2021

Forecasting of the inflation rates in Kenya: a comparison of ANN, ARIMA and SARIMA.

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Forecasting of the Inflation Rates in Kenya: A comparison of ANN, ARIMA and SARIMA

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Submitted in partial fulfillment of the requirements for the Degree of Master of Science, Statistical Sciences at Strathmore University.

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December 2021

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Declaration and Approval

Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Victor Kiprono Kogei

Signature ....

Date 10/11/2021..............................

Approval

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Abstract

Monetary policies like price stability are regulated by the Central Bank of Kenya (CBK). Price stability is a key indicator of stable and predictable inflation. Accuracy and reliability in forecasting the inflation rates or predicting its trend correctly are very essential to investors, academia and policymakers. This call for the need to have models with an accurate prediction of the inflation rates to spur investment and economic growth.

The use of an intelligence-based model has been found to be robust in forecasting financial and economic series like inflation rates and stock prices. This research, therefore, employs the use of the artificial neural network to forecast the inflation rates in Kenya and compared its performance with statistical models ARIMA and SARIMA. The artificial neural network models emulate the information processing capabilities of neurons of the human brain, thus making them flexible to map input and output well. A major advantage of ANNs is its ability to capture linear and non-linear data due to lack of assumptions, unlike statistical models.

The inflation rates data, Gross domestic product (GDP) and exchange rates were the variables used. The variables are monthly data from January 2012 to February 2021. The prediction performances of the three models were evaluated through RMSE, MAE and MAPE.

The results obtained show that artificial neural networks outperformed ARIMA and SARIMA models. The implication is that the government can adopt an artificial neural network for forecasting inflation rates in Kenya.

Contents

Acknowledgment

I acknowledge and deeply appreciate my classmates for there support and contributions towards this report. Much regards goes to my friend and classmate Joram for unselfishly supporting and believing in me to ensure success of the thesis.

I salute my supervisor Prof Samuel Mwalili for his rich knowledge in the field of scientific research. He played a key role though constant guide and review of my project. I really treasure time and effort accorded to my work. Much regards goes to my lectures who greatly mentor my carrier path. Finally i appreciate Strathmore University fraternity and more particularly department of Mathematical science for the excellent work done. Much appreciation is accorded to Almighty God His gracious gift of health and life.

Dedication

This thesis is dedicated to my uncle whom he supported me throughout my study . I salute and respect him beyond measure for his inspiration and generously supporting my education en devours in one of the reputable University in Kenya.

To my grand mother,for her prayer and guide throughout my life.

Abbreviations

ANNs	Artificial Neural Networks
ARIMA	Autoregressive integrated moving average
CBK	Central Bank of Kenya
CPI	consumer price index
KNBS	Kenya National Bureau of Statistic
MAE	Mean absolute error
MAPE	Mean absolute percentage error
SARIMA	Seasonal autoregressive integrated moving average
VAR	Vector autoregressive
RMSE	Root Mean Square Error

Chapter 1

Introduction

1.1 Background of the study

Inflation is defined as a persistent increase in the prices of commodities(goods and services), which reduces the purchasing power of a currency over a given period. Inflation can also be expressed as a situation where demand for goods and services exceeds their supply in the economy (Hall and Welsh, 1985). Price stability is a key factor of desirable monetary policy that enhances economic growth and development in a flourishing economy. It is now globally accepted that price stability is paramount for modern well-functioning economies (Ocampo, 2008). High inflation will raise the cost of living to fixed-income workers because inflation erodes the real value of their earnings. Inflation gains global attention since it results in low savings and high interest rates, leading to increased borrowing costs and slowing down investment and economic growth. These mention scenarios explain why it's a crucial issue of concern to policymakers, especially when it raises to a higher level.

Economists also argue that inflation is a function of demand and supply of money, where it arises when the supply of money is greater than the demand for money. Goods imported from a country affected by inflation will also cause the prices of goods to rise in the domestic market.

In Kenya, the Consumer Price Index(CPI) is widely used to measure the inflation rate. KNBs defines CPI as a measure of the weighted aggregate change in retail prices paid by consumers for a given basket of goods and services. Goods in the basket include; Food and nonalcoholic beverages, Alcoholic beverages, Tobacco Narcotics, Clothing and footwear, housing, water, electricity, gas and other fuels, Furnishings, Household Equipment and Routine Household Maintenance, Health, Transport, Communications, Recreation Culture, Education, Restaurant Hotel, and Miscellaneous goods and services. CPI is an economic indicator. It is the foremost widely used measure of inflation and, by proxy, of the effectiveness of the government's policy. The CPI gives the government, business, and citizens thought about prices changes within the economy and can act as a guide to make informed decisions about the economy. CPI is computed as:

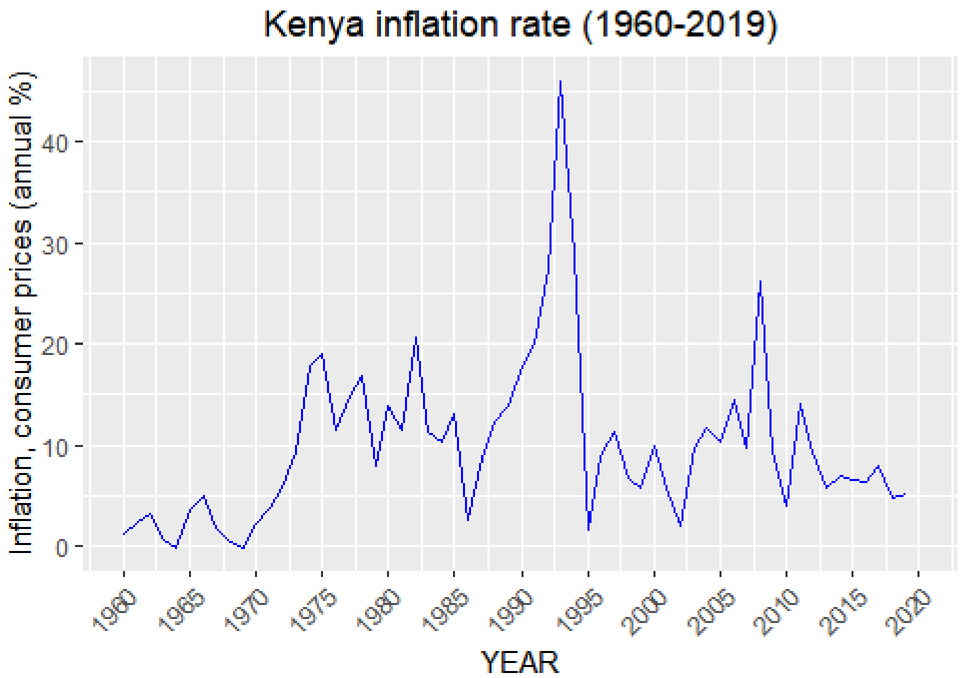
$$CPI = \frac{\text{Cost of the market basket in a given year}}{\text{Cost of the market basket in the base year}} * 100$$

.

Empirical research has been carried out in forecasting using time series approaches that assume the normality of the data. The commonly involved models include: Autoregressive Integrated Moving Average (ARIMA), Vector Autoregressive (VAR), and generalized Autoregressive conditional heteroskedasticity (GARCH) model since they are easy in their development and implementation . However, these statistical techniques are limited by their assumption of linearity of the data and thus fail to factor in real-life economic data, which are mostly non-linear (Khashei and Bijari, 2011). In contrast, the relatively recent and accurate soft computing technique, the artificial neural networks (ANNs) have overcome the deficient linear models by incorporating non-linear data in their analysis. The ANNs model does not conform to any distribution and captures well data with an outlier. The forecasting ability of Artificial Neural networks has been compared to that of autoregressive models by several researchers. This research found out that Neural Network-based models are accurate, precise, and efficient in forecasting. For these reasons, Centrals banks and policymakers have adopted ANNs for forecasting GDP, stock exchange, and other macroeconomic indicators (Haider and Hanif, 2009).

From the relevant literature search, it was discovered that research on forecasting the inflation rate in Kenya had been conducted; however, no study has attempted to compare ANNs with Seasonal linear models. This study commenced by testing the ARIMA and SARIMA models to prove their forecasting ability of Kenyan inflation rate as a priori study, then develop ANNs model and finally compared their performances.

Kenya has experienced a fluctuating inflation rate since independence, with the highest ever experience inflation rate in 1993 at 45.98% and lowest in 1969 at -0.17 (Durevall and Ndung'u, 2001). The chart below shows the annual inflation rate from 1963 to 2019.



