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Comparison of Forecasting Techniques for Short-term and Long-term Real Life Problems

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Abstract

In this paper, we analyze the most appropriate short-term and long term forecasting methods for our practical life where several methods of time series forecasting are available such as the Moving Averages method, Linear Regression with Time, Exponential Smoothing, Holt‘s Method, Holt-Winter‘s Method etc. This paper mainly concentrates on the Holt- Winters Exponential Smoothing technique as applied to time series that exhibit seasonality. The accuracy of the out-of-sample forecast is measured using MSE, MAPE, MAD. We will observe that the empirical results from the study indicate that the Holt-Winter‘s Multiplicative Forecasting Method processes as the most appropriate forecasting method for the sets of real life data that will be analyzed.

Keywords: Exponential Smoothing; Holt’s Method; Smoothing Constants; Forecast Error Holt-Winter‘s Method etc.

I. Introduction

When the result of an action is of consequence, but cannot be known in advance with precision, forecasting may reduce decision risk by supplying additional information about the possible outcome. Once data have been captured for the time series to be forecasted, the analyst’s next step is to select a model for forecasting. After selecting a model, the next step is its specification. The process of specifying a forecasting model involves selecting the variables to be included, selecting the form of the equation of relationship, and estimating the values of the parameters in that equation. After the model is specified, its performance characteristics should be verified or validated by comparison of its forecasts with historical data for the process it was designed to forecast. Error measures such as MAPE- Mean absolute percentage error, MSE- Mean square error, MAD-Mean absolute deviation[1] may be used for validating the model measure has an important effect on the conclusions about which of a set of forecasting methods is most accurate Time-series forecasting assumes that a time series is a combination of a pattern and some random error[2]. The goal is to separate the pattern from the error by understanding the pattern‘s trend, its long-term increase or decrease, and its seasonality, the change caused by seasonal factors such as fluctuations in use and demand. Several methods of time series forecasting are available such as the Moving Averages method, Linear Regression with Time, Exponential Smoothing etc[3]. This paper concentrates on the Holt- Winters Exponential Smoothing technique as applied to time series that exhibit seasonality.

At present, among linear and nonlinear methods, 70 different forecasting models are there at least for quantitative demand forecasting. The models have similar basic concepts but follows disparate techniques from different areas[4]. There are many different research works, but it cannot be identified which technique is better considering all the circumstances.

Ksenija Dumičić et al. authors found challenging enough to explore potential forecasting models suitable for predicting the future values of unemployment rate, since recent analysis conducted by Eurostat revealed some interesting trends. For the purpose of the empirical analysis, five European countries, namely: Croatia, Greece, Italy, Portugal and Spain were selected, even though, substantial differences exist among them, in the analyzed period; they all recorded substantially high unemployment rates[5] .The aim of this paper was to select the most accurate forecasting method for predicting the future values of the unemployment rate and several forecasting techniques adequate for forecasting time series with trend component, were explored. The results of the empirical analysis showed that the optimal model for forecasting unemployment rate in Greece was Holt-Winters` additive method. In the case of Spain, according to MAPE, the optimal model is double exponential smoothing model. Furthermore, for Croatia and Italy the best forecasting model for unemployment rate is Holt-Winters` multiplicative model. Finally, the best model to forecast unemployment rate in Portugal is Double Exponential Smoothing Model. Furthermore, when we explored the actual data published by Eurostat for the unemployment rate for first quarter of 2014 and the forecasted data, we came to different conclusions. Accordingly, we concluded that in all analyzed countries, but Italy, Model 1, or double exponential smoothing method, shown to be the most accurate, whereas, in the case of Italy, Model 3 or Holt- Winters` additive method, gave the most accurate forecasts.

Mikhail Aseev et.al described the method of forecasting time series of cash withdrawals in ATMs. The hybrid model is based on two methods: Holt-Winters additive method and Markov chain-based model. The combination occurs with the help of weight coefficients which are calculated on the basis of work of each model. Holt-Winters method forecasts time series with trend and seasonal variations. Markov chain enables to forecast patterns of basic time series, such as peaks or holes. The composition of these two approaches will allow banks and other financial organizations to predict cash withdrawals more accurately than the methods used separately[6].

