GOLD SALES FORECASTING: THE BOX-JENKINS METHODOLOGY

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Abstract

The study employs the Box-Jenkins Methodology to forecast South African gold sales. For a resource economy like South Africa where metals and minerals account for a high proportion of GDP and export earnings, the decline in gold sales is very disturbing. Box-Jenkins time series technique was used to perform time series analysis of monthly gold sales for the period January 2000 to June 2013 with the following steps: model identification, model estimation, diagnostic checking and forecasting. Furthermore, the prediction accuracy is tested using mean absolute percentage error (MAPE). From the analysis, a seasonal ARIMA(4,1,4)×$(0,1,1)_{12}$ was found to be the "best fit model" with an MAPE value of 11% indicating that the model is fit to be used to predict or forecast future gold sales for South Africa. In addition, the forecast values show that there will be a decrease in the overall gold sales for the first six months of 2014. It is hoped that the study will help the public and private sectors to understand the gold sales or output scenario and later plan the gold mining activities in South Africa. Furthermore, it is hoped that this research paper has demonstrated the significance of Box-Jenkins technique for this area of research and that they will be applied in the future.

Keywords: Gold Sales, ARIMA, Box-Jenkins, GDP, MAPE
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1. INTRODUCTION

The Box-Jenkins methodology has gained more popularity since their book publication in 1970. The Box-Jenkins method which does not require establishing assumptions on the interdependence of variables could be used to test applicability on data series undergoing dynamic fluctuation. More significantly, this technique does not introduce too much personal bias into the process of forecasting. The Box-Jenkins technique is considered as a suitable forecasting tool when the components describing the time series are fluctuating quite rapidly over time (Bowerman and O'Connell, 1993; Wong et al., 2005). At the same time, the Box-Jenkins method is a reliable and convenient tool among numerous common time series skills. Therefore, this research paper adopted the Box-Jenkins methodology to construct a forecasting model for South Africa gold sales. The technique is based on the idea that a time series in which successive values are highly dependent can be regarded as being generated from a series of independent shocks. Analysing such series leads to the class of Autoregressive Integrated Moving Average (ARIMA) models. An autoregressive (AR) process is fundamentally a regression equation where a variable is related to its own previous values instead of to a set of independent variables (Chatfield, 2000).

The gold mining sector played a substantial role as a basis industry in the evolution of South African industry. The gold mining industry has been the dominant foreign exchange earner for the country over the past century. More recent statistics indicate that gold export earnings in 1980 accounted for over 50% of South Africa's merchandise exports in that year. However, recent figures published by Statistics South Africa show that South Africa has been slipping down the table from the world's top producer less than a decade ago to sixth position. According to the Mineweb (2013), China is currently leading, followed by Australia, the USA, Russia and Peru in that order. In 1970, South Africa produced almost 80% of global gold production now it manages only around 6%, which is a very big fall (Mineweb, 2013). There has been a noticeable decline in gold production (extraction) and mining contribution to South Africa's Gross Domestic Product (GDP). In terms of employment, the mining industry reported an annual decrease of over 6% from December 2008 to December 2009 (StatsSA, 2013). South Africa's mineral industry is export-oriented, due to the small domestic market for most commodities.

In another report by Statistics South Africa (2013), annual mineral sales was estimated to have decreased by 8.5% in May 2013 and the largest negative growth rates were recorded for gold with a value of -42.6%, i.e. from May 2012 to May 2013, gold sales decreased by 42.6% as illustrated in Table 1. This was the largest negative growth rate observed for gold sales in 2013.

Table 1. Year-on-year percentage change in gold sales at current prices

Date	% change
December 2012	-16.1
January 2013	12.4
February 2013	-9.1
March 2013	3.3
April 2013	-13.6
May 2013	-42.6

There is a general decline in the gold sales over the years and this could have long negative results in the future. According to an article in the Mineweb (2013),

"More recent statistics indicate that gold export earnings in 1980 accounted for over 50% of South Africa's merchandise exports in that year. However, recent figures published by Statistics South Africa show that South Africa has been slipping down the table from the world's top producer less than a decade ago to sixth position".