1.2 Statement of the problem

Monetary policies like price stability are regulated by the Central Bank of Kenya (CBK). Price stability is a key indicator of stable and predictable inflation. Inflation predictability creates confidence in the country resulting in economic growth and development.

There is a need for accurate forecasted inflation rates to maintain price stability, which stabilises inflation rates. For this challenge to be addressed, there is a need to develop models with accurate prediction ability. Currently, linear models used in forecasting inflation rates in Kenya lack reliable accuracy when variables are subject to change over time. For linear models like ARIMA and SARIMA, data linearity is assumed, while evidence shows that macroeconomic series contain non linearity (Pollin and Zhu, 2009). The assumption of linearity render linear models inadequate to forecast macroeconomic series like inflation rate.

The artificial neural network that solves the limitation of linear models by capturing both linear and non-linear data is employed. According to Stock and Watson (1998) in their bid to compare linear and non-linear models in forecasting macroeconomic series data, they discovered that non-linear models produce accurate forecast than linear models. Also, study was conducted on the comparison of linear forecasting models and neural networks, application of EURO inflation and EURO DIVISIA where, ARIMA and multivariate VAR was used as linear models. The study found out that Neural networks performed better than linear models in forecasting inflation.

The adaptability of the artificial neural network makes them most suitable for forecasting macroeconomic series like inflation rates since assumptions like linear models do not limit them. The effectiveness of ANN in forecasting will benefit stakeholders by reducing uncertainty.

1.3 Significance of the study

The study is significant in the financial market in the following ways.

(i) The crucial outcome of this study was developing an inflation forecasting model in Kenya.

(ii) Improve inflation forecasting ability for Kenya.

(iii) Comparing the forecasting performance of linear models with the non-linear model will make it possible for inflation forecasters to choose the best model for Kenya.

1.4 Limitation of the study

This research was characterized by the following limitation.

1. The data sourced from website could not be confirmed if they are real accurate data

2. The study was also limited by time constraints.

1.5 Objectives of the study

1.5.1 Main objective

The main objective of this study was to formulate Artificial Neural Network (ANNs) model and compare its performance in forecasting the Kenyan inflation rate with ARIMA and Seasonal Autoregressive Integrated Moving Average (SARIMA).

1.5.2 Specific objectives

(i) Formulation of an artificial neural network (ANN) model for forecasting inflation rate in Kenya.

(ii) To compare forecasting performance with ARIMA and SARIMA.

(iii) To forecast future Kenyan inflation rates (12 months ahead).

1.6 Contribution of the research work

This study contributed to the existing literature through:

(i) Formulation of artificial intelligence model and comparing its prediction performance with statistical method.

(ii) Establishment of the basis for choosing an inflation forecasting model suitable for Kenya.

1.7 Scope of the study

This project utilized monthly data of the Kenyan inflation rates obtained from the Kenya National Bureau of Statistics (KNBS) websites from January 2012 to February 2021. Exchange rates and GDP rates of the same period were sourced from the Central Bank of Kenya website. The Data splitting was done to train the model, test the model accuracy and validate the same models. Finally, Mean Absolute Error (MAE), Root Mean Square Error(RMSE), and the Mean Absolute Percentage Error(MAPE) were essential for accessing the prediction performances of the models.

The rest of this paper is organized as follows; literature review in chapter 2, methodology in chapter 3, results in chapter 4 and finally, the conclusion in chapter 5.

Chapter 2

Literature review

2.1 Overview

This section tackle on introduction, time series models, artificial intelligence model, comparison of the models and finally, summary and conclusion.

2.2 Introduction

Inflation

Inflation is defined as a persistent increase in the price of goods and services, which results in the reduction of purchasing power of money. Economists argue that inflation set in when demand for goods in the economy exceeds the supply. Central Bank of Kenya is the public institution mandated by the constitution to control inflation in an economy.

Empirical evidence shows that businesses and households performed poorly when high and unpredictable inflation set in (Barro et al., 1996). For this reason, therefore, through sound monetary policies, central banks should emphasize attaining price stability in an economy. Price stability is characterized by benefits including reducing uncertainty about general price development, increasing the benefits of holding cash, reducing risk premiums associated with interest rates, and preventing arbitrary income and wealth distribution (Ianc and Ciurlău, 2016).

Inflation is contributed mainly by fluctuating exchange rates and an increase in money circulation in the economy. Inflation reduces economic growth through the reduction of investments and savings in the country.

Determinants of inflation

Gyebi and Boafo (2013) attempts to identify the macroeconomic factors responsible for inflation in Ghana for the period 1990 to 2009. They concluded that real exchange rate and money supply are the primary macroeconomic factors responsible for inflation in Ghana by exerting pressure on the prices level to move up.

Iya and Aminu (2014) investigated the determinants of inflation in Nigeria's economy between 1980 and 2012. The results revealed that exchange rates and interest rates influence inflation positively.

Pindiriri (2012), in his study to examines the causes of inflation in post-dollarized Zimbabwe, discovered that the country's inflation is majorly affected by exchange rates and interest rates. GDP and money supply also had a significant influence on the inflation increase.

Huang et al. (2010), in their study entitled " what's determine China's inflation," concluded that excess liquidity is a significant determinant of inflation trajectory in China. The study further commented that GDP and exchange rates are also crucial for raising the prices of goods.

Jaradat et al. (2011) conducted empirical research on the most critical internal and external factors affecting the inflation dynamics in Jordan and measuring the impact of these factors on the inflation dynamics. The results indicated that GDP, exchange rates, and money supply are statistically significant for inflation change in Jordan.

Kirimi (2014) established the main determinants of inflation in Kenya from 1970-2013 using theoretical and empirical literature reviewed to explain inflation causation in Kenya. The study revealed that exchange rates and money supply had a positive relationship with inflation while GDP and corruption perception negatively influence inflation. Wages pressure and political instability did not affect inflation.

Ochieng et al. (2016) investigated the determinants of inflation on the Kenyan economy. Based on the findings, they concluded that real GDP growth, price fluctuations (changes in oil prices), and the previous period's inflation rate (lag inflation rate) are the ideal factors that affect inflation in Kenya.

The study asserts a significant relationship between real GDP growth and exchange rates on inflation rates.

Researches have suggested several models for forecasting the inflation rate in Kenya under both times series models and artificial intelligence models.

2.3 Time series models

These models assume that the data are linear and have four elements: trend, seasonality, cyclical, and error terms components. The most commonly used time series model for forecasting is Autoregressive Integrated Moving Average (ARIMA). The model relies on the past values of the series as well as previous errors for forecasting. We can expand the ARIMA model to take care of seasonal components to form Seasonal Autoregressive Integrated Moving Average (SARIMA). The order of the non-seasonal model and seasonal model is denoted as follows; ARIMA (p,d,q) and SARIMA (p,d,q)(P, D, Q)s. Times series models are limited to linear data making them unsuitable for predicting non-linear series.

2.4 Artificial Neural Network

Artificial Neural Network (ANNs) is popularly used for forecasting both linear and non-linear data. ANN is a soft computing technique widely used by researchers in forecasting in the engineering, medical, social, economics, and business field (Adebiyi et al., 2014). ANNs imitate the human cognitive system by processing information using neurons like the brain of human beings. The model was created to mimic the processing and information learning ability of the human brain. Therefore, the model receives information, recognizes the trend and pattern, and predicts according to the pattern learned (Kubilius et al., 2019).

2.4.1 The human neural

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 brain's functions (i.e., learning) is the neural network (Yusif et al., 2015). The human brain contains approximately 10 billion interconnected neurons creating its massively parallel computational capacity. The human neuron comprises four main regions in its structure: The cell body, the dendrites, the axon, and the synapses. The cell body is the heart of the neuron; they process inputs, the dendrites accept inputs, the axon turns processed inputs to output, and finally, the synapse passes the information between the neurons. The neural network can predict based on the pattern of the signals received. Figure 2.1 shows the biological structure of the human neuron.

