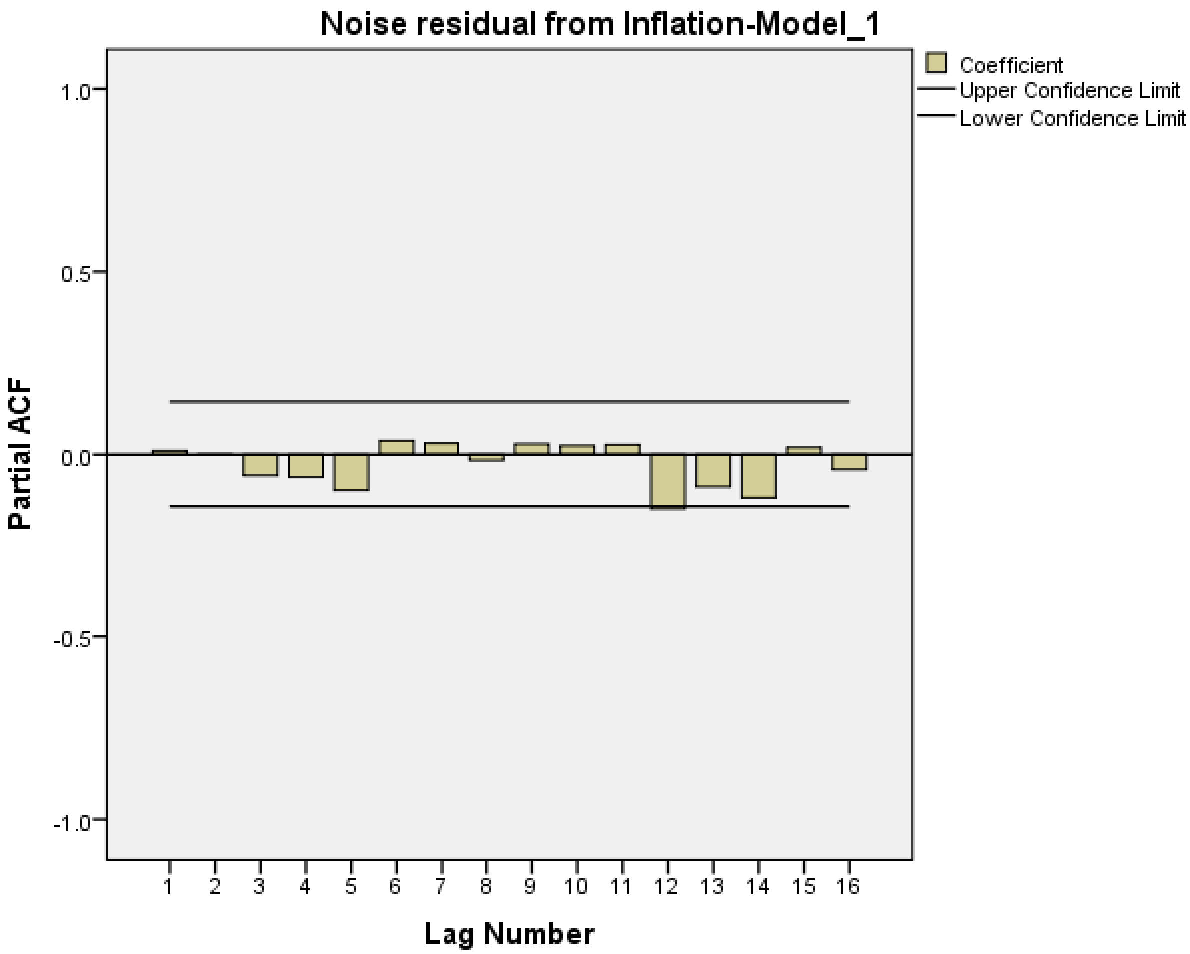


Figure 13: PACF residuals.

Figure 12 and 13 indicate that the residuals are random since there are no residual values that are larger than the set boundaries. Thus the chosen ARIMA model is appropriate for forecasting inflation.

4.3.6 Forecasting

This was done using the excel real statistics add on for the period July 2017 to January 2019. The results are shown by the table below

Month-Year	Actual Inflation	Predicted Inflation	Error
July -2017	7.47	7.859215638	-0.38922
August -2017	8.04	7.974488587	0.065511
September -2017	7.06	8.301477747	-1.24148
October -2017	5.72	8.436021905	-2.71602
November -2017	4.73	8.396178814	-3.66618
December -2017	4.5	8.788285066	-4.28829
January -2018	4.83	8.834639646	-4.00464
February -2018	4.46	8.268882627	-3.80888
March -2018	4.18	7.760042381	-3.58004
April -2018	3.73	7.420140073	-3.69014
May -2018	3.95	7.399568602	-3.44957
June -2018	4.28	8.928181547	-4.64818
July -2018	4.35	9.880032577	-5.53003
August -2018	4.04	10.48979543	-6.4498
September -2018	5.7	10.89665945	-5.19666
October -2018	5.53	11.18318041	-5.65318
November -2018	5.58	11.39832368	-5.81832
December -2018	5.71	11.57113151	-5.86113
January -2019	4.7	11.71882941	-7.01883

Table 10: Table for ARIMA forecasted inflation

Table 11 shows that the estimated inflation values were greater than the real inflation values. The predicted values become even greater with the lapse of time. This demonstrated that the model became less accurate over time. Therefore, ARIMA (1, 1, 12) is a good model for short term forecasting.

4.4 Comparative evaluation of the ANN model with ARIMA model

This was done by calculating and comparing the RMSE values of the models. This is shown in the tables below.

