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On Holt Winters Algorithm with Decomposition for Forecasting Financial Time Series with Complex Seasonal Patterns

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Abstract

One of the most important challenges when analyzing and forecasting the time series is the stability of the series and determining components of the time series such as trend and seasonal. Exponential Smoothing methods can be thought of as peers and alternatives to Box-Jenkins ARIMA class of time series forecasting methods, but the most important aspect of the exponential smoothing approach is that the time series does not have to be stable. The study introduces reviewing and comparing a variety of Exponential Smoothing models; Simple Exponential Smoothing (SES), Holt's Linear Exponential Smoothing or Double Exponential Smoothing (DES) and Holt Winters Algorithm or Triple Exponential Smoothing (TES). Additionally; creation temporal patterns to forecast the monthly stock returns of the Saudi Stock Index by using a variety of Exponential Smoothing models. The results of the study concluded that the Holt Winters Algorithm or triple exponential smoothing model is the best model since it produces the lowest Mean Absolute Percentage error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Deviation (MSD) values which are 4,380, 244783 compared to 4, 385, 246837 for SES, and 5, 410, 270734 for DES, and thus can be used to predict the monthly stock returns of the Saudi Stock Index.

Keywords: Single Exponential Smoothing, Holt's Linear Exponential Smoothing, Holt Winters Algorithm, Moving Average, Financial Time Series Analysis.

1. Introduction

Exponential smoothing is a time series forecasting technique for univariate data that can be extended to incorporate data with a systematic trend or seasonal component. It is a potent forecasting technique that can be used instead of the well-known Box-Jenkins ARIMA family of methods. The Box-Jenkins ARIMA methods generate a model whose prediction is a weighted linear sum of recent past observations or lags. While exponential smoothing forecasting methods share the property that a prediction is a weighted sum of previous observations, the model explicitly assigns an exponentially decreasing weight to previous observations. Previous observations are weighted based on a geometrically decreasing ratio. Rob J. Hyndman and George Athanasopoulos (2013) indicate, *"Forecasts produced using exponential smoothing methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older. In other words, the more recent the observation, the higher the associated weight."*

The most important aspect of the exponential smoothing approach is that the time series does not need to be stable (see; [10], [13], [16], [17], [18]).

2. Literature Review

Univariate and multivariate time series analysis are two categories of time series analysis. Using the exponential function, time series data can be smoothed using the exponential smoothing technique. The analysis can now include model data with trends and seasonal components thanks to various forms of exponential smoothing. Because of its ease of use and efficiency, exponential smoothing is regarded as one of the most popular time series forecasting techniques. By giving varying weights to different time periods according to their significance, it can adjust to shifts in data trends and generate precise predictions. Charles C. Holt

develops on linear exponential smoothing, which is also known as double exponential smoothing. It has two smoothing parameters, α and γ, and is used to forecast time series data with a linear trend but no seasonal pattern (see; [2], [3], [4], [5], [7], [8], and [14]).