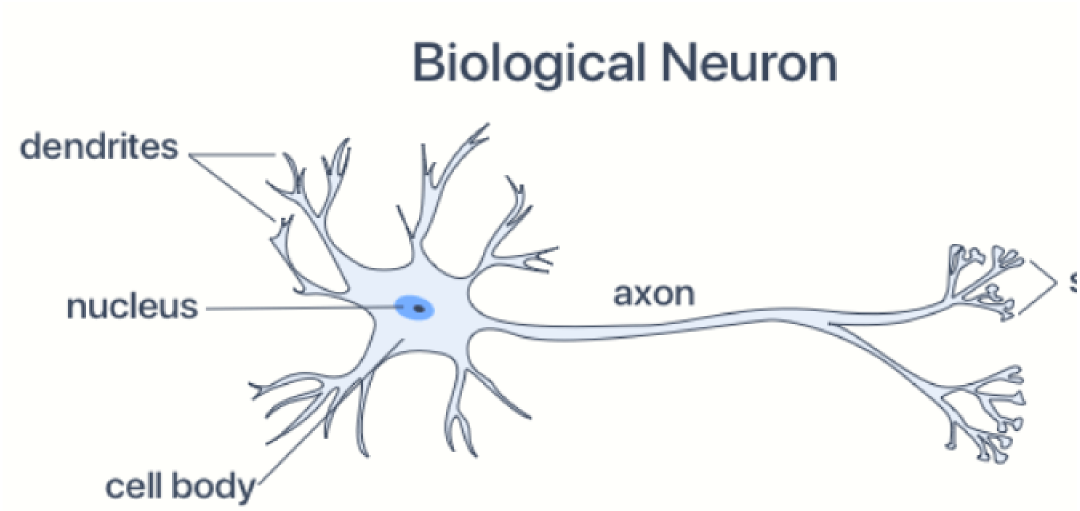


Figure 2.1: Biological human neuron

2.4.2 Artificial neural

The artificial neuron is a mimic of the natural human neuron. ANN learns by an experience like people. An ANN is configured for a specific application, such as pattern recognition and time series forecasting, through a learning process. Three distinct functional operations take place in a neuron. These are:

- Input function
- Activation function
- The output function

As shown in Figure 2.2

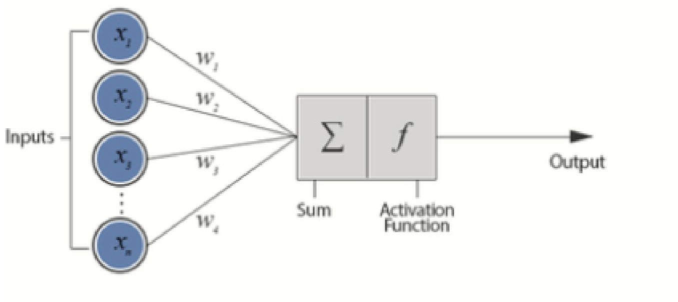


Figure 2.2: Functions of a neuron

Input function

In an artificial neural network, a neuron is connected to other neurons and depends on them to receive the information that it processes. There is no limit to the number of connections a neuron may receive information from. The information that a neuron receives from others is regulated through the use of weights. When a neuron receives information from other neurons, each piece of information is multiplied by weight with a value between -1 and +1, which allows the neuron to judge how important the information it receives from its input neurons is. These weights are integral to how a network works and is trained. Specifically, training a network means modifying all the weights regulating information flow to ensure output attains minimization of RMSE.

Activation function

The second portion of a neuron is the summing and activation functions. The information sent to the neuron and multiplied by corresponding weights is added together and used as a parameter within an activation function. Numerous activation functions exist in ANN literature, including; linear, hyperbolic tangent function and log-sigmoid and logistic sigmoid.

Output function

Finally, once the activation function returns a corresponding value for the summed inputs, these values are sent to the neurons that treat the current neuron as an input. The process repeats, with the current neuron's output being summed with others and more activation functions accepting the sum of these inputs. The only time this may be ignored is when the current neuron is an output neuron. In this case, summation and normalization are applied.

2.4.3 Architecture of ANNs

This entails ordering neurons to layers and layers to neurons. 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 an intermediate layer, called the hidden layer, can 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 (Banerjee et al., 2005). The output units finally produce the outputs or forecasts. Figure 2.3 below shows the flow of network processes in the multilayer architecture.

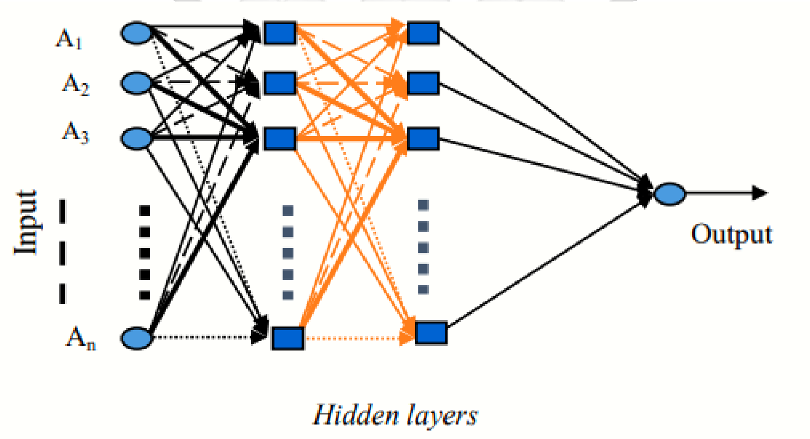


Figure 2.3: Multilayer Back propagation neural network with one output neuron

The architecture can either be forward propagation or back- propagation.

2.4.4 Training of ANNs

Training ANN entails serving it with known input data and commanding it to predict a known output. In an artificial neural network, training is either supervised or unsupervised.

Supervised learning

In this case, ANN is provided with input and output that it desires. The obtain and expected output is compared and calculates the error. The objective is to minimize the error; so, the computed errors are returned to the network to adjust the connection weights, hence back-propagation.

Un-supervised learning

Only the input is provided and the model decide on which method to utilize.

2.4.5 Designing ANNS

When designing the network of the ANN model, Network parameters and their values need to be identified. These parameters are; input variable, hidden layers, hidden layer nodes, learning rates, momentum rates, and network training. Additionally, specification of the type of network to be designed, size of the data, and activation function to be used is necessary.

2.5 Comparison of ANN, ARIMA and SARIMA

Adebiyi et al. (2014) did a comparison of ANN and ARIMA to model and forecast stock prices in Ghana. The empirical results revealed that the neural network is superior to ARIMA model.

Al-Maqaleh et al. (2016) forecasted the inflation rate in the Republic of Yemen using the consumer price index (CPI). The research utilized an Artificial neural network and classical statistical method, vector autoregressive model. The experimental results show that artificial neural networks give better predictive values due to their ability to deal with the nonlinear and stochastic data better than traditional statistical modeling techniques.

Estiko and Wahyuddin (2019) Compared the prediction performance of the neural network and ARIMA model on inflation rates of Indonesia. They discovered that NN models outperformed the ARIMA model since it had the lowest RMSE value.

2.6 Summary and Conclusion

From the literature, artificial neuron network have strength over linear models when focusing on forecasting. ANN are well adaptive with non-linear data and also have the ability of mapping inputs to outputs. This is not the case with linear models which are restricted by the assumption of linearity. The literature further points out that exchange rates and GDP have a significant influence on the inflation rate in Kenya therefore, this determinant will be utilized as inputs variables.

In Kenya, no research has been undertaken to model inflation rates using an Artificial Neural network and compared it with ARIMA and its extended version called SARIMA. This study is conducted to fill that gap.

Chapter 3

Methodology

3.1 Introduction

This chapter comprises the formulation of ANN, ARIMA, and SARIMA models and the methodology of comparing and forecasting the models.

3.2 ANN formulation

Input function

The inputs $X_1, X_2, \ldots, X_n$ are fed into the neuron. Each input is multiplied by a random weights to form sum and product ($\sum W_i X_i$. Inputs weights are used to regulate the input values to the artificial neuron and range between -1 and +1. The weighted inputs are constantly adjusted as ANN is trained to achieve convergence. The input function is shown mathematically below.

$$W_o + W_1X_1 + W_2X_2 + \cdots + W_nX_n = \sum_{i=1}^{n} W_iX_i \tag{3.1}$$

Where, W_o represent bias.

Activation function

An activation function is a limiting function that can be linear or not that represent the neuron state. The most used activation function is the logistic sigmoid which is represented as:

$$\Gamma(v) = \frac{1}{1+e^{-v}}$$

Output function

The information passes input and hidden layer and are displayed in the form of output in a single layer.

Backpropagation

The output layer receives a training input sample corresponding to each desired target sample, then the error is computed according to the following Equations;

$$s_k = |t_k - y_k| dy_k$$

Where,

s_k is the prediction error, t_k is the desired output, y_k is the output of the model and dy_k represent gradient descent.