The following could be listed as contributing factors: sudden changes in gold demand levels, price-cutting manoeuvres of the competition, strikes, large swings of the economy, interest rates, inflation rates and seasonality. A decline in gold sales has affected many related sectors and contributed negatively towards South Africa's annual GDP. The forecasting of gold sales is essential to help in calculating the volume of mining production which affects GDP and its components. The main objective of this study is to apply a Box-Jenkins' ARIMA model approach to model South Africa's monthly gold sales and to use the identified ARIMA model to forecast future South African gold sales and the other objective is to compare the year-on-year percentage change findings with the Statistics South Africa gold findings.

The paper is set out as follows. Section 2 discusses some of literature relating to our study. Section 3 briefly outlines the methodological framework. Section 4 presents the results and discussions. Concluding remarks is given in section 5.

2. LITERATURE REVIEW

Ping, Miswan and Ahmad (2013) carried out a study on forecasting the prices of Kijang Emas, the official Malaysian gold bullion. Their study employed two methods, which are Box-Jenkins ARIMA and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). Using Akaike's information criterion (AIC) as the goodness of fit measure and mean absolute percentage error (MAPE) as the forecasting performance measure, they found that the gold prices data can be characterized by GARCH (1,1) model. Their conclusion was based on the fact that GARCH (1,1) had both a lower SIC and MAPE value than ARIMA (1,1,1) in forecasting its future values.

Mahipan, Chutiman and Kumphon (2013) applied both Box-Jenkins and Artificial Neural Network methods to prediction the rate of unemployment in Thailand. In their paper, they determined the stationary and seasonality of the data and the Augmented Dickey-Fuller test.

(ADF) and autocorrelation (ACF) were used respectively. The ADF test for stationary showed that the series had a unit root implying that the original series was non-stationary. The data became stationary after first order difference. Examination of the correlogram indicated that Seasonal ARIMA model was appropriate. The Box-Jenkins methodology proved more efficient to estimate the rate of unemployment in Thailand. MAPE was used to show that SARIMA, SARIMA$(0,1,1)_{12}$ provided satisfactory representation of the unemployment rate data.

Khan (2013) applied Box-Jenkins' ARIMA approach for building forecasting model using the gold price sample (in US$ per Ounce). The results showed that ARIMA(0,1,1) is the most appropriate model to be used for forecasting the gold price. Patel (2013) investigated the role of gold as a strategic prophecy against inflation and exchange rate and found that gold can act as a hedge against inflation and exchange rate in two different ways. Firstly, gold price act as an internal hedge against inflation of the country. This means, that if inflation increases, gold price would also increase. Secondly, gold price also acts as an external hedge. This means if exchange rate decrease, price of gold will increase. Ranson (2005) examined the role of gold and oil as predictor of inflation. He found that gold price is more reliable barometer of the inflation than oil price because the effect on official inflation statistics is reliably indicated by how far policy actions have allowed the price of gold to rise.

3. METHODOLOGY

The study present uses a monthly general gold production data for the period January 2000 to June 2013. The Box-Jenkins methodology employed in this study is based on the analysis of pattern changes in the past history of the observations and it uses a four-phase approach (Box, Jenkins and Reinsel, 1994). Namely: tentative model identification, model estimation, diagnostic checking and forecasting.

3.1. Tentative Model Identification

A plot of the original data should be run as the initial point in determining the most appropriate model. Stationarity tests can be performed to determine if differencing is necessary. Besides looking at the graphical presentation of the time series values over time to determine stationary or non-stationary, the sample ACF also gives visibility to the data. Non-stationary data displaying trend behaviour can be transformed through regular differencing. In this study more focus is based on first and second regular differencing.

The initial work on stationarity testing came from Dickey and Fuller (1979), who conceptualised the technique as "testing for a unit root". This is a formal test employed in this study to check for stationarity in the time series data. Within the framework of the Box-Jenkins methodology, there is an overall model which can be decomposed into three basic models. The ARIMA can be decomposed into an AR, Moving Average (MA) and Autoregressive Moving Average (ARMA) model.

3.2. Model Estimation

This phase involves estimation of the parameters of the models identified (specified) in the first phase. The least squares approach is employed in model estimation.