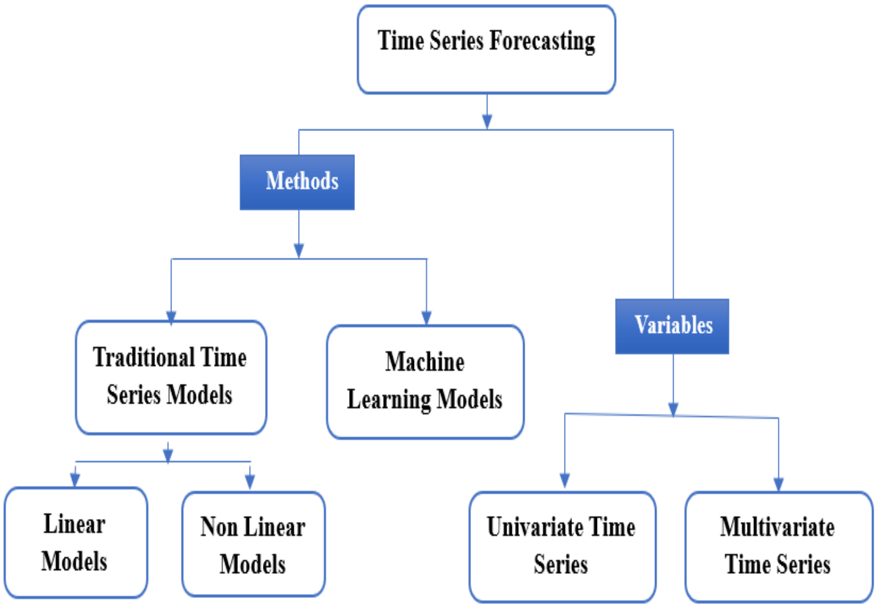

Figure (1): The Time Series Forecasting Methods

Figure (1) displays classification of time series forecasting techniques.

There are three main types of exponential smoothing. The simplest of the exponentially smoothing methods is called simple exponential smoothing or single exponentially smoothing (SES), is a time series forecasting method for univariate data without a trend or seasonality. It assumes that the time series has no trend or seasonality and it models one component (α). The forecast for the next period is based on the weighted average of the previous observation and the forecast for the current period. Equation (1) shows the formula for simple exponential smoothing.

$$S_t = \alpha x_t + (1-\alpha)S_{t-1} \qquad (1)$$

Where S_t is the smoothed value at time t, x_t is the observed value at time t, S_{t-1} is the previous smoothed statistic, and α is the smoothing parameter between 0 and 1. The smoothing parameter α controls the weight given to the current observation and the previous forecast (See; [17], [18], [19]).

Charles C. Holt (1957) extended simple exponential smoothing to allow the forecasting of data with a trend, which is known as Holt's linear method or double exponential smoothing. It uses two smoothing parameters, α and γ, to forecast time series data with a linear trend but no seasonal pattern. Equations (2) and (3) consist of Holt's linear method formulas.

$$S_t = \alpha x_t + (1-\alpha)(S_{t-1} + b_{t-1}) \quad (2)$$
$$\beta_t = \beta(s_t - s_{t-1}) + (1-\beta)b_{t-1} \quad (3)$$

Where b_t is the slope and best estimate of the trend at time t, α is the smoothing parameter of data $(0 < \alpha < 1)$, and β is the smoothing parameter for the trend $(0 < \beta < 1)$; (See; [1], [3], [6], [8], [9], [12]).
Charles C. Holt (1957) and Winters, P. R. (1960) extended Holt's method to capture seasonality. This method is called Holt Winters method or Triple exponential smoothing, which is extends Holt's method with a seasonality component. It is suitable for stochastic data series with stationery and non-seasonality that call for forecasts in the following structure:

$$s_0 = x_0$$
$$s_t = \alpha \frac{x_t}{c_t - L} + (1-\alpha)(s_{t-1} + b_{t-1}) \quad (4)$$
$$b_t = \beta(s_t - s_{t-1}) + (1-\beta)b_{t-1} \quad (5)$$
$$c_t = \gamma \frac{x_t}{s_t} + (1-\gamma)c_{t-L} \quad (6)$$

Where s_t is smoothed statistic; it's the simple weighted average of current observation Y_t, s_{t-1} is previous smoothed

statistic, α is smoothing factor of data $(0 < \alpha < 1)$, t is time period, b_t is best estimate of a trend at time t, β is trend smoothing factor $(0 < \beta < 1)$, c_t is seasonal component at time t, and γ is seasonal smoothing parameter $(0 < \gamma < 1)$; (See; [3], [8], [9], [12], [18]).

Holt Winters Algorithm is the most accurate of the three methods of Exponential Smoothing methods. Holt Winters' method should be used when the time series data has trend and seasonality.

$$S_t = \alpha[x_t + (1-\alpha)x_{t-1} + (1-\alpha)^2 x_{t-2} + \cdots + (1-\alpha)^{t-1}x_1] + (1-\alpha)^t x_0 \qquad (7)$$

Where $x_{t-1}, x_{t-2}, \ldots$ are past observations; x_t is the current observation.