N A Elmunim et.al they discussed on a comparison between Additive and Multiplicative Holt-Winter statistical method which was carried out during fifteen-month period at UKM station, Malaysia and the accuracy of each model was tested. The comparative analysis between the two models indicated that the Multiplicative model (70-93%) is slightly more

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accurate than the Additive model (68-92%), in most of the months during the period chosen. Thus, it can be concluded that Multiplicative model is a more reliable model with a relatively higher accuracy than the Additive model in forecasting the ionospheric delay over UKM. The comparison of the Holt-Winter models is very important in knowing the best model that can forecast the delay with the least amount of error while still giving a better forecast results to improve the accuracy performance of GPS positioning by correcting ionospheric errors[7].

The rest of the paper is organized as follows. In Section 2, we will analyze different existing forecasting methods. In Section 3,we will make a comparison among different Forecasting Technique by using real life problem. In section 4, we will make a conclusion among different forecasting techniques.

II. Analysis of Existing Method

In this section, we will discuss on different types of existing method of forecasting techniques.

Exponential Smoothing Method

The simplest of the exponentially smoothing methods is naturally called "simple exponential smoothing" (SES) or "single exponential smoothing". This method is suitable for forecasting data with no trend or seasonal pattern.

Exponential Smoothing is a method that can be applied to time series data for presentation to make forecasts. The time series data themselves are a sequence of observations[8]. The observed occurrence may be an essentially random process, or it may be an orderly, but noisy, process. Whereas in the simple moving average, the past observations are weighted equally; Exponential smoothing assigns exponentially decreasing weights over time.

The simplest form of exponential smoothing is given by the following formula:

$$F_{t+1} = \alpha A_t + (1-\alpha)F_t$$

Where,

F_{t+1} =Forecast for period $t+1$

$F_t =$ Forecast for the previous period (i.e.period t)

$\alpha =$ Smoothing constant (percentage) and $0 < \alpha < 1$

$A_t =$ Actual demand or sales for the previous period

We can interpret the new estimate of level may be seen as a weighted average of A_t, the most current information of average level and F_t be the previous estimate of that level. Small values of α imply that the revision of the old forecast, in light of the new demand, is small; the new forecast is not very different from the previous one. The method requires an initial forecast F_1which has to be either assumed or estimated.

In the next section we will discuss about double exponential smoothing technique which is known as Holt's Method.

Holt's Method

We have already known Exponential smoothing technique which actually is known as single Exponential method. But, single Exponential method does not work well in some cases especially when the data include trend or linear trend as we say. In that case, "double exponential smoothing method" is used worldwide.

Double exponential smoothing employs a level component and a trend component at each period. Double exponential smoothing uses two weights, (also called smoothing parameters), to update the components at each period. It should be noted that Holt's method performs well where only trend but no seasonality exists.

Here, the time series exhibits a trend; in addition to the level component, the trend (slope) has to be estimated. The forecast, including trend for the upcoming period $t+1$, is given by

$$F_{t+1} = L_t + T_t$$

Here, $L_t$is the estimate of level made at the end of period t and is given by

$$L_t = \alpha A_t + (1-\alpha)F_t$$

$T_t$is the estimate of trend at the end of period t and is given by

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

$\beta$is also a smoothing constant between 0 and 1 and plays a role similar to that of α.

Initialization

The initial estimated base label L_0 is assumed from the last period observation and initial trend T_0 is the average monthly or weekly change.

$L_0 =$ Last period's observation

$T_0 =$ Average monthly or weekly increase

In the next section we will discuss about triple exponential smoothing technique which is known as Holt- Winter's Method.