3.3. Diagnostic Checking

Diagnostic testing in the Box-Jenkins methodology essentially involves the statistical properties of the error terms (normality assumption, weak white noise assumption) as well as common testing procedures on the estimates. As mentioned earlier, ε_t is expected to follow a white noise process. Graphical procedure and formal testing procedure can be used to test adequacy of the model. In the graphical procedure a plot of the residuals is examined to check for outliers. To check the overall acceptability of the overall model, the Ljung-Box (1978) test can be used as follows:

H_0: Model is adequate versus H_1: Model is inadequate

Test statistic:

$$Q^* = n^{'}(n^{'}+2)\sum_{l=1}^{k}\frac{1}{n^{'}-l}r_l^2(\hat{a}) \qquad (1)$$

where $n^1 = n - d$, n is the number of observations and d is the degree of non-seasonal differencing used to transform the original time series values into stationary. The $r_l^2(\hat{a})$ is the square of the autocorrelation of the residuals at lag l (Bowerman, O'Connell and Koehler, 2005). If the p-value is greater than significant level α or equivalently Q^* is less than chi-square distribution, the null hypothesis cannot be rejected concluding that the model is adequate. According to Verbeek (2004), if a model is rejected at this stage; the model-building cycle has to be repeated.

3.4. Forecasting

The final and most important stage of the Box-Jenkins process is forecasting. There are two broad types of forecasts: one step ahead forecasts are generated for the next observation only whereas multi-step ahead forecasts are generated for 1,2,3,…..,s steps ahead. Many researchers suggest that Box-Jenkins' ARIMA is the most accurate forecasting model. ARIMA wins over other models; Holt's forecast model and a combination of Box-Jenkins and Holt's in regression, by providing lowest mean MAPE (Warant, 2006). There are many simple measures of prediction accuracy, for instance the mean squared error (MSE), mean absolute error (MAE) and mean squared deviation (MSD). However the most appropriate simple error measure for this study is the MAPE given by the following equation:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_t - f_t|}{y_t} \qquad (2)$$

This test statistic can be used to compare the accuracy of forecasts based on two entirely different series (Hanke and Wichern, 2005). According to Lewis (1982), the level of accuracy for the MAPE test is divided into four stages as shown in Table 2. Each level of accuracy gives the percentage of the accuracy of predicted value compared to the original time series value (Muda and Hoon, 2012).

Table 2. Level of accuracy for MAPE test

MAPE value	Level of accuracy
MAPE ≤ 10%	Very accurate
10% < MAPE ≤ 20%	Accurate
20% < MAPE ≤ 50%	Medium
50% ≤ MAPE	Less accurate

4. RESULTS AND DISCUSSION

This section of the study carries out the four Box-Jenkins technique's steps to analyse the gold sales data.