Exponential functions are utilized to determine weights that decrease exponentially with time. The three most widely used forms of exponential smoothing are the Holt-Winters method, trend-corrected exponential smoothing, and simple exponential smoothing. Holt's technique was expanded upon by Winters in order to account for seasonality (See; [10], [11], [14], [18], [19]).

Figure (2): Classification of Univariate Time Series Methods

Figure (2) shows classification of univariate time series methods.

The remainder of the paper has been organized as follows: The study problem is presented in Section (3). The study's objective is stated in Section (4). In Section (5), the data set and software are introduced. In Section (6), Results and Discussion are introduced. Section (7) contains a conclusion and remarks.

3. Problem of the Study:

The stability of the series and its categorized components (trend and seasonal components) present important challenge. Thus, the most accurate time series prediction results can be achieved through a thorough examination of the time series' elements, specifically its trend and seasonality.

4. Objectives of the Study:

This study aims to address potential fixes for the following difficulties:

- **The time series data's analysis and identification of its trend and seasonal components.**
- **Introducing and discussing Single Exponential Smoothing, Holt's Linear Exponential Smoothing, and Holt Winters Algorithm, as well as comparing their performance in financial time series forecasting.**

5. Data Set and Software:

The study's database consists of monthly stock returns for the Saudi stock index obtained from the Tadawul stock exchange in Saudi Arabia between January 2016 and December 2020. The study employed MINITAB and SPSS software.

6. Results and Discussion:

6.1Analysis of Saudi' Stock Market

A non-stationary time series is one whose statistical characteristics vary over time. Therefore, a time series that exhibits seasonality or a trend is non-stationary. This is due to the fact that the mean, variance, and other

characteristics at any given time are impacted by the trend or seasonality. Identifying stationarity in time series data:

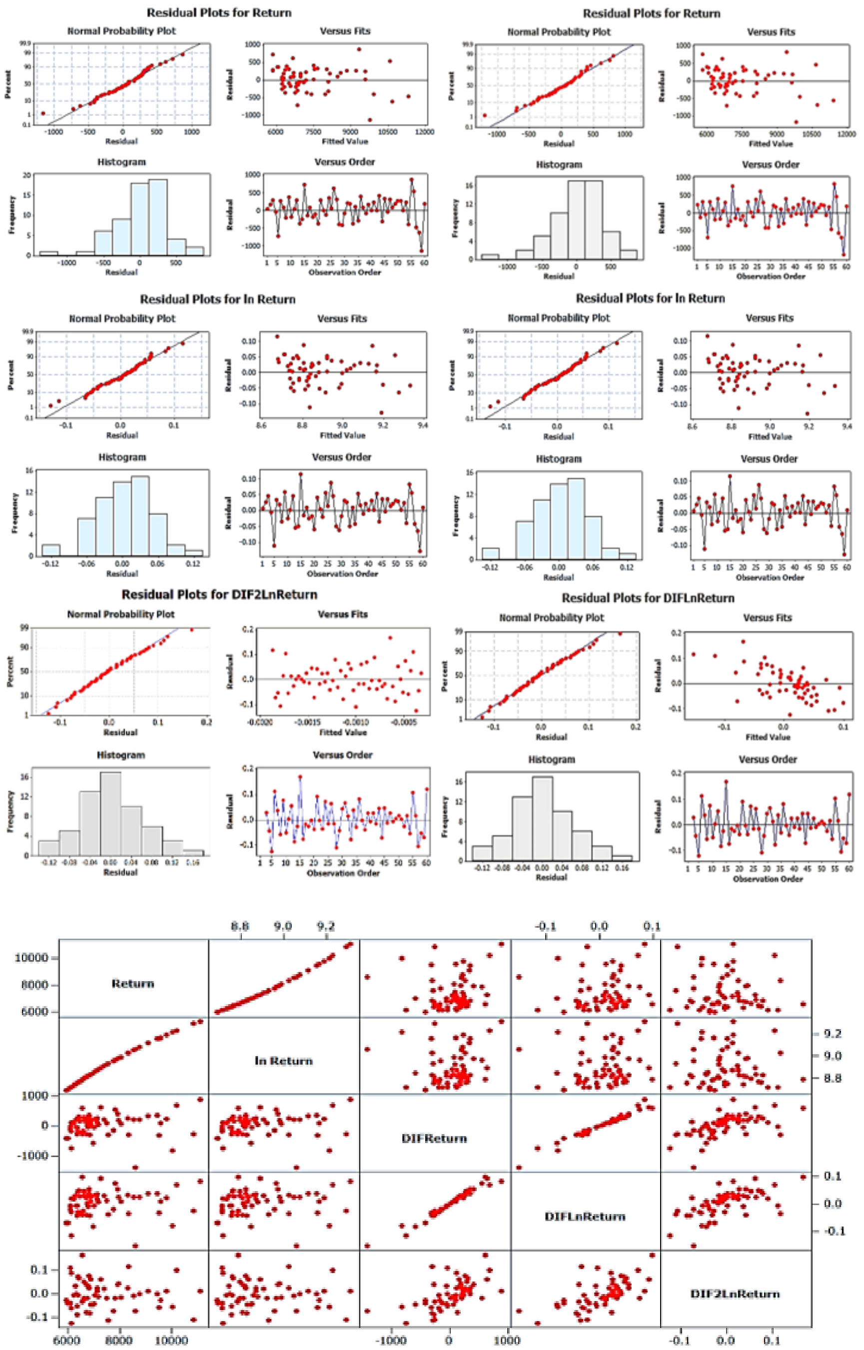

Figure (3): Detecting Stationarity in Time Series Data

An analysis based on data plotted against time to look for potential patterns over time is shown in Figure (3).

6.2Combined Trend Analysis and Decomposition Data

Trend analysis is combined with decomposition when the data exhibits seasonality that can be well-fitted by decomposition and a trend that is well-fitted by the quadratic, exponential growth curve, or S-curve models. Time series are decomposed into linear and seasonal components, error, and forecasting using this technique.

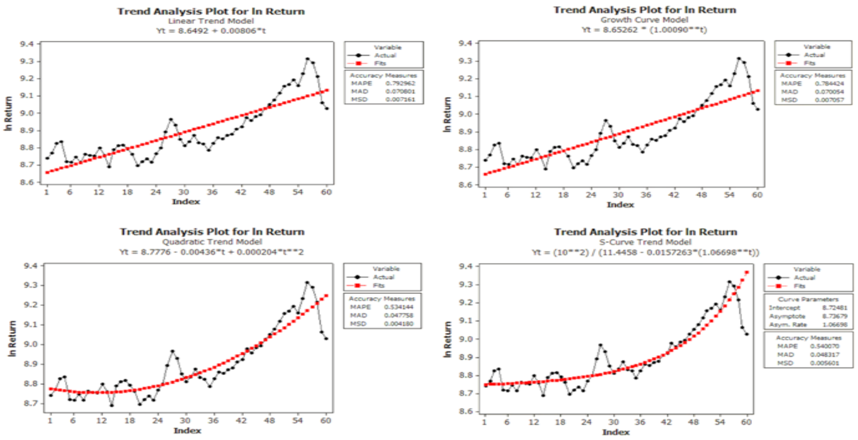

Figure (4): Trend Analysis of Return Time Series

Table (1): The three measures of accuracy of the fitted values

	Linear	Quadratic	Growth-Curve	S-Curve
MAPE	0.792	0.534	0.784	0.540
MAD	0.070	0.047	0.070	0.048
MSD	0.007	0.004	0.007	0.005

Figure (4) and Table (1) show the best fitted trend line is the Quadratic as following:

$$Y_t = 8.7776 - 0.00436 * t + 0.000204 * t^2$$

The fitted values' three accuracy measures are Mean absolute percentage error (MAPE), Mean absolute deviation (MAD), and Mean squared deviation (MSD). The seasonal pattern does not fit the trend model well, but the overall trend seems to fit it well. Decomposition on the stored residuals must be used, along with trend analysis, decomposition fits, and forecasts, to better fit this data.

