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RESEARCH ARTICLE

A Comparison between Brown's and Holt's Double Exponential Smoothing for Forecasting Applied Generation Electrical Energies in Kurdistan Region

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ABSTRACT

The process of producing electricity from sources of energy is known as electricity production. Electric also is not freely accessible in environment, thus it should be "manufactured" (i.e., converting another kinds of energy to electrical energy) by utilities with in electricity industry (transportation, distributing, and so on). Moreover, the objective of this study is to compared of Brown's as well as Holt's Double Exponential Smoothing (DES) also build a best forecasting time series model among two smoothing model forecasting, as well as focuses on optimizing characteristics to use the golden section technique. This exponential smoothing approach has been one of the time series forecasting methods that would be used to forecast (Generation Electrical) with in Kurdistan area. The issue that arises with this technique is determining the appropriate parameters to reduce predict inaccuracy. In addition, data used in this paper are (Generation Electrical) in Kurdistan region for (132) months from 2010 to 2020. The study revealed that such data are trending modeled, indicating that a DES approach from Brown and Holt can be used with the (Stratigraphic and Minitab) software. There are the same results but the result of analysis more depend on the R-program. The difference among the forecast findings acquired with optimum parameters as well as the assaying data was utilized to assess the feasibility of the forecast by completing normality and randomness tests. Ultimately, the outcomes of parameterization show that the optimal value of α that in DES Brown is (0.22) as well as the optimal MAPE is 9.23616%, whereas in DES Holt the optimal is (0.95) as well as the optimal β is (0.05) through the optimal MAPE of 8.08586%. This MAPE of a DES Brown technique is greater than the MAPE of a DES Holt approach. Feasibility experiments revealed that both approaches are capable of predicting. Depending on the value of MAPE as well as evaluation process, DES Holt's was recognized as the main prediction model.

Keywords: Generation electrical, Energies, double exponential smoothing parameter optimization, electricity production

INTRODUCTION

The method of constructing electric power from various forms of energy production is known as electricity production. The Kurdistan Region Local Generation are Hydro Power Station, Gas power plant (PP), Steam PP, Heavy Feul PP, Deisel PP, Erbil Combined Cycle PP, and Suly Combined Cycle PP and Thermal. To estimate the forecasting applied Generation Electrical Energies in Kurdistan region, a (Brown's and Holt's) Double Exponential Smoothing (DES) approaches would be created as well as contrasted to see that methodology is superior for forecasting generation electrical energies in Kurdistan. Furthermore, there was usually a timing lag among awareness of the imminent event or necessity also its manifestation. The fundamental reason for planning as well as predicting is to account for this advance time. There was not need for the planning when the lead time is nil or pretty limited. If indeed a lead time was considerable as well as the event's outcome was dependent on definable variables, planning could play a major role. Prediction is required in these contexts to assess while the event would happen or the need may arise, because as appropriate steps could be taken. Furthermore, predicting the future is a planning method created to assist management in meeting the uncertainty of a future relied on previous data as well as predictive modeling. Prediction is the science and art of forecasting the future developments by utilizing past data as well as projected this into the future with the use of a systematic method model.

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Forecasting demand requires the application of a certain approach. Many predicting approaches work on the same principle of using previous data to forecast or project future data. In other ways, predicting can be seen as a critical and necessary help to management that serves as the foundation of efficient operations. Several organizations have failed in the past as a result of an ineffective forecasting approach on which the company's whole strategy was based. Forecasting effectively assists in the decrease of unneeded inventories, the improvement of product availability, and also the degree of customers' satisfaction. The major driving factor for profit generation in today's business world is satisfying customer's requirements at the correct time and even in the appropriate amount. As a result, predicting with as much precision as feasible is critical to ensuring product availability at the lowest possible cost. The forecast's reliability would be evaluated using Mean Absolute Percentage Error (MAPE) tool. MAPE displays a forecast's reliability in the percentage form. Since it was simple to read, (due to its percentage form).[1-3] A MAPE reliability estimate is typically more commonly employed. The smaller MAPE score indicates that now the prediction model performs well. Table 1 shows the range of a MAPE score.