3.2.1 Building ANN model

Splitting the data

The data was partitioned into three parts training, testing and validation on the proportion 70%, 20% and 10% respectively. Model training involved feeding inputs to the ANN model and conducting iterations 10,000 times by adjusting inputs weights until error is minimized. The training data set was used to access model prediction accuracy, while validation set was used to turn the model.

Architectural networks

Architecture structure and learning algorithm are crucial in developing ANN model. Architecture structures are determined by choosing the number of layers and neuron nodes in each layer and according to Saemi et al. (2007) there is no general rule of selecting the best architecture other than trial and error until the lowest error is achieved. The links that connect the neurons of a layer to the neurons of another layer are called weights. These weights are determined by a learning algorithm that updates their values. This study used a backpropagation algorithm which updates the weights based on the difference between the output value of the ANN and the desired real value.

To obtain the best model, the repeated trials on the training data set was applied until the lowest error is obtained.

The neuron obtains output by learning the patterns of the data. The general procedure of learning is outlined below.

1. Taking an input pattern from training data set
2. Obtain a neural net output with that input
3. Find the error between the neural network output and the desired output for the selected pattern.
4. Update the interconnecting weights using the found error in order to minimize that error
5. Repeat steps 1 to 4 for all the learning patterns, until minimum RMSE is attained.

Figure 3.1 shows the proposed neural network architecture with training error of 334.72 after 51 steps.

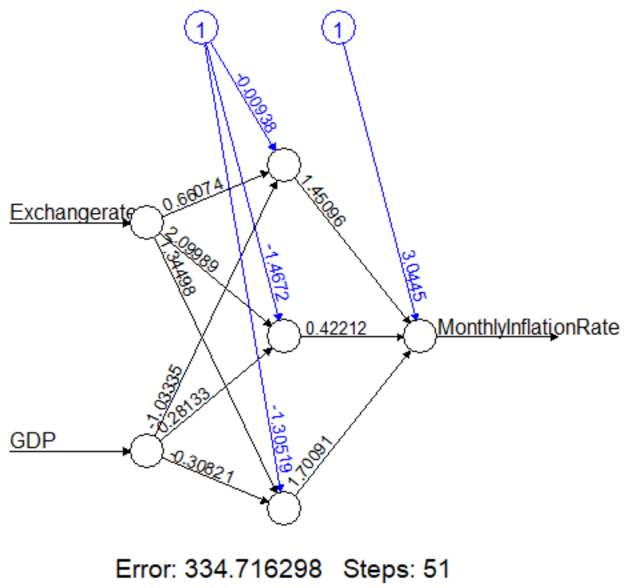


Figure 3.1: Proposed architectural networks

3.3 Formulation of ARIMA and SARIMA models

An ARIMA model is a combination of Autoregressive (AR) which shows the relationship between present and past values, a random value w_t and a Moving average (MA) model, which shows that the present values have something to do with the past residuals.

The ARIMA model is applied in the case where the series has no seasonal features. The series should to be stationary, implying the mean and variance should be time-invariant; otherwise, differencing of the data to be stationary is necessary. A nonseasonal ARIMA model is classified as an ARIMA (p,d,q) model where the parameter p refer to the the number of auto-regressive lags, the parameter d refers to the order of integration that make the data stationary and the parameter q give the number of moving average lags. The mathematical notation of ARMA (p,q) is:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + ... + \phi_p X_{t-p} + \theta_1 w_{t-1} + \theta_2 w_{t-2} + \cdots + \theta_q w_{t-j} + w_t \tag{3.2}$$

Which can be summarized as:

$$X_t = \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{j=1}^{q} \theta_j w_{t-j} + w_t \tag{3.3}$$

Where
$w_t \sim WN(0, \sigma_w^2)$; the errors follows normal distribution

$$\phi_1, \phi_2, .., \phi_p(\phi_p \neq 0), \theta_1, \theta_2, \cdots, \theta_q(\theta_q \neq 0) \tag{3.4}$$

are model parameters
w_t is random error term at time t
integers p and q are the order of the model.

Differencing of order d is define as

$$\bigtriangledown^d = (1 - B)^d \tag{3.5}$$

A process X_t is said to be ARIMA(p,d,q) if;

$$\bigtriangledown^d X_t = (1 - B)^d X_t \tag{3.6}$$

The mathematical notation of ARIMA(p,d,q) model by using lag polynomial is given as

$$\phi(B)(1 - B)^d X_t = \theta(B) w_t \tag{3.7}$$

where w_t follows a white noise (WN) process, B is the lag operator ,

$$\phi(B) and \theta(B) \tag{3.8}$$

are the auto-regressive operator and the moving average operator respectively and defined as follow:

$$\phi(B) = 1 - \phi_1(B) - \phi_2(B)^2 - \cdots - \phi_p(B)^2 \tag{3.9}$$

$$\theta(B) = 1 + \theta_1(B) + \theta_2(B)^2 + \cdots + \theta_q(B)^2 \tag{3.10}$$

$\phi(B) \neq 0$ and if $|B| < 1$ then X_t is stationary and if d=0 then the model collapse to ARMA (p,q)

The SARIMA model sometimes called the multiplicative seasonal auto-regressive integrated moving average model is denoted as SARIMA (p,d,q)$\times$(P,D,Q)$_s$.
Mathematical formulation of SARIMA(p,d,q)*(P,D,Q)$_s$ model of lag polynomial is given as:

$$\phi_p(B^s)\theta_p(B)(1-B)^d(1-B^s)^D X_t = \Theta_Q(B^s)\Phi_q(B)w_t \tag{3.11}$$

where

p, d and q order of non-seasonal AR, differencing and non-seasonal MA respectively
P, D, and Q order of seasonal AR, differencing and seasonal MA respectively
S represent seasonal order for example S=12 for monthly data
X_t represent the observable time series data at time t
w_t represent white noise or error term
B represent backward shift operator where, $BX_t = X_{t-1}$
$\phi_p(B^s)$ and $\theta_p(B)$ are the non seasonal and seasonal autoregressive operators respectively
$\Theta_Q(B^s)$ and $\Phi_q(B)$ are the non seasonal and seasonal moving average operators respec-

tively.

3.3.1 Splitting the inflation rates data

The inflation rates data were used as the only variable for modelling ARIMA and SARIMA. The model used 70% of the data to train the models (Jan 2012 -Dec 2019),while 30% to test forecasting performance of the models.

3.3.2 Data validation

For the data to be tested using time series models, it has to be stationary. If the inflation rate data are discovered to be non-stationary, then transformation through differencing is performed. The descriptive statistical summary and the distribution plot of the time series will be used at the initial stage to assert if the data are stationary.

3.3.3 Stationary check

For an ARMA model to be stationary the roots of the characteristics equation $\theta_p(B) = 0$ must lie outside the unit cycle, Likewise for the invertibility the root of $\Theta_Q(B^s) = 0$ must fall outside the unit cycle. For Seasonality stationarity the roots of the characteristics equation $\theta_p(B) = 0$ must lie outside the unit cycle. Similarly, for seasonal invertibility, the roots of the characteristics equation $\Phi_q(B) = 0$ must fall outside the unit cycle.
To model the series we check the structure of the data in order to obtain some preliminary knowledge about the stationarity of the series; whether there exist a trend or a seasonal pattern. A time series is said to a stationary if both the mean and the variance are constant over time. A time plot of the data is suggested to determine whether any transformation is needed before performing formal tests. If the data is non-stationary, we difference the data series to make them stationary. Then an Augmented Dickey-Fuller Test (ADF Test) is used to determine the stationarity of the data.

Augmented Dickey-Fuller Test (ADF Test

The ADF test is used to test for unit root. The testing procedure for the ADF test is the same as for the Dickey–Fuller test but it is applied to the model. A random walk with drift and trend is represented as;

$$\Delta X_t = \alpha + \beta_t + \gamma X_{t-1} + \delta_i \Delta X_{t-1} + \cdots + \delta_{p-1} \Delta X_{t-p+1} + w + t \tag{3.12}$$

where δ is a constant, β is the coefficient on a time trend and p the lag order of the autoregressive process. Imposing the constraints $\delta = 0$ and $\beta = 0$ corresponds to modeling a random walk and using $\beta = 0$the constraint corresponds to modelling a random walk with a drift.

The null-hypothesis for an ADF test: $H_0 : \gamma = 0$ verses $H_1 < \gamma = 0$

Where H_0 is the null hypothesis (has unit root) and H1: Does not have unit root.

The modelling of an ARIMA and SARIMA model as proposed by Box–Jenkins consist of model identification, model selection and diagnostic checks of the selected model.