Holt-Winter's Method

Holt's Winter method deal with time series which contain both trend and seasonal variations. The Holt-Winters method has two versions, additive and multiplicative Suppose we have a sequence of observations $\{Y_t\}$, beginning at time $t = 0$ with a cycle of seasonal change of length L. The method calculates a trend line for the data as well as seasonal indices that weight the values in the trend line based on where that time point falls in the cycle of length L. $\{L_t\}$ represents the smoothed value of the constant part for time t. $\{T_t\}$ represents the sequence of best estimates of the linear trend that are superimposed on the seasonal changes. $\{S_t\}$ is the sequence of the seasonal correction factors. To initialize the seasonal indices S_{t-n} there must be at least one complete cycle in the data. The output of the algorithm is again written as F_{t+1}, an estimate of the value of x at time $t+1$[9].

In the next section we will discuss about Holt- Winter's Method with Multiplicative Seasonality.

Holt-Winter's Method with Multiplicative Seasonality

The multiplicative method is preferred when the seasonal variations are changing proportional to the level of the series. The multiplicative method, the seasonal component is expressed in relative terms (percentages) and the series is seasonally adjusted by dividing through by the seasonal component[10]. Within each year, the seasonal component will sum up to approximately *s*.

Here, $L_t$is the estimate of level made at the end of period t and is given by

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + T_{t-1})$$

$T_t$is the estimate of trend at the end of period t and is given by

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

S_t is the sequence of the seasonal correction factors and is given by

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s}$$

The forecast, including trend for the upcoming period $t+1$, is given by

$$F_{t+1} = (L_t + T_t)S_{t-s+1}$$

In the next section we will discuss about Holt- Winter's Method with Additive Seasonality

Holt-Winter's Method with Additive Seasonality

The additive method is preferred when the seasonal variations are roughly constant through the series. With the additive method, the seasonal component is expressed in absolute terms in the scale of the observed series, and in the level equation the series is seasonally adjusted by subtracting the seasonal component. Within each year the seasonal component will add up to approximately zero.

Here, $L_t$is the estimate of level made at the end of period t and is given by

$$L_t = \alpha\,(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + T_{t-1})$$

$T_t$is the estimate of trend at the end of period t and is given by

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$$

S_t is the sequence of the seasonal correction factors and is given by

$$S_t = \gamma\,(Y_t - L_t) + (1-\gamma)S_{t-s}$$

The forecast, including trend for the upcoming period $t+1$, is given by

$$F_{t+1} = L_t + T_t + S_{t-s+1}$$

III. Comparison Among Different Forecasting Technique by Using Real Life Problem

In this section, we are going to discuss about practical use of forecasting techniques in RMG sector in Bangladesh and make a comparison among Exponential method, Holt's method, Holt's-Winter's additive and Holt's-Winter's multiplicative method.

An established RMG factory in Gazipur produced different types of woven products such as Shirts, Pants and Trousers. Actual demand (thousands) of these products in different weeks is given in Table 1. We have to make a comparison to make a decision which method is best for forecasting.

Table 1. Actual demand (thousands) for different weeks

Week	Demand
1	72
2	116
3	136
4	96
5	77
6	123
7	146
8	101
9	81
10	131
11	158
12	109

Here Table1 shows actual demand (thousands) for different weeks of different types of woven products such as Shirts, Pants and Trousers.

Table 2. Forecasting demand (thousands) for different weeks for different techniques

Week	Demand	Exponential	Holt's	Holt Winter's multiplicative	Holt Winter's additive
1	72	115	102.469	72.3122	103.17
2	116	110.7	107.133	115.943	98.41
3	136	111.23	115.441	136.839	103.52
4	96	113.707	113.699	95.5382	111.68
5	77	111.936	107.771	76.3919	107.61
6	123	108.443	112.534	123.409	106.94
7	146	109.899	121.656	145.324	112.98
8	101	113.509	119.498	101.68	117.45
9	81	112.258	113.001	81.597	112.08
10	131	109.132	118.164	130.481	115.6
11	158	111.319	128.491	153.833	123.52
12	109	115.987	126.563	107.956	124.8

Here Table2 discuss Forecasting demand (thousands) for different weeks of different types of woven products such as Shirts, Pants and Trousers by using Exponential method , Holt's method, Holt's-Winter's additive and Holt's-Winter's multiplicative method.