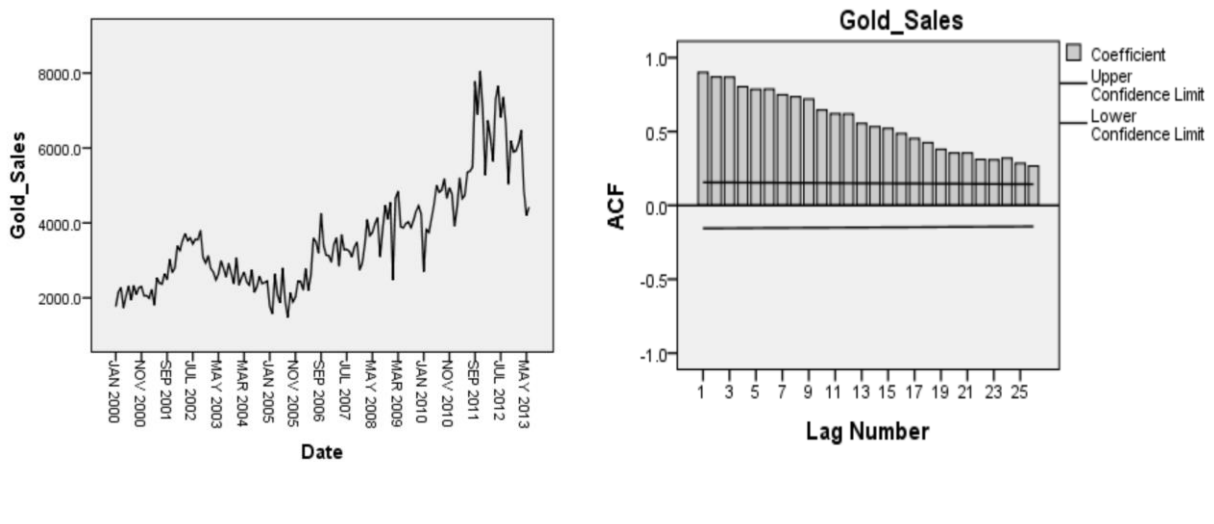
4.1. Step 1: Model Identification

The first step in developing a Box-Jenkins model is to determine if the series is stationary and if there is any observed pattern. The data is plotted as shown in Figure 1 below.

Figure 1. Original Plot of Gold Sales

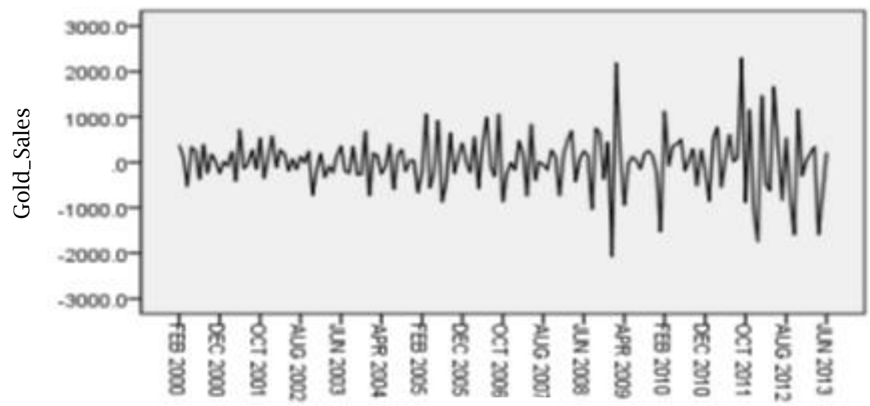
(a) Gold series plot

(b) ACF plot of the original data



The series in figure 1(a) appears to be increasing over time even though there seems to be a decline (negative trend component) between 2002 and 2005. Moreover, there are irregular fluctuations in the series. This is evidence that the gold sales data is not stationary. The ACF plot also proves that the time series is nonstationary because an extreme slow decay is observed in figure 1(b). The next step is to transform the data to be stationary by (regular) first differencing.

Figure 2. First differenced plot of the Gold sales



Date

Transforms: difference (1)

The first differenced series in figure 2 above seems to fluctuate around the zero mean, implying that it is stationary with respect to mean. A more formal approach is also used to test for stationarity.

4.1.1. Unit root test

H_0: The first differenced Gold sales data has a unit root

H_1: The first differenced Gold sales data does not have a unit root

Table 3. Unit root test

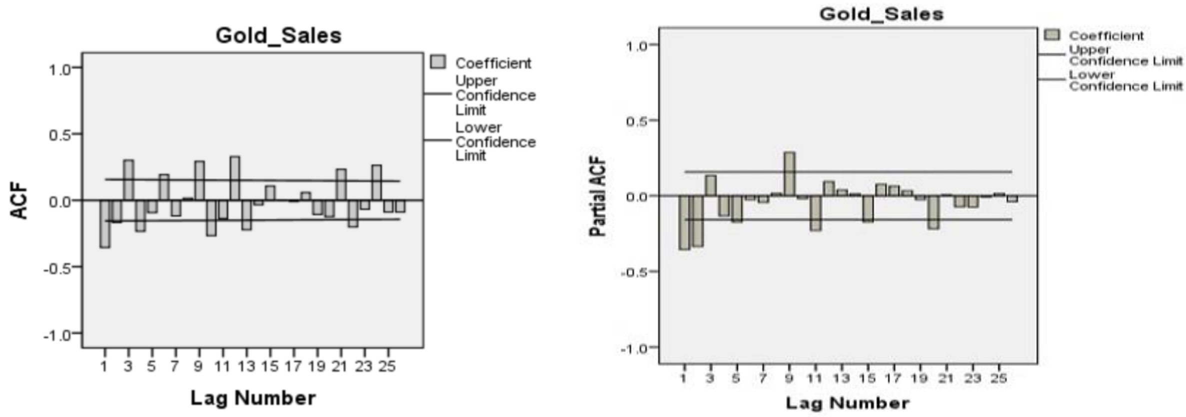
Variable	t-Statistic	Prob.
D(GOLD_SALES)	-9.851796**	0.0000