3.3.4 Model identification

This involves the use of techniques to determine the value of p,q, P, Q by using Autocorrelation function (ACF) to determine order q and Q while Partial Auto correlation function (PACF) to determine the order of P and P. The number of times the data was seasonally and non.seasonally differentiated gives the value of d and D. The theoretical PACF has non-zero partial autocorrelations at lags 1, 2, ..., p and has zero partial autocorrelations at all lags, while the theoretical ACF has non zero autocorrelation at lags 1, 2, . . . , q and zero autocorrelations at all lags.

	AR (P)	MA (q)	ARMA (p,q)
ACF	Tail of at lag k	Cut off after lag q	Tail off
PACF	Cuts off after lag p	Tail off at lag k	Tail off
7			

Table 3.1: Behavior of ACF and PACF for Non-seasonal ARMA(p,q)

	AR (P)	MA (Q)	ARMA (P,Q)
ACF	Tail of at lag ks	Cut off after lag Qs	Tail off at lag ks
PACF	Cuts off after lag Ps	Tail off at lag ks	Tail off at lag ks
7			

Table 3.2: Behavior of ACF and PACF for Pure Seasonal ARMA(P,Q)S

3.3.5 Model selection

The second step involves the estimation of models parameters for the tentative models that have been selected to ascertain if they are the best models. The parameters with the lowest Akaike Information Criterion (AIC), Normalized Bayesian Information Criterion (BIC), and maximum log-likelihood values were considered the best model. These information criteria judge a model by how close its fitted values tend to be to true values, in terms of a certain expected value. The information criterion value assigned to a model is only meant to rank competing models1 and tell you which one is the best among the given alternatives. The criterion attempts to find the model that best explains the data with a minimum of free parameters but also includes a penalty that is an increasing function of the number of estimated parameters. This penalty discourages overfitting (Kuha, 2004). The maximum likelihood estimation (MLE) will also be used to estimate the ARIMA and SARIMA models. In the general case, the AIC, BIC and log likelihood take the form as shown below:

$$AIC = 2k - 2log(B) \tag{3.13}$$

$$BIC = -2log(B) + klog(n) \tag{3.14}$$

$$Log(B) = -\frac{n}{2}log(2\pi) - \frac{n}{2}log\delta^2 - \frac{1}{2\delta^2}\sum_{t=1}^{n} w_{t^2} \tag{3.15}$$

Where,

k represents the number of parameters in the model.

B is the likelihood of the data

δ is the constant variance and

n is the historical data

3.3.6 Diagnostic Checks

The estimated model has to be checked if it is really a series. Diagnostic checks are performed on residuals to ascertain if they are randomly and normally distributed. A plot of the ACF of the residuals is checked to confirm if they are white noise.

$$w_t \sim WN(0, \sigma_w^2)$$

An overall check of the model adequacy was made using the Ljung-Box Q statistics. Ljung-Box statistic proposed by Ljung and Box (1978) is used to check if a given observable series is linearly independent. The test usually check if there is higher order serial correlation in the residuals of a given model. The test examines the null hypothesis of the linearly Independence of the series. The Ljung - Box test statistic is given by:

$$\Theta(m) = N(N+2)\sum_{k=1}^{m}\frac{\hat{p_k}^2}{N-k} \tag{3.16}$$

Where,
N is the sample size
m is the number of times lags are included on the data
$\hat{p_k}^2$ is the sample autocorrelation at lag k
$\Theta(m)$ is the asymptomatic chi-square with m degrees of freedom.

3.4 Forecasting performance

The accuracy for each model can be checked to determine how the model performed in terms of in-sample forecast. In terms of out-sample forecasting, some of the observations are left out during model building. The accuracy of the model was compared using statistic such as mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE). The model with a minimum of MAE or RMSE is considered to be the best for forecasting. The mathematical expression are defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{X}_t - X_t)^2} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(w_t)^2} \tag{3.17}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|\hat{X}_t - X_t| = \frac{1}{n}\sum_{t=1}^{n}|w_t| \tag{3.18}$$

where X_t is the actual observation , $\hat{X}_t$ is the forecasted value and n is the sample size.

Chapter 4

Results

4.1 Data

The inflation rates data was sourced from KNBS websites, while the GDP and exchange rates data were available on the Central bank of Kenya website. The Kenyan constitution mandates these institutions to collect and keep accurate data for public use. For this reason, the data obtained are authentic.

4.2 Data description

The table below (Table 4.1) shows inflation rate descriptive statistics. The inflation data is not normally distributed since the mean and median are not equal.

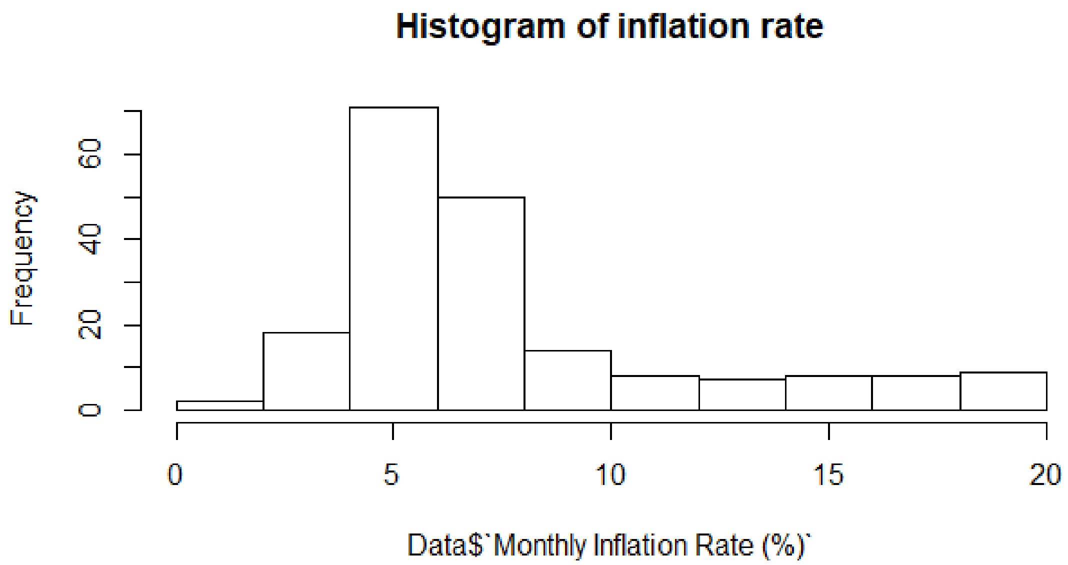


Figure 4.1: Histogram

From the histogram above (Figure 4.1) confirm also that the inflation rate data are

	Year	Monthly Inflation Rate (%)
X	Length:195	Min. : 1.850
X.1	Class :character	1st Qu.: 4.715
X.2	Mode :character	Median : 6.260
X.3		Mean : 7.628
X.4		3rd Qu.: 8.415
X.5		Max. :19.720

Table 4.1: Descriptive statistics of variable

skewed.

4.3 ANN evaluation

Network architecture [2-3-1] was proposed as the best network since it had the lowest errors (334.71). The analysis was computed using R programming software. 70% of the data was used for training and 30% as testing data.

4.3.1 Forecast performance

Table 4.2 below shows the actual inflation rates versus forecasted values using the ANNs model. From the results, the model predicted close to the actual values.

	Actual values	ANN forecast	Errors
2020 Jan	5.78	5.23	0.55
2020 Feb	7.17	6.61	0.56
2020 Mar	5.84	5.95	-0.11
2020 Apr	6.01	5.97	0.04
2020 May	5.33	5.28	0.05
2020 Jun	4.59	5.00	-0.41
2020 Jul	4.36	3.98	0.38
2020 Aug	4.36	4.57	-0.21
2020 Sep	4.20	4.31	-0.11
2020 Oct	4.84	4.72	0.12
2020 Nov	5.33	5.30	0.03
2020 Dec	5.62	5.98	-0.36
2021 Jan	5.69	6.57	-0.88
2021 Feb	4.67	6.89	-2.25

Table 4.2: Actual verses forecasted inflation rate data using ANN

4.4 ARIMA and SARIMA evaluation

4.4.1 Checking stationary

The time series plot of the inflation rate (Figure 4.2) shows that the data could be having a trend. Furthermore, the ACF plot exhibits a slow decay which signals that the data is not stationary. Additionally, the PACF plot in Figure 4.3 shows only one significant spike at lag 1. The Duckey- fuller test (ADF) and Kwiatkowski– Phillips–Schmidt–Shin (KPSS) test (Table 4.3) also indicates that the inflation data are not stationary. The intuition behind the ARIMA model and SARIMA model is the stationarity of the series (constant mean and variance). Hence data transformation through differencing was necessary to make the data stationary.