6.3Decomposition of Time Series:

Decomposition is used to separate time series into linear and seasonal components, in addition to error, with the goal to provide forecasts.

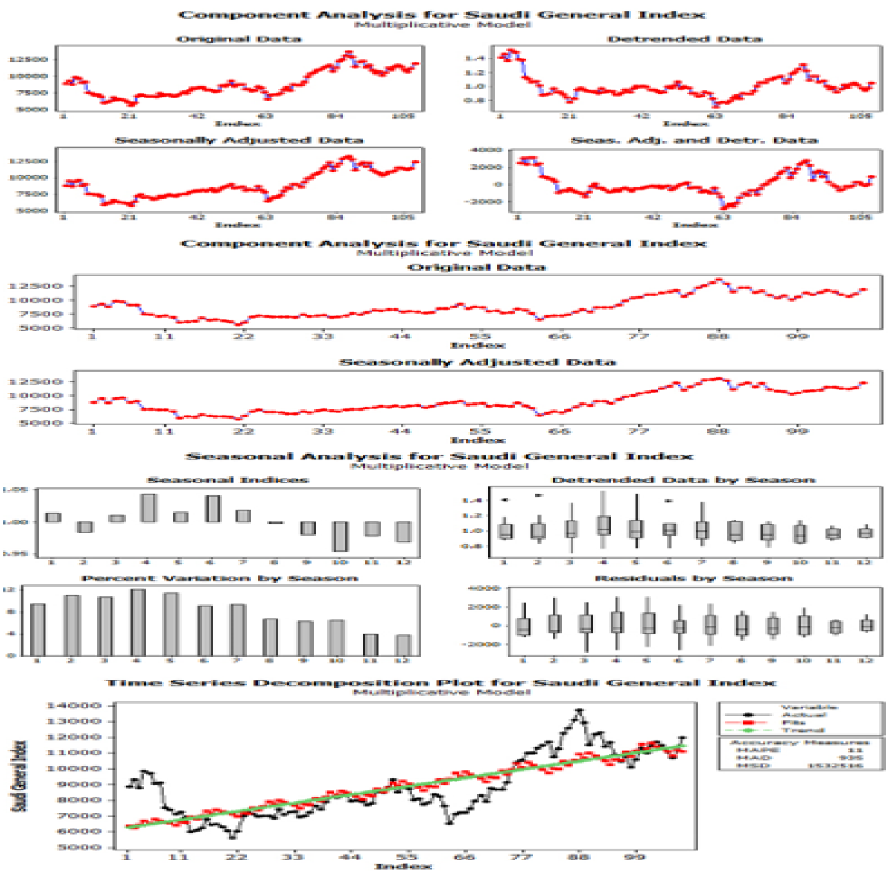

Figure (5): Decomposition of Return Time Series

With the exception of the first annual cycle's portion being underpredicted and the last annual cycle's portion being overpredicted, Figure (5)'s first graph illustrates how well the detrended residuals from trend analysis fit by decomposition. The second graph's lower right plot further illustrates this point: the residuals are highest at the start of the series and lowest at the conclusion. Fitted trend equation using multiplicative model:

$$Y_t = 6234 + 48.4 * t$$

MAPE, MAD, and MSD are equal to 11, 935, and 1532516.

6.4Simple Exponential Smoothing (SES):

In simple exponential smoothing (SES), previous observations are given exponentially decreasing weights, and the weight assigned to the most recent observation is controlled by a single smoothing parameter (α).