*Note: *, **, *** indicates the Mackinnon critical values for ADF at 1%, 5% and 10% levels are -3.475, -2.882 and -2.578 respectively.*

The Augmented Dickey Fuller Test statistic │ADF│= 9.85>2.88 therefore we reject the null hypothesis. Also the p-value for ADF is 0.00 which is less than 5% level of significance. This implies that the first differenced data does not have a unit root and hence it is stationary.

Figure 3. ACF and PACF plot of the first differenced data

(a) ACF plot of Gold sales (b) PACF plot of Gold sales



Looking at the ACF and PACF plots in Figure 3, the ACF has spikes up to lag 4 and dies down in a damp sine-wave fashion while the PACF decays quicker after lag 5. This implies that MA(4) and AR(5) model might be appropriate for the data. Spikes are also observed at lag 12, 24 in the ACF plot. The spike at lag 9 has been ignored because according to Bowerman *et al.* (2005), spikes at higher lags are sometimes ignored to simplify the initial tentatively identified model. From the behaviour of the ACF and PACF above, it can be concluded that the Gold_Sales data has is seasonal component and that the first differencing did not take away that component. Seasonal differencing is then performed on the differenced Gold sales series using the formula below:

$$z_t = y_t - y_{t-12} \quad (3)$$

Figure 4. ACF and PACF plot after first differencing and seasonal differencing

(a) ACF plot of Gold sales

(b) PACF plot of Gold sales

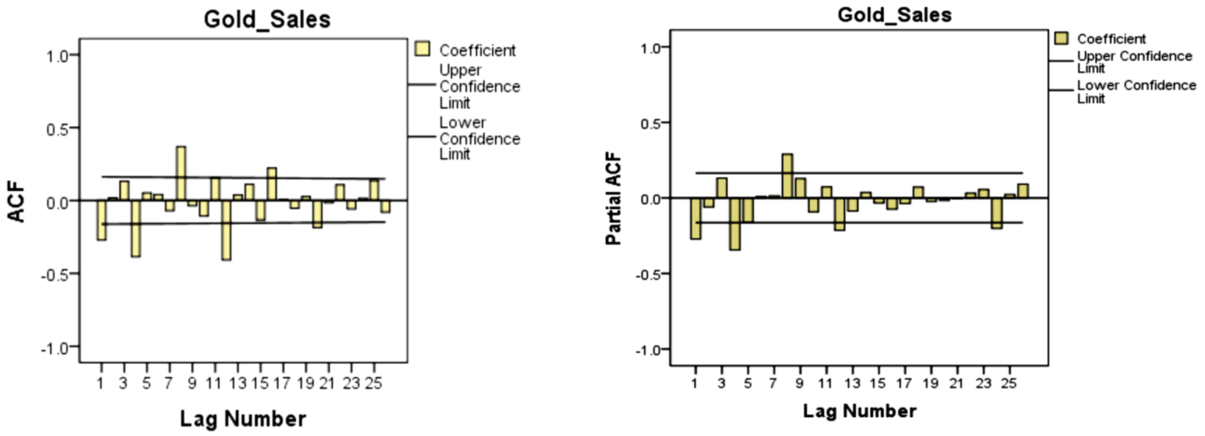


Figure 4 shows the ACF and PACF plots of Gold sales data after seasonal differencing. In order to tentatively identify a Box-Jenkins seasonal model, the behaviour of the ACF and PACF plot is examined at lags s=12, 24 etc; the ACF plot cuts off after lag 12 (there is no correlation at lag 24) and the PACF dies down fairly quickly in a damped exponential fashion after lag 12. This implies that the model should include a seasonal moving average term ε_(t-12) (Bowerman, O'Connell and Koehler, 2005). It is now clear in these plots that both the ACF and PACF decay quicker after lag 4 indicating that seasonal ARIMA(4,1,4)×$(0,1,1)_{12}$ is appropriate. Since it is already mentioned that the model should probably also be described by using the non-seasonal process ARIMA(5,1,4). The model SARIMA(5,1,4)$(0,1,1)_{12}$ is estimated.