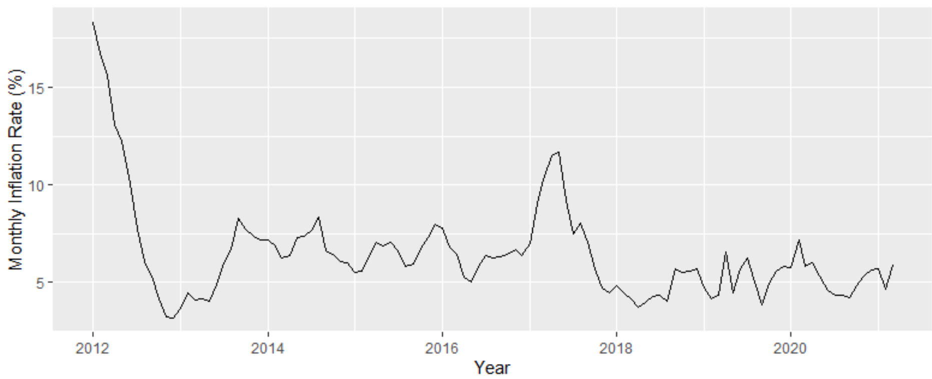


Figure 4.2: General trend of Kenyan's monthly inflation rate

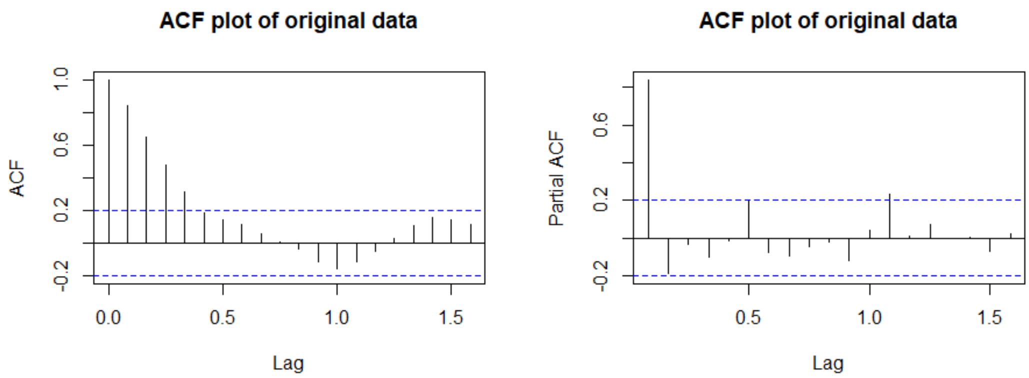


Figure 4.3: ACF and PACF of original inflation data

	p-value
ADF	0.06973
KPSS	0.02558

Table 4.3: p- values of original data

4.4.2 Making the inflation data Stationary

Differencing was applied to the data to make them stationary. After differencing of order one, the data became stationary, as shown by the plot in Figure 4.4, with no trend and having constant mean and variance oscillating around zero. The ADF and KPSS also confirmed that the data are stationary after order 1 (Table 4.4). The data had no seasonal component because there were no significant spikes at multiples of 12, as shown by the ACF plot in Figure 4.5.

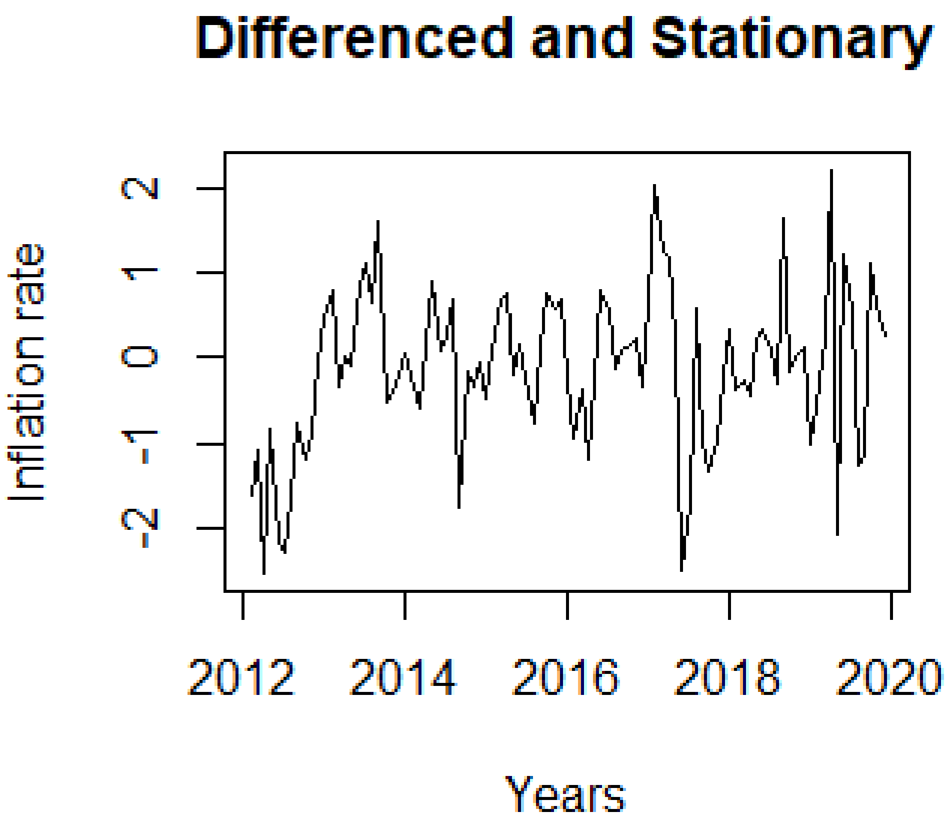


Figure 4.4: plot of differenced data

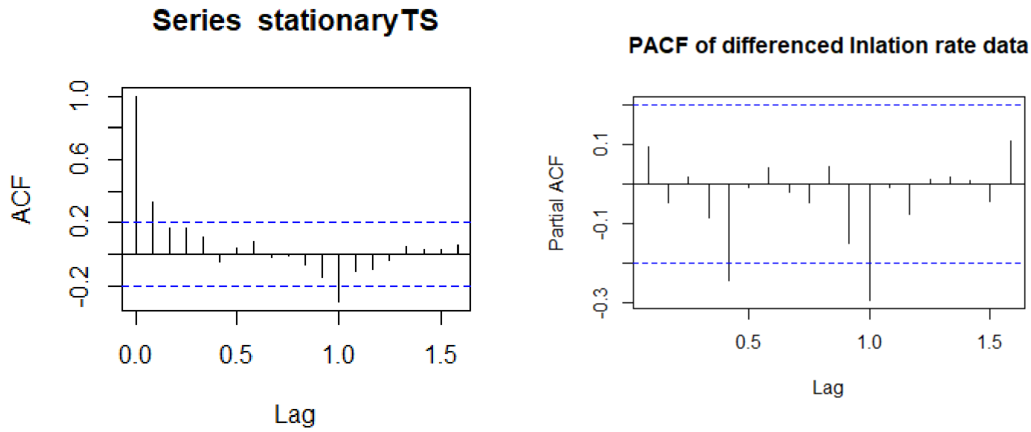


Figure 4.5: ACF and PACF plot of differenced data

	p-value
ADF	< 0.01
KPSS	> 0.05

Table 4.4: P- values of differenced data

4.4.3 ARIMA parameters identification

The most appropriate way to estimate the terms for seasonal and non-seasonal Autoregressive models (ARIMA) is to look at the autocorrelation plot and partial autocorrelation plot of stationary data, which is tentative order of p,d, P, Q. From Figure 4.5, ACF plot indicates MA(1) while, PACF plot shows an AR(1) and differencing of order I(1) was used to transform the data. This give rise to a tentative model of order ARIMA(1,1,1). Other possible non-seasonal Auto regressive models are ARIMA(1,1,0), ARIMA(0,1,1), ARIMA(2,1,1), ARIMA(1,1,2), ARIMA(0,1,0) and ARIMA(1,1,3).

4.4.4 Model selection

Table 4.5 below gives a list of models with their respective values of log-likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC).