RESEARCH METHOD (DES)

Simple exponential smoothness does not really work well while there is a trends in the information, that is inconvenient. For such cases, various techniques have been developed that under term " DES " or "2nd exponential smoothing," and that is the recursion applying of the an exponentially filtering twice, hence the term " DES." Brownos DES technique is indeed a prediction approach that is utilized while the data have a trend line as well as being non-stationary. This really is comparable to the terminology used for quadruple exponential smoothing, that also refers to the recursion depth. The main concept underlying DES would include a component that accounts for the potential of the series displaying some kind of the trend. That slope parameter was kept up to date by using exponential smoothing. When such data reveals a trend, this approach is employed. Exponential smoothing through trend is similar to simple smoothing, however that both components should be updated throughout every level-periodic as well as its trends. This level is the smoothed estimate based on the data values at the conclusion of the each period. A tendency is a smoothed estimate of average growth at the ending of each period.[1,3-6] A basic concept of these technique was illustrated in equation (1),

$$Z_{t+1} = \propto X_t + (1-\propto) Z_t \tag{1}$$

Where
Z_{t+1}: Prediction one period ahead.
X_t: Actual data at period t

Table 1: MAPE score significantly

MAPE	Significantly
<10%	Excellent forecasting ability
10–20%	Good forecasting ability
20–50%	Reasonable forecasting ability
>50%	Bad forecasting ability

Z_t: Prediction at period t
$\propto$: Smoothing parameter ($0 < \propto < 1$)

Brown's Linear Exponential Smoothing

Exponential smoothing through a tendency works similarly to basic smoothing, with the exception that two components - level as well as trend - should be adjusted each period. A level was the smoothed estimation of a data's values just at ending of each period. This tendency was the smoothed estimation of average growth at every period's conclusion. Brown's straight exponential smoothing (Brown's DES) was widely used only for data with a trend line. This is utilized because when data exhibits a trending as well as to generate a linear trend. The Brown's exponential smoothing methodology is therefore appropriate for modeling time series through trend however no seasonality. That a DES brown technique comprises the single parameter $\propto$ with a value between 0 and 1. That parameter value was being utilized to reduce the observed value (real value) in the older era exponentially.[1,4,7]

DES Utilizing Brown's Technique through the m-period-ahead forecast is provided by:

$$Z_{t+m} = \hat{a} + \hat{b}(m) \tag{2}$$

This is just a simple linear regression model.

Where:

Z_{t+m}: Ahead forecast in (m) period

$(\hat{a}.\hat{b})$: Unknown Parameters

To find the m-period-ahead forecast using following steps

Step (1). To find coefficients of linear trend as follows:

$$\hat{a}_t = 2(S_t^1) - (S_t^2) \tag{3}$$

Where (S_t^1) is the single -Smoothing Measurement and (S_t^2) is the double-Smoothing Measurement. Then,

$$\hat{b}_t = \frac{\propto}{1-\propto}(S_t^1 - S_t^2) \tag{4}$$

Where (α) is the single exponential smoothing, therefore:

$$S_t^1 = \propto X_t + (1-\propto) S_{t-1}^1 \tag{5}$$

$$S_t^2 = \propto S_t^1 + (1-\propto) S_{t-1}^2 \tag{6}$$

Note. The values of $(S_1^1 = S_1^2 = X_1)$ in period (t = 1).

Holt's Linear Exponential Smoothing

Holt (1957) expanded simple exponential smoothing to permit for trends predictions in data. This approach employs a prediction equation as well as 2 smoothing equations (one for each level as well as one for each trend).[4,7-10]

$$\hat{Z}_{t+m} = L_t + m b_t \quad \text{Forecast Equation} \tag{7}$$

$$L_t = \propto Z_t + (1-\propto)(L_{t-1} + b_{t-1}) \quad \text{Level Equation} \tag{8}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta) b_{t-1} \quad \text{Trend Equation} \tag{9}$$

Where:
L_t: Denotes an estimate of the level of the series at time t.
b_t: Denotes an estimate of the trend (slope) of the series at time t.

∝: Smoothing constant for the data (0<∝<1)
β: Smoothing constant for the trend estimate (0<β<1)
m: The number of periods ahead to be forecast
$\hat{Z}_{t+m}$: Double forecast value of period (t+m)

Note: Initialization