Step 2: Estimation and Selection

Table 4 summarise the output for estimating the model SARIMA(5,1,4)$(0,1,1)_{12}$. In table 4(b), the parameter estimates are given together with their t-ratios and their significance level (p-value). For the non-seasonal AR(p) progress it is concluded that lag 1,2,3 and 5 are not significantly different from 0 at 5% level of significance because their p-values are greater than 0.05. Only ∅_4 of lag 4 is significantly different from 0 (p-value=0<0.05) and hence a non-seasonal AR(4) model is appropriate. Similarly for non-seasonal MA(q) progress only θ_4 of lag 4 is significantly different from 0, implying that MA(4) is suitable for the Gold sales data. The seasonal SMA(P) progress is highly significant at lag 1, which shows that the $SMA(1)_{12}$ is identified correctly. The p-value associated to a constant mean δ is much greater than the significant level, so the constant term should not be included in the model.

Table 4(a). Model Statistics

Model	Number of predictors	Model Fit Statistics		Ljung-Box Q(18)			Number of Outliers
		R-squared	Normalized BIC	Statistics	DF	Sig.	
Gold_Sales-Model_1	0	0.877	12.878	9.095	8	0.334	0

Table 4(b). ARIMA Model Parameters

				Estimate	SE	T	Sig.
Gold_Sales-Model_1	Gold_Sales No transformation	Constant		-3.122	9.437	-0.331	0.741
		AR	Lag 1	-0.226	0.398	-0.567	0.572
			Lag 2	-0.068	0.210	-0.326	0.745
			Lag 3	-0.129	0.175	-0.738	0.462
			Lag 4	-0.782	0.142	-5.515	0.000
			Lag 5	-0.360	0.196	-1.841	0.068
		Difference		1			
		MA	Lag 1	0.228	0.402	0.568	0.571
			Lag 2	-0.017	0.380	-0.044	0.965
			Lag 3	-0.141	0.278	-0.508	0.612
			Lag 4	-0.493	0.205	-2.410	0.017
		Seasonal Difference		1			
		MA, Seasonal	Lag 1	0.674	0.088	7.670	0.000

Table 4(a) shows that this model has an R^2 of 0.877 implying that about 87.7% of the variations in Gold_Sales data have been accounted for by the model; however this model has been over-parameterized because additional parameters which have been proven to be insignificant are included unnecessarily. Thus, the objective is to choose the model with minimum BIC. Other models have also been fitted as a model selection step. Competing models are shown in table 5 below.

All the 4 models seem to be suitable for Gold_Sales data because they have large R^2 value; however the model with the minimum information criterion indicates better fit. Therefore, Model 4 is chosen. Table 6 shows the parameter estimates for the chosen model.

Table 5. Comparison of Models

No	Model	R-squared	BIC	Ljung-Box Q*
1	$SARIMA(5,1,4) \times (1,1,1)_{12}$	0.877	12.878	9.095
2	$SARIMA(5,1,4) \times (0,1,1)_{12}$	0.877	12.838	9.083
3	$SARIMA(4,1,4) \times (1,1,1)_{12}$	0.879	12.824	9.841
4	$SARIMA(4,1,4) \times (0,1,1)_{12}$	0.862	12.709	16.138

Table 6. Model Parameters for $SARIMA(4,1,4) \times (0,1,1)_{12}$

				Estimate	SE	T	Sig.
Gold_Sales-Model_4	Gold_Sales No Transformation	AR	Lag 4	-0.630	0.131	-4.794	0.000
		Difference		1			
		MA	Lag 1	0.408	0.076	5.372	0.000
			Lag 4	-0.331	0.138	-2.405	0.017
		Seasonal Difference		1			
		MA, Seasonal	Lag 1	0.666	0.087	7.629	0.000

The estimated parameter in table 6 gives the following equation:

$$z_t = -0.630z_{t-4} - 0.408\varepsilon_{t-1} + 0.331\varepsilon_{t-4} - 0.666\varepsilon_{t-12} + \varepsilon_t \quad (4)$$

The next step is to perform diagnostic checks to test of the selected model is adequate to be used for further analysis.