From the table above ARIMA (0,1,1) was considered the best model with the least AIC value (244.59) and low standard errors (0.854) compared to the other models. The next step was to check if its residuals satisfy the properties of the white noise. We expect residuals of the model to be random with constant mean and non changing variance.

Order	AIC	BIC	log likelihood	variance	std
ARIMA(1,1,1)	245.54	253.17	119.77	0.7303	0.855
ARIMA(1,1,0)	276.85	281.94	-136.42	1.076	1.037
ARIMA(0,1,1)	244.59	249.67	-120.29	0.7289	0.854
ARIMA(2,1,1)	247.38	257.56	-119.69	0.7365	0.858
ARIMA(1,1,2)	247.34	257.51	–119.67	0.7364	0.858
ARIMA(0,1,0)	292.82	295.36	-145.41	1.292	1.137
ARIMA(1,1,3)	249.33	262.05	-119.66	0.744	0.862

Table 4.5: AIC,BIC and log likelihood of suggested ARIMA models

4.4.5 Checking residuals of $ARIMA(0, 1, 1)$

From Figure 4.6 below, it's notable that the model's residuals satisfy the properties of white noise, with residuals being random and follows normal distributions. The ACF and PACF function of residuals also have no significant spike beyond the confidence band.

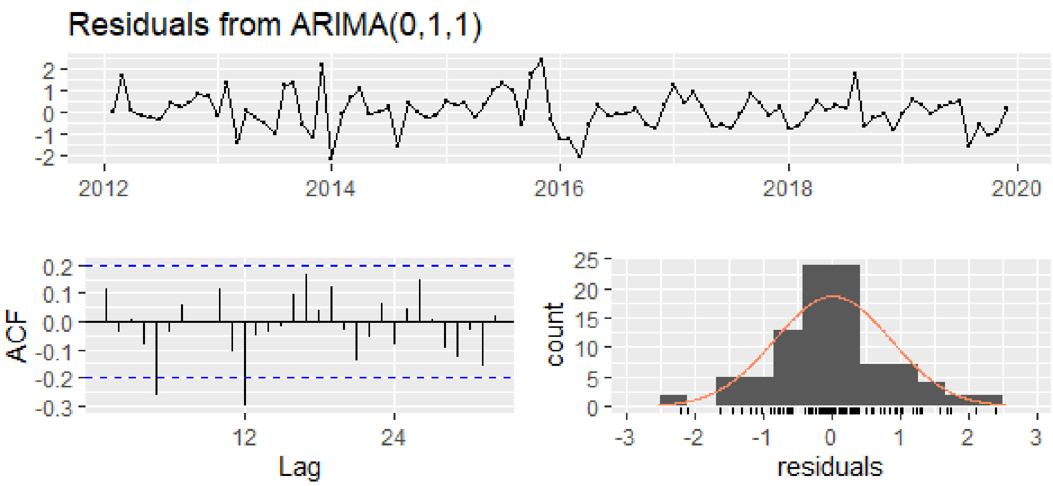


Figure 4.6: Residuals of ARIMA(0,1,1)

4.4.6 SARIMA parameters identification

SARIMA is the seasonal part of ARIMA. The ACF and PACF plots in Figure 4.5 show a significant spike outside the band at lag 10. This signal that seasonal moving average or seasonal autoregressive could be present in the data. The seasonal integration is zero since the data was not seasonally differenced, i.e., I(0). From the Figure 4.5 we can have a tentative order of $SARIMA(0, 1, 1)(1, 0, 1)_{12}$. Other possible models combination are shown in Table 4.6.

4.4.7 Model selection

We then selected the best model based on the lowest AIC and BIC and the maximum log-likelihood values.

Order	AIC	BIC	log likelihood	variance	std
SARIMA(1,1,1)(1,0,1)	234.9	247.62	-112.45	0.7303	0.8546
SARIMA(0,1,1)(1,0,1)	233.39	243.56	-112.65	1.076	1.037
SARIMA(1,1,1)(1,0,1)	234.9	247.62	-115.55	0.7289	0.8538
SARIMA(0,1,1)(0,0,1)	232.41	240.04	-113.21	0.7365	0.8582
SARIMA(0,1,0)(0,0,1)	284.01	281.1	-140.01	0.7364	0.8581
SARIMA(0,1,1) (0,0,2)	233.01	233.46	-243.18	1.292	1.1367

Table 4.6: AIC, BIC and log likelihood

From the Table 4.6 above, SARIMA$(0,1,1)(0,0,1)_{12}$ was the best with lowest AIC (232.41) and lowest BIC value of 240.14.

4.4.8 Checking residuals of SARIMA$(0,1,1)(0,0,1)_{12}$

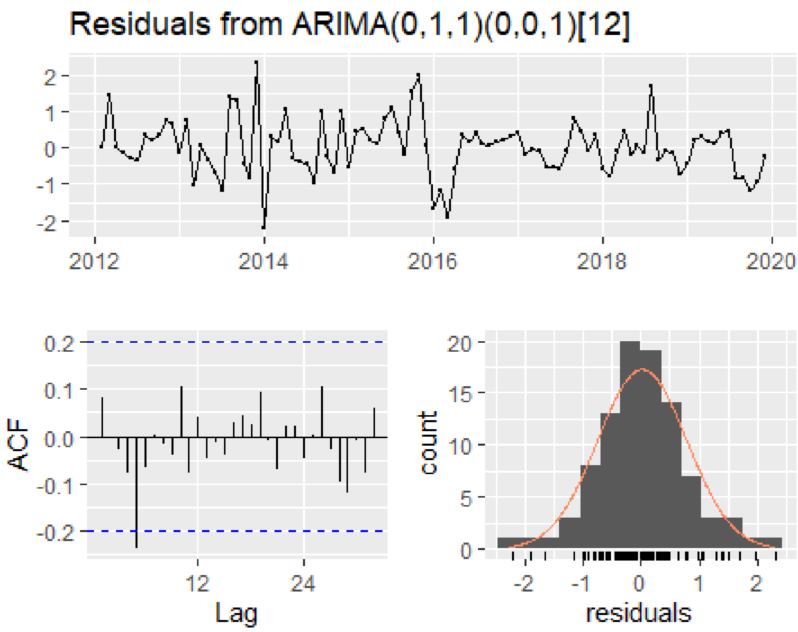


Figure 4.7: Plot of residuals diagnostics

After identifying the best model, we check residuals if they are indeed white noise.

A good model should have residuals without trend, no outlier and should have constant mean and variance. Furthermore, the ACF plot of residuals shouldn't have significant spikes. The chosen model is a good fit since the ACF plot (Figure 4.7) confirmed that residuals are white noise with its residuals following a normal distribution.

Thus SARIMA(0,1,1)(0,0,1)$_{12}$ is suitable for forecasting inflation.

4.5 Comparing forecasting performances

After fitting the three models ARIMA, SARIMA and ANN, using the training data set, we then evaluated their performances using the testing data set as shown in Table 4.7.

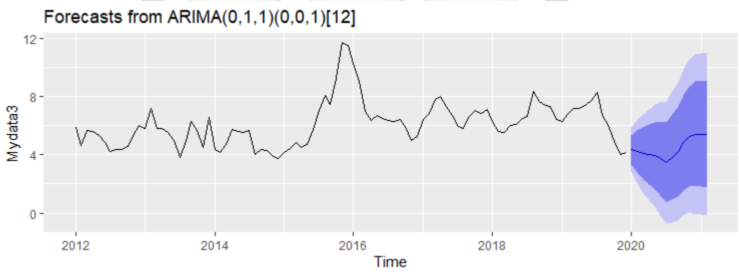


Figure 4.8: Forecasted plot

	Actual data	ARIMA forecast	SARIMA forecast	proposed ANN
2020 Jan	5.78	4.51	4.35	5.23
2020 Feb	7.17	4.83	4.25	6.61
2020 Mar	5.84	5.09	4.09	5.95
2020 Apr	6.01	5.29	4.00	5.97
2020 May	5.33	5.45	3.94	5.28
2020 Jun	4.59	5.57	3.72	5.00
2020 Jul	4.36	5.67	3.47	3.98
2020 Aug	4.36	5.75	3.85	4.57
2020 Sep	4.20	5.81	4.24	4.31
2020 Oct	4.84	5.86	4.82	4.72
2020 Nov	5.33	5.90	5.29	5.30
2020 Dec	5.62	5.93	5.42	5.98
2021 Jan	5.69	5.95	5.42	6.57
2021 Feb	4.67	5.97	5.42	6.89
RMSE	-	0.79	0.75	0.58

Table 4.7: Actual data verses forecast inflation data

4.6 Models comparison

Finally, we assess the prediction accuracy of the three models. The most suitable model for forecasting the Kenyan inflation rate should have the lowest RMSE, MAE and MAPE and from the results in Table 4.8, we concluded that an artificial neural network is the most suitable model for inflation rates prediction.

