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A COMPARISON OF DECOMPOSITION TIME SERIES METHOD AND WINTERS' SEASONAL EXPONENTIAL SMOOTHING IN FORECASTING SEASONAL TEMPERATURE IN NIGER STATE, NIGERIA

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ABSTRACT: *In economics and in other fields of life, it is traditional to decompose time series into a variety of components while on the other hand, exponential smoothing is a procedure for continually revising an estimate in the light of more recent experiences. This work set out to compare the forecasting performances of two simple univariate time series analysis, the decomposition and winters' methods. To achieve this, the methods were applied to stationary and normally distributed data, and stationary time series that is not normally distributed. In the two data sets considered, the results revealed that the decomposition method outperformed the winters' seasonal exponential smoothing method. We therefore conclude that both methods are capable forecasting short sample time series, and that the decomposition method forecast better.*

KEYWORDS: Decomposition, Time series, Winters' method, Seasonal, Exponential smoothing, Forecasting and temperature.

INTRODUCTION

Forecasting is one of the main objectives of the time series analysis. Forecasting is the art of saying what will happen in the future. In Cooray, (2008) forecasting as a discipline should satisfy the following criteria: objective, validity, reliability, accuracy, confidence and sensitivity.

In time series analysis, there are many forecasting technique that are normally used to forecast time series data with trend and seasonality. The models include decompositions, exponential smoothing method, Winters' seasonal method and Box-Jenkins seasonal ARIMA methodology that are normally applied to univariate time series data (Cooray, 2008; Salvatore and Reagle, 2002). Though these methods seem simple, it has been found that they yield better forecast similar to that of more complex models (Suhartono and Subanar, 2005; Taylor, 2003; Shoesmith and Pinder, 2001; Faraway and Chatfield, 1998; Chatfield and Yar, 1988; Abraham and Ladolter, 1986; Roberts, 1982; Makridakis, Hibon, and Moser 1979). While other author have suggested that forecast can be improved upon by combination of other method. For instance, some suggested combining judgmental and statistical forecasts (Lawrence, Edmundson and O'Connor, 1986), combination of forecasting techniques (Russell and Adams, 1987).

In this present work, we will compare decomposition and Winters' seasonal methods under two different settings (i). when the time series data is stationary and normally distributed (ii).

When the time series data is stationary and but does not follow a normal distribution. This becomes necessary because of the importance of testing the time series characteristics (Hendry and Juselius, 2000; Engle and Kozicki, 1993).

The aim of this paper therefore is to compare decompositions and Winters' seasonal method on time series data under the two settings earlier stated. And thereafter apply these forecasting techniques on seasonal temperature time series data in Niger State, Nigeria.

MODEL SPECIFICATION

Decomposition of Time Series Data

In economics and other fields of life, it is traditional to decompose time series into a variety of components, some or all which may be present in a particular instance (Pollock, 1993). Given Y_t, Y_t can be decomposed into the following form

$$Y_t = T_t + C_t + S_t + \varepsilon_t \quad \text{(Additive Model)}$$
$$Y_t = T_t \times C_t \times S_t \times \varepsilon_t \quad \text{(Multiplicative Model)}$$

where T_t is the trend; C_t is the cyclical; S_t is the seasonal variation and ε_t is the irregular component

There two distinct purposes for which we might wish to effect such decompositions

1. To give a summary decomposition of the salient features of the time series
2. To predict future values of a particular time series data.

Detailed on the decomposition of time series data are reported in Kirchgassner and Wolters (2007); Suhartono and Subanar, (2005); Falk, (2006); Cryer and Chen, (2008).

The main advantages of the decomposition method are the relative simplicity of the procedure and the minimal start-up time. The disadvantages include not having sound statistical theory behind the method, the entire procedure must be repeated each time a new data point is acquired, and, no outside variables are considered. However, the decomposition method is widely used with much success and accuracy, especially for short term forecasting (Cooray, 2008).

Winters' Seasonal Exponential Smoothing

Winters' seasonal exponential smoothing is an iterative process in which we smooth the data using different combination of the weights. The combination that produces the smallest MAPE, MAD or MSD is the optimal set of weights. The Winters' seasonal exponential smoothing technique employs the smoothing process in three periods. They include to estimate the average level, to estimate the slope component, to estimate the seasonal component of the time series. The Winters' method is able to account for some error in the forecast by the updating procedure.

The equations of the Winters' method are as follows

(i). To update the level (a) or average level of the series

$$a_t = \alpha\left[\frac{y_t}{S_i(t-1)}\right] + (1-\alpha)(a_{t-1} + b_{t-1})$$

(ii). To update the slope (b)

$$b_t = \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1}$$

(iii). To update the seasonal component (S_i)

$$S_{i(t+1)} = \gamma\left[\frac{y_t}{a_t}\right] + (1-\gamma)S_{it}(t-L)$$

(iv). To obtain, a one step ahead forecast

$$\hat{y}_{t+1}(t) = (a_{t-1} + b_{t-1})S_{it+1}(t+1-L)$$

where $\alpha =$ smoothing constant for level $(0<\alpha<1)$; $\beta =$ smoothing constant for trend estimate $(0<\beta<1)$; $\gamma =$ smoothing constant for seasonality estimate $(0<\gamma<1)$; L = length of seasonality

detailed are reported in Cooray, (2008), and, Suhartono and Subanar, (2005).