4.2. Step 3: Diagnostic Checking and Forecasting

The value of Ljung-Box's Q* is given in Table 5 as Q = 16.138 with a p-value of 0.305. Since the p-value is greater than 5% level of significance, we fail to reject the null hypothesis and conclude that there is enough statistical evidence to infer that the chosen model is adequate. SARIMA(4,1,4)×$(0,1,1)_{12}$ is adequate enough to be used for further analysis. Diagnostic checking has shown that SARIMA(4,1,4)×$(0,1,1)_{12}$, met the assumptions, so this model is used to forecast values for the next months, from July 2013 to June 2014. The MAPE is carried out using the following formula to determine the level of accuracy of the predicted values:

$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_t - f_t|}{y_t} = 11.003\%$

The MAPE value falls between 10% and 20%, which means that the prediction of gold sales can be concluded as accurate and the fitted model of SARIMA(4,1,4)×$(0,1,1)_{12}$ can be used for forecasting the gold sales in South Africa. Table 7 shows the forecasted Gold_Sales values for the next twelve months.

Table 7. Gold sales forecasts

Month	Forecast	Lower CI limit	Upper CI limit	Month	Forecast	Lower CI limit	Upper CI limit
Jul-13	4478.5	3427.8	5529.2	Jan-14	3644.8	1905.6	5384
Aug-13	4979	3758.2	6199.8	Feb-14	4517.3	2684.7	6349.9
Sep-13	5879.1	4509.2	7249	Mar-14	4860.8	2870.9	6850.7
Oct-13	4927.8	3423.5	6432.1	Apr-14	4169.7	2089.8	6249.7
Nov-13	5360.6	3825.2	6896	May-14	4588.1	2421.9	6754.4
Dec-13	4748.8	3108.3	6389.2	Jun-14	4848.8	2599.6	7098.1

Looking at values on table 7, one can say the overall sales for 2014 will drop. The forecasted year-on-year percentage change for January 2014 is calculated as follows: From the original gold sales data; the gold sales for January 2013 was 5926.1 and the forecasted value for January 2014 is 3644.8, thus the forecasted percentage change is calculated as follows:

$$\frac{(3644.8 - 5926.1)}{5926.1} * 100 = -38.5 \quad (5)$$

The gold sales are estimated to have an annual decrease of 38.5% and this change is estimated to fall between -67.8% and 9.1%.

5. CONCLUSIONS

The time series model that had been identified for the gold sales data is seasonal ARIMA(4,1,4)×$(0,1,1)_{12}$. Diagnostic checking and accuracy test proved that this model is adequate and fit enough to be used for forecasting South Africa's gold sales data. In addition, the forecast values shows that there will be a decrease in the overall gold sales for the first six months of 2014. The largest decrease is predicted to be in January. The South African gold sales are predicted to have a year-on-year decrease of 38.5% in January 2014, and this change is estimated to fall between -67.8% and -9.1%. One can infer that the year-on-year percentage change is predicted to improve when compared to Statistics South Africa's June findings where they found the year-on-year percentage change in May to be -42.6%. The findings of this study will help the private and public sectors to understand the gold sales or output scenario and later plan the gold mining activities in South Africa. The findings of this study should also form a useful basis for researchers and practitioners to explore the applicability of the Box–Jenkins method in modelling gold sales. In conclusion Box–Jenkins method seems to have a stronger avenue for modelling gold sales as such a method has been regarded as an accurate, reliable, simple and widely applicable time-series model by researchers (O'Donovan, 1983; Wheelwright and Makridakis, 1985; Goh and Teo, 2000).

The Box-Jenkins procedures, although used extensively in price forecasting, have been used very rarely for gold sales, it is hoped that this paper has demonstrated the relevance of this technique for this area of research and that they will be applied in the future. It is recommended that future work should consider using GARCH models to provide a volatility clustering measure of the gold series.

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