Table 3. Error calculation

Error1	Error2	Error3	Error4	(Error1)^2	(Error2)^2	(Error3)^2	(Error4)^2
43	30.469	0.3122	31.17	1849	928.36	0.097469	971.5689
5.3	8.867	0.0575	17.59	28.09	78.62369	0.003306	309.4081
24.77	20.559	0.8392	32.48	613.5529	422.6725	0.704257	1054.95
17.707	17.699	0.4618	15.68	313.5378	313.2546	0.213259	245.8624
34.9363	30.771	0.6081	30.61	1220.545	946.8544	0.369786	936.9721
14.557	10.466	0.4093	16.06	211.9062	109.5372	0.167526	257.9236
36.101	24.344	0.6758	33.02	1303.282	592.6303	0.456706	1090.32
12.509	18.498	0.68	16.45	156.4751	342.176	0.4624	270.6025
31.258	32.001	0.597	31.08	977.0626	1024.064	0.356409	965.9664
21.868	12.836	0.5191	15.4	478.2094	164.7629	0.269465	237.16
46.681	29.509	4.1671	34.48	2179.116	870.7811	17.36472	1188.87
6.987	17.563	1.0437	15.8	48.81817	308.459	1.08931	249.64
∑=295.674	253.582	10.3708	289.82	∑=9379.595	6102.176	21.55461	7779.245

Table 3 shows the error calculation by using Exponential method , Holt's method, Holt's-Winter's additive and Holt's-Winter's multiplicative method compare with our actual demand (thousands) for different weeks of different types of woven products such as Shirts, Pants and Trousers where,

Error1= Exponential Method –Demand
Error2= Holt's Method –Demand
Error3= Holt's Winter's Multiplicative Method –Demand
Error4= Holt's Winter's Additive Method –Demand

Table 4. Shows the way how to calculate error values

G1	G2	G3	G4
59.72222	42.31806	0.433611	43.29167
4.568966	7.643966	0.049569	15.16379
18.21324	15.11691	0.617059	23.88235
18.44479	18.43646	0.481042	16.33333
45.37182	39.96234	0.78974	39.75325
11.83496	8.508943	0.332764	13.05691
24.72671	16.67397	0.462877	22.61644
12.38515	18.31485	0.673267	16.28713
38.59012	39.50741	0.737037	38.37037
16.69313	9.798473	0.39626	11.75573
29.54494	18.67658	2.637405	21.82278
6.410092	16.11284	0.957523	14.49541
∑=286.5061	251.0708	8.568154	276.8292

Here, Table 4 shows the way how to calculate error values by using Exponential method , Holt's method, Holt's-Winter's additive and Holt's-Winter's multiplicative method compare with our actual demand (thousands) for different weeks of different types of woven products such as Shirts, Pants and Trousers where,

G1=(Error1/Demand)*100
G2=(Error2/Demand)*100
G3=(Error3/Demand)*100
G4=(Error4/Demand)*100

Now we will discuss how we will find Mean Absolute Deviation (MAD), Mean Squared Error (MSE) and Mean Absolute Percent Error (MAPE) for Exponential method , Holt's method, Holt's-Winter's additive and Holt's-Winter's multiplicative method[17].

For Exponential Smoothing Method,
MAD=∑ Error1 /n = 295.674/12 =24.6395
MSE=∑ Error1 ^2/n-1 = 9379.595/11 = 852.6905
MAPE={(∑ Error1 /Demand)*100}/n = 286.5061/12 = 23.8755 %

For Holt's Method,
MAD=∑ Error2 /n = 253/12 =21.1318
MSE=∑ Error2 ^2/n-1 = 6102.176/11 = 554.7433
MAPE={(∑ Error2 /Demand)*100}/n = 251.0708/12 = 20.9225 %