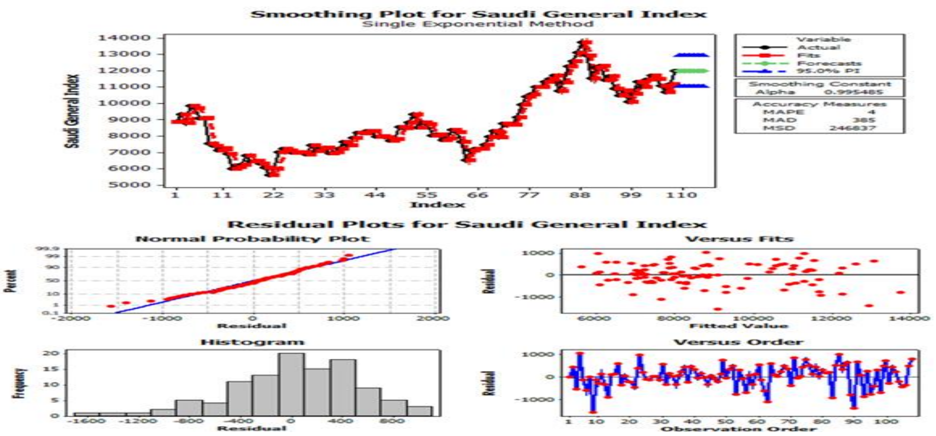

Figure (6): Simple Exponential Smoothing for Financial Time Series

Figure (6) shows that the MAPE, MAD, and MSD for a single exponential smoothing model are 4, 385 and 246837, respectively, with α = 0.995485. The optimal ARIMA model is used to estimate the value of α, resulting in the best smoothing. The value of α indicates that the model focuses on recent past observations.

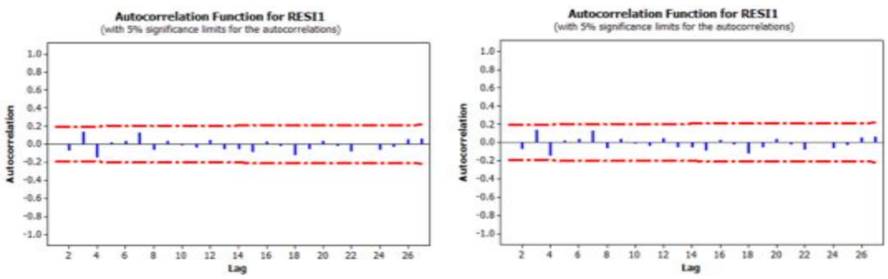

Figure (7): ACF and PACF for Residuals by Simple Exponential Smoothing of Monthly Stock Returns of the Saudi Stock Index

Figure (7) shows the autocorrelation function and partial autocorrelation function for residuals and a 95% confidence interval is constructed reflects the stationarity and good estimation value of α for accuracy forecasting.

6.5Holt's Linear Exponential Smoothing (Double Exponential Smoothing (DES))

Holt's Linear Exponential Smoothing uses two smoothing parameters: α for trend and β for level.

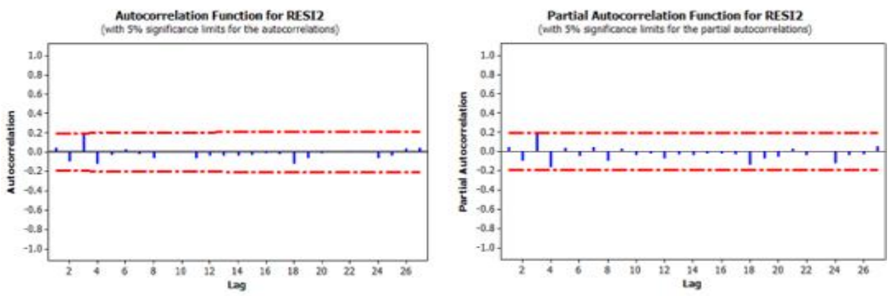

Figure (8): Holt's Linear Exponential Smoothing for Monthly Stock Returns of the Saudi Stock Index

Figure (8) shows that for the double exponential smoothing (DES) fit, the three accuracy measures (MAPE, MAD, and MSD) were 5, 410, and 270734. Smoothing parameters: α = 0.16546 for trend and β = 0.02016 for level.