Month-Year	Actual Inflation	Predicted Inflation	Error
July -2017	7.47	7.859215638	-0.38922
August -2017	8.04	7.974488587	0.065511
September -2017	7.06	8.301477747	-1.24148
October -2017	5.72	8.436021905	-2.71602
November -2017	4.73	8.396178814	-3.66618
December -2017	4.5	8.788285066	-4.28829
January -2018	4.83	8.834639646	-4.00464
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September -2018	5.7	10.89665945	-5.19666
October -2018	5.53	11.18318041	-5.65318
November -2018	5.58	11.39832368	-5.81832
December -2018	5.71	11.57113151	-5.86113
January -2019	4.7	11.71882941	-7.01883

Table 11: RMSE Table for ARIMA model forecasting

The RMSE for ARIMA is 19.49365

Month-Year	ouput (inflation)	Desired Output (Inflation)	Error
July -2017	6.924388	7.470164	-0.545776
August -2017	6.913756	8.040748	-1.126992
September -2017	6.94388	7.060832	-0.116952
October -2017	6.945652	5.719428	1.226224
November -2017	6.958056	4.730652	2.227404
December -2017	6.956284	4.500292	2.455992
January -2018	7.01476	4.829884	2.184876
February -2018	7.004128	4.459536	2.544592
March -2018	7.000584	4.17956	2.821024
April -2018	7.021848	3.729472	3.292376
May -2018	7.043112	3.9492	3.093912
June -2018	7.039568	4.280564	2.759004
July -2018	7.039568	4.349672	2.689896
August -2018	7.034252	4.039572	2.99468
September -2018	7.051972	5.699936	1.352036
October -2018	7.071464	5.529824	1.54164
November -2018	7.016532	5.57944	1.437092
December -2018	6.982864	5.710568	1.272296
January -2019	6.98818	4.700528	2.287652

TABLE 12: RMSE Table for ANN model forecasting

The RMSE for the ANN MODEL IS 9.520245755

The RMSE value of the ANN model as indicated in the calculations above, is much smaller than that of the linear model. Based on the RMSE values, it can be concluded that the ANN model is better at forecasting inflation when compared to the linear model.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.0 Introduction

Economists and planners are expected to advise their clients (Government and private investors) on strategies that can maintain a stable macroeconomic environment and hence attract investment and guarantee economic growth. Mostly, it is the Economists who have ease of access to economic planning tools and data. Currently, economists use time series analysis techniques (Econometrics) to predict economic performance. By extension, they are responsible for predicting inflation on a month to month basis and also annually. Time series techniques are depended on the experience of the user, are subjective and generally point an inflation trend and not the most likely inflation of a certain period. Without a more accurate prediction method, the economists may not be able to provide the requisite advice to the Government and other clients. There however exists Artificial intelligence techniques that can be utilised to develop tools that are capable of predicting inflation more accurately.

5.1Achievements

The first objective of the research project was to investigate existing forecasting models that have been used to forecast inflation. From literature review, the most popular models used by economists and planners are: VAR, BVAR, ARD lag, random walk, SVAR, ARIMA and ANN models. From literature, Neural Network models forecast more accurately as opposed to the linear models. The performance of time series models is varied. No single linear model can be said to forecast more accurately than the other. In fact, the performance linear models is dependent on the researchers' experience.

The second objective was to design an AI model for predicting inflation in Kenya. This was achieved through a series of experimental studies using available data and knowledge from the reviewed literature. The research determined a configuration of 3:12 as achieving the highest prediction accuracy. This configuration consists of three input neurons, which correspond to the three inputs into a network that aims at predicting the one inflation value. The model has one hidden layer with 12 neurons. The model has one output, being the predicted monthly inflation based on the three monthly inputs.

Third objective was to develop a prototype based on the identified model using a suitable programming environment. This achieved by using Neuroph studio to translate the designed model into a prototype that was used to forecast inflation. The prototype was evaluated experimentally using 70% of the data for training for the period January 2003 to March 2014. Data for the period April 2014 to June 2017 was used for testing the model.

The fourth objective was to test and assess the performance of the AI model in predicting inflation in Kenya. The AI model was subjected to inflation forecasting and its performance compared to that of actual Inflation. It performance was found to have some small deviation from the actual inflation. However, the AI model had a much lower RMSE compared to the RMSE of the ARIMA model. This makes the AI tool a better inflation forecasting tool when compared to the ARIMA model.

5.2 Contributions of the Research

This study, contributed to the body of knowledge through the development of an ANN model for inflation forecasting which has a comparatively low RMSE when measured against the ARIMA model. The low RMSE value makes the ANN model a better forecasting tool when compared to the ARIMA model.

The ANN will help economic planners make more accurate inflation forecasts and thus be capable of creating economic policies that can maintain inflation at a stable rate. Stable inflation gives investors confidence of investing in an economy thus spurring economic development.

5.3 Limitations of the Research

This study used secondary, thus its accuracy and veracity cannot be authenticated. In addition, the available data that could meet the research objectives is inadequate, yet ANN models require large volumes of data so that their accuracy is enhanced.

ANN require a lot of experiments to be conducted. Depending on the ANN configuration, experiments took a lot of time and computing resources.

5.4 Recommendations

First, there is need to formulate a generic model that can be used to model other Economic parameters. The generic model will serve diverse economic forecasts and reduce the costs associated with economic modeling. To further enhance the model accuracy, there is need to explore ANN configurations with more than two hidden layers and more than 12 neurons per hidden layer. In addition, further research should be done to improve on estimating the ANN parameters. This is because estimation of ANN parameters is a trial and error task and there are no set steps or standards for doing it. Finally, training of ANN should be improved by using genetic algorithms. Genetics algorithms have the capacity to improve on the ANN training process since they estimate parameters more accurately.

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