For Holt-Winter's Additive Method,
MAD=∑ Error3 /n = 289.82/12 =24.1517
MSE=∑ Error3 ^2/n-1 = 7779.245/11 = 707.2041
MAPE={(∑ Error3 /Demand)*100}/n = 276.8292/12 = 23.0691 %

For Holt-Winter's Multiplicative Method,

MAD=∑ Error4 /n = 10.3708/12 =0.8642

MSE=∑ Error4 ^2/n-1 = 21.5546/11 = 1.959

MAPE={(∑ Error4 /Demand)*100}/n = 8.5682/12 = 0.7140

For comparison, we take some data and calculate the forecast value using Exponential Smoothing Method, Holt Method, Holt-Winter's Multiplicative Method, Holt-Winter's Additive Method. We are using MS Excel with the Solver add-in to calculate the optimal values of α, β and γ to give the smallest MAD, MSE, MAPE for the forecasts. The optimal values found for α and β and γ lie in (0,1) .We are able to calculate the forecasts for the next year (season) because the seasonal from the previous year exist.

In terms of quality, Holt's Winter Multiplicative Model has significantly smaller MAPE = 0.7140% compared to that of Holt's Winter Additive Model MAPE = 23.0691%, Holt's Model MAPE = 20.9225%, Exponential Model MAPE= 23.8755%. Holt's Winter Multiplicative model has significantly smaller MAD = 0.8642 compared to that of Holt's Winter additive model MAD = 24.1517,Holt model MAD = 21.1318, Exponential Model MAD= 24.6395. Holt's Winter multiplicative model has significantly smaller MSE = 1.959 compared to that of Holt's Winter additive model MSE = 707.2041,Holt model MSE =554.7433 , Exponential Model MSE=852.6905 .

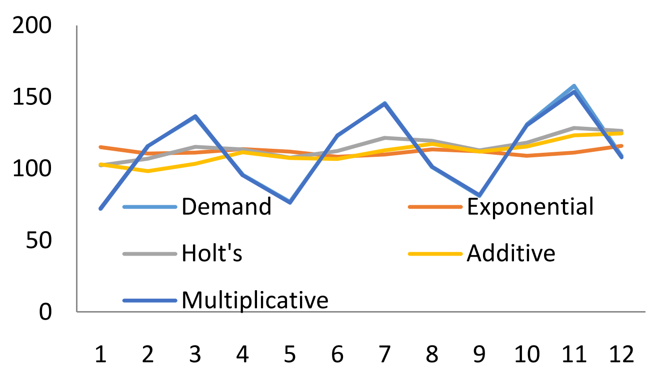

Fig. 1. Comparison Between Exponential Smoothing, Holt's Method, Holt-Winter's Multiplicative And Additive Seasonality

Fig.1 also shows that Holt's Winter's Multiplicative method gives us best forecasting accuracy among all other forecasting method. For comparison here we take some data and calculate the forecast value using Exponential Smoothing Method, Holt Method, Holt-Winter's Multiplicative Method, Holt-Winter's Additive Method. We are using MS Excel to plot the graph. Multiplicative Winter's Method has the highest degree of model adequacy, and forecast accuracy. Moreover, Multiplicative Winter's Method applies three smooth constant α, β, γ, which allow strongest adaptability to capture the observation. In terms of interpretability, we concluded that Multiplicative Holt-Winter's Method may be a strongly suitable model, because sales seems to maintain a linear trend with a consistent multiplicative seasonal pattern in an increasing variation sales peaks.

IV. Conclusion

In this paper, we studied the two main HW models such as Additive model for time series exhibiting additive seasonality and Multiplicative model for time series exhibiting Multiplicative seasonality Model parameters α, β, γ are initialized using the data of the given years. The accuracy of the out-of-sample forecast is measured using MSE, MAPE, MAD. From the analysis, we observed that, the Multiplicative Winter's Method has the highest degree of model adequacy, and forecast accuracy. So we conclude that, the Multiplicative Holt-Winter's Method can be used as a strongly suitable model rather than other methods, because it gives less forecasting errors.

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