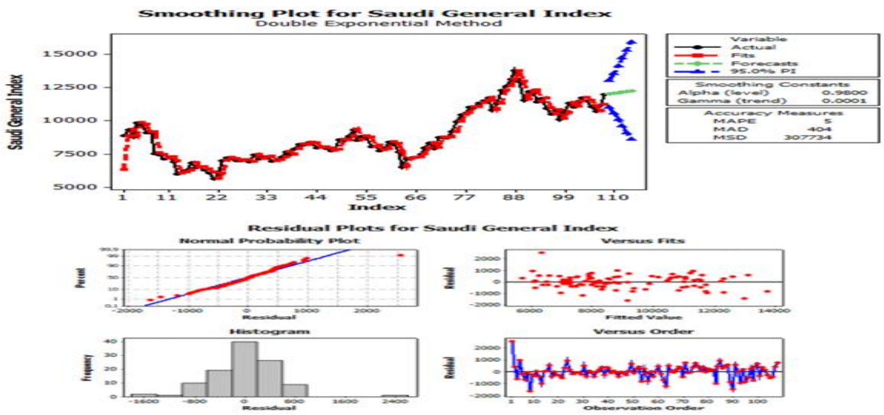

Figure (9): ACF and PACF for Residuals by Holt's Linear Exponential Smoothing of Monthly Stock Returns of the Saudi Stock Index

Figure 9 shows the autocorrelation and partial autocorrelation functions for residuals, indicating stationarity and a good estimation value of (α, β) for accurate forecasting.

6.6Triple Exponential Smoothing (Holt Winters Algorithm (TES))

The Holt Winters Algorithm is a variant of double exponential smoothing that accounts for seasonality. The smoothing parameters include seasonality (γ), trend (β), and level (α). It works well with trending and seasonal time series data.

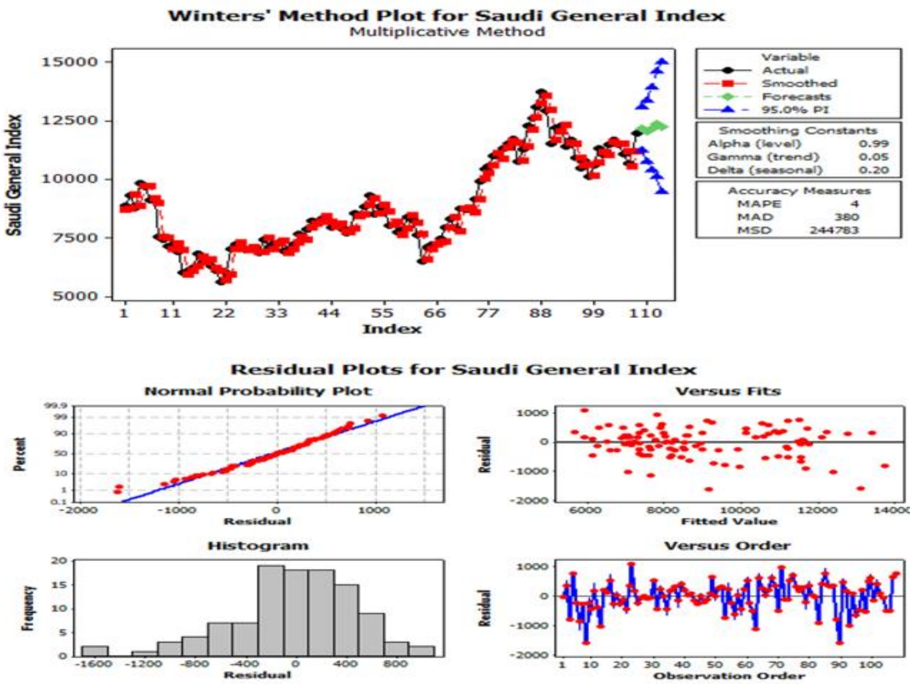

Figure (10): Holt Winters Algorithm for Monthly Stock Returns of the Saudi Stock Index