	RMSE	MAE	MAPE
$SARIMA(0,1,1)(0,0,1)_{12}$	0.7589	0.5634	9.7559
$ARIMA(0,1,1)$	0.7983	0.5788	9.8204
ANNs	0.5836	0.3359	7.3526

Table 4.8: Comparing forecasting performance

4.7 12 months forecast

Artificial Neural Networks (ANN) has emerged as the best prediction model; thus, we computed twelve months inflation prediction (March 2021 to Feb 2022) alongside their 95% confidence intervals. The forecast in Table 4.9 shows an increasing trend.

	Forecast	lower bound	Upper bound
2021 Mar	5.90	5.40	6.40
2021 Apr	5.98	5.48	6.48
2021 May	5.99	5.49	6.49
2021 Jun	6.05	5.55	6.6.55
2021 Jul	6.12	5.62	6.62
2021 Aug	6.14	5.64	6.64
2021 Sep	6.27	5.77	6.77
2021 Oct	6.39	5.89	6.89
2021 Nov	6.43	5.93	6.93
2021 Dec	6.48	5.98	6.98
2022 Jan	6.50	6.00	7.00
2022 Feb	6.67	6.17	7.17

Table 4.9: 12 months forecast of inflation rate

Chapter 5

Conclusion and Recommendation

5.1 Conclusion

The Central bank of Kenya (CBK) and policymakers are expected to advise the government and other stakeholders on the appropriate strategies to maintain a favourable macroeconomic environment. It will go a long way in benefiting the economy by attracting investors and spur economic growth.

This study used two-time series models (ARIMA and SARIMA) and artificial intelligence (ANN) to model and forecast the Kenyan inflation rates. The artificial neural network model performed better than statistical techniques implying that inflation rates are non-linear.

The study observed that the ANNs model was able to forecast inflation values with minimum errors. We also achieved this level of accuracy by varying the number of hidden layers. The study points out that the backpropagation algorithm used in an artificial neural network is an efficient tool for forecasting inflation values.

An important area of focus for the Central bank of Kenya should be using emerging machine learning techniques to enhance inflation and other macroeconomic forecasting. This would help in improving the resulting policy-making decision based on accurate feedback from the predicted values.

The first objective was the formulation of an artificial intelligence model for forecasting the inflation rate. This objective was achieved through the development of an ANN model with four hidden layers and with backpropagation algorithms. The model presented forecasts with minimal errors making it the best prediction technique.
The study also achieved the second objective with artificial intelligence being superior to statistical methods. This is credited to ANN having no prior assumptions.

We finally computed a 12 months inflation prediction with confidence intervals. This would help policymakers and planners to see inflation ahead of time.

5.2 Recommendation and Further studies

The following are the recommendations done from the findings of the study.

(i) The study recommends adopting an artificial neuron network for forecasting the inflation rate in Kenya.

(ii) Inflation forecasting should be viewed as a crucial part of the processing of developing feasible policy measures for mitigating inflation rates.

(iii) More consideration needs to be made on the suitability of the model on other data that are not stochastic.

Further studies are recommended on other machine learning algorithms like Random forest and decision trees.

Bibliography

Adebiyi, A. A., Adewumi, A. O., and Ayo, C. K. (2014). Comparison of arima and artificial neural networks models for stock price prediction. *Journal of Applied Mathematics*, 2014.

Al-Maqaleh, B. M., Al-Mansoub, A. A., and Al-Badani, F. N. (2016). Forecasting using artificial neural network and statistics models. *International Journal Education and Management Engineering*, 3:20–32.

Banerjee, A., Marcellino, M., and Masten, I. (2005). Leading indicators for euro-area inflation and gdp growth. *Oxford Bulletin of Economics and Statistics*, 67:785–813.

Barro, R. J. et al. (1996). Inflation and growth. *Review-Federal Reserve Bank of Saint Louis*, 78:153–169.

Durevall, D. and Ndung'u, N. S. (2001). A dynamic model of inflation of kenya, 1974-96. *Journal of African Economies*, 10(1):92–125.

Estiko, F. I. and Wahyuddin, S. (2019). Analysis of indonesia's inflation using arima and artificial neural network. *Economics Development Analysis Journal*, 8(2):151–162.

Gyebi, F. and Boafo, G. K. (2013). Macroeconomic determinants of inflation in ghana from 1990-2009. *International journal of business and social research (IJBSR)*, 3(6):81–93.

Haider, A. and Hanif, M. N. (2009). Inflation forecasting in pakistan using artificial neural networks. *Pakistan economic and social review*, pages 123–138.

Hall, P. and Welsh, A. H. (1985). Adaptive estimates of parameters of regular variation. *The Annals of Statistics*, pages 331–341.

Huang, Y., Wang, X., and Hua, X. (2010). What determines china's inflation? *China Economic Journal*, 3(1):69–86.

Ianc, M. M. F. and Ciurlău, L. (2016). The price stability-important lever within the economy. *Ovidius University Annals, Economic Sciences Series*, 16(2):498–501.

Iya, I. and Aminu, U. (2014). An empirical analysis of the determinants of inflation in nigeria. *Journal of Economics and Sustainable Development*, 5(1):140–150.

Jaradat, M., Al-Zeaud, H. A., and Al-Rawahneh, H. (2011). An econometric analysis of the determinants of inflation in jordan. *Journal of Middle Eastern Finance and Economics*, 15:121–132.

Khashei, M. and Bijari, M. (2011). A novel hybridization of artificial neural networks and arima models for time series forecasting. *Applied soft computing*, 11(2):2664–2675.

Kirimi, W. N. (2014). *The determinants of inflation in Kenya (1970–2013).* PhD thesis, University of Nairobi.

Kubilius, J., Schrimpf, M., Kar, K., Hong, H., Majaj, N. J., Rajalingham, R., Issa, E. B., Bashivan, P., Prescott-Roy, J., Schmidt, K., et al. (2019). Brain-like object recognition with high-performing shallow recurrent anns. *arXiv preprint arXiv:1909.06161.*

Kuha, J. (2004). Aic and bic: Comparisons of assumptions and performance. *Sociological methods & research*, 33(2):188–229.

Ocampo, J. A. (2008). A broad view of macroeconomic stability. *The Washington consensus reconsidered*, pages 63–94.

Ochieng, O., MS, M., and Gideon, M. (2016). The determinants of inflation in the kenyan economy.

Pindiriri, C. (2012). Monetary reforms and inflation dynamics in zimbabwe. *International Research Journal of Finance and Economics*, 90:207–222.

Pollin, R. and Zhu, A. (2009). Inflation and economic growth: A cross-country non-linear analysis. In *Beyond inflation targeting*. Edward Elgar Publishing.

Saemi, M., Ahmadi, M., and Varjani, A. Y. (2007). Design of neural networks using genetic algorithm for the permeability estimation of the reservoir. *Journal of Petroleum Science and Engineering*, 59(1-2):97–105.

Stock, J. H. and Watson, M. W. (1998). A comparison of linear and nonlinear univariate models for forecasting macroeconomic time series.

Yusif, M. H., Eshun Nunoo, I. K., and Effah Sarkodie, E. (2015). Inflation forecasting in ghana-artificial neural network model approach.

Appendix A

Budget

Item	**Amount (Ksh.)**
Wifi	Ksh 9,000.00
Printing materials	Ksh 1,500.00
Travelling	Ksh 1,200.00
Airtime	Ksh 3,000.00
Cyber café	Ksh 1,000.00
Total	**Ksh 15,700.00**

Appendix B

Similarity report

15th November 2021

Mr Kiprono Victor,
victor.kogei@strathmore.edu

Dear Mr Kiprono,

RE: Forecasting of the Inflation Rates in Kenya: A Comparison of Arima and Sarima

This is to inform you that SU-IERC has reviewed and **approved** your above **SU-master's** research proposal. Your application reference number is **SU-IERC1130/21.** The approval period is **15th November 2021 to 14th November 2022.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-IERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-IERC within 48 hours of notification
iv. Any changes, anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-IERC within 48 hours
v. Clearance for export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days upon completion of the study to SU-IERC.

Prior to commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

for: Prof Fred Were,
Chairperson; SU-IERC

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