Data

We generated a set of time series data that is stationary and normally distributed given as Y_t~N(33.828,8.8566) for n=144 and n=288 using MINITAB software. Secondly, we collected a data set of monthly maximum temperature from January 1981 to December 2010 for Niger State, Nigeria. The data was obtained from the National Cereals Research institute (NCRI) meteorological station, Badeggi, Niger State, Nigeria.

Measures of Accuracy

Mean Absolute Error or Deviation (MAE or MAD) has a formular $MAD = \frac{\sum_{i=1}^{n}|e_i|}{n}$. this error measure deviations from the series in absolute terms, which means, regardless of whether the errors are positive or negative. This measure tells us how much our forecast is biased. This measure is one of the most common ones used for analyzing the quality of different forecasts. MAPE, or Mean Absolute percentage Error, measures the accuracy of fitted time series values. It is expressed as a percentage. Is given as $MAPE = \frac{\sum_{i=1}^{n}\left|\frac{e_t}{x_t}\right|}{n}x100$.

MSD stands for Mean Squared Deviation. MSD computed using the same denominator, n, regardless of the model. So one can compare MSD values across models. It is given by $MSD = \frac{\sum_{i=1}^{n} |e_t|^2}{n}$. In summary, for all the three measures, the smaller the value, the better the fit of the model (Cooray, 2008; Fildes and Makridakis, 1995; Drury, 1990).

Analysis and Results

In this work, we generated data that is stationary and normally distributed. The time series data was generated by Y_t~(33.828,8.8566) for sample sizes n=144 and n=288. In this section we will reports only the optimal results. The results are reported in table 1.

Table 1: Results from the Generated time series data

Methods	Parameters	MAPE	MAD	MSD
Decomposition	n=144	6.71888	2.25646	8.50314
Winters’	α=0.2,β=0.1,γ=0.1; n=144	7.63089	2.54529	9.94617
Decomposition	n=288	7.07229	2.34701	9.12920
Winters’	α=0.09,β=0.05,γ=0.06; n=288	7.7893	2.5846	10.1197

Source: The Authors

The table 1 shows results from decomposition and winters’ methods for sample sizes n=144 and n=288. The results revealed that MAPE, MAD and MSD for decomposition are less than that of the winters’ method. This shows that for the sample sizes considered, the decomposition method outperformed the winters’ method.

In the second case considered was on the time series data collected from NCRI, Badeggi, Niger State for seasonal temperature from January 1981 to December 2010. In the analysis we used the data from January 1981 to December 2009 that is (n=348) while the remaining data from January 2010 to December 2010 were used for comparing the forecasts from both methods considered. We are to note here that the temperature data is stationary but not normally distributed.

Table 2: Results for seasonal temperature from January 1981 to December 2009 for Niger State.

Methods	Parameters	MAPE	MAD	MSD
Decomposition	n=348	2.60037	0.81723	1.95951
Winters'	α=0.15,β=0.16,γ=0.16; n=348	3.18111	1.02186	2.15208

Source: The Authors

The table 2 shows the MAPE, MAD and MSD for the decomposition method and for the winters' method. The result revealed that the MAPE, MAD and MSD for decomposition method were lowest compare to that of the winters' method. This further shows that the decomposition method is more superior to the winters' method in terms of forecasting accuracy.

Table 3: The actual temperature and the forecasts from the decomposition and winters' methods

Months(2010)	Actual Temperature ^{O}C	Decomposition forecast	Winters' Forecast
Jan	35	34.6792	34.8626
Feb	38	37.2961	37.7269
Mar	38	38.3314	39.0849
Apr	38	37.1880	37.5192
May	35	34.5359	34.9397
Jun	33	32.5378	32.9533
Jul	31	30.8497	30.5874
Aug	31	30.8882	30.5510
Sep	31	31.1279	31.4063
Oct	32	33.0770	33.1420
Nov	35	34.9682	35.4335
Dec	35	34.4363	35.3710

Source: The Authors

The table 3 shows the actual temperature data and the forecasts from the decomposition and winters' method. The result shows that the decomposition method forecast more accurately compared to winters' method.

DISCUSSION OF RESULTS

This work set out to compare the forecasting accuracy or performances of two simple univariate time series analysis. The methods employed are the decomposition and winters' methods, while the MAPE, MAD and MSD criteria were used in selecting the best model that forecast accurately. The methods were applied to both generated data and real life data. In the first case, time series data were generated by Y_t~(33.828,8.8566) for sample sizes n=144 and n=288, the data was both stationary and normally distributed. The results from the analysis revealed that the decomposition method forecast better than the winters' method because the decomposition method possess the smallest MAPE, MAD and MSD respectively.

Further, the decomposition and winters' methods were applied to seasonal temperature data collected from NCRI, Badeggi, Niger State from January 1981 to December 2009 (n=348). The data was stationary but not normally distributed. In this case also, decomposition method outperformed the winters' method with the smallest MAPE, MAD and MSD respectively. And lastly, the forecast from both decomposition and winters' methods were compared to the actual temperature data which further revealed that the decomposition method forecast better than the winters' method, this result is similar to the results obtained by Suhartono and Subanar, (2005).

CONCLUSION

In this work two simple univariate time series models were considered. We concluded that the decomposition and the winters' methods are capable to forecast better for short sample time series. In the two methods considered, the decomposition method forecast accurately.

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