Figure (10) shows the default time series plot with the series and fitted values. The level, trend, and seasonal component smoothing weights, as well as the three metrics used to evaluate the fitted value's accuracy (MAPE, MAD, and MSD), are displayed. The multiplicative model yielded the following results for time series data: 4, 380, and 244783 for MAPE, MAD, and MSD, with α = 0.99, β = 0.05, and γ = 0.20.

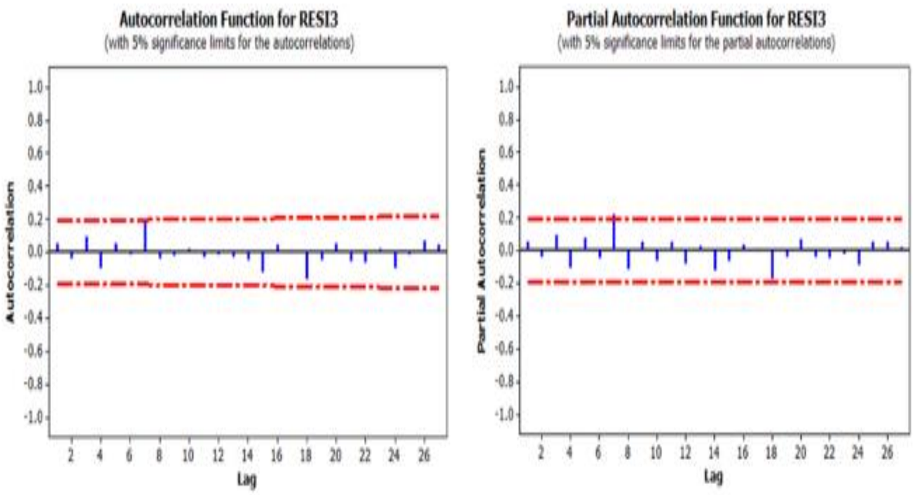

Figure (11): ACF and PACF for Residuals by Holt Winters Algorithm of Monthly Stock Returns of the Saudi Stock Index

Figure (11) shows autocorrelation and partial autocorrelation functions for residuals, indicating stationarity and a good estimation value of (α, β, γ) for accurate forecasting.

Table (2): The Measures of Accuracy of the Fitted Models

Methods	MAPE	MAD	MSD
SES	4	385	246837
DES	5	410	270734
TES	4	380	244783

Table (2) shows a performance comparison of simple exponential smoothing (SES), double exponential smoothing (DES), and triple exponential smoothing (TES). The best-fitting technique is triple exponential smoothing or Holt Winters algorithm.

7. Conclusion and Remark:

This study presents an analysis and comparison of univariate time series models by contrasting forecasting results of monthly stock returns for the Saudi stock index using the decomposition procedure and exponential smoothing time series forecasting models to solve one of the most important challenges when analyzing and forecasting time series, which is the series' stability and determining components of the time series such as trend and seasonal.

The application results can be summarized in the following concepts:

- **Single-exponential smoothing (SES) is used for time series data that does not have a trend or seasonal component.**
- **Holt's linear exponential smoothing or double exponential smoothing (DES) can be used on time series data with a trend but no seasonality.**
- **Use Winters' method to smooth time series data for short to medium-term forecasting, particularly when the magnitude of the seasonal pattern is not proportional to the data size.**
- **The Holt Winters Algorithm or triple exponential smoothing model is the best model because it produces the lowest (MAPE, MAD, and MSD) values, which are 4,380, 244783 compared to 4, 385, 246837 for SES and 5, 410, 270734 for DES, and thus can be used to predict the monthly stock returns of the Saudi Stock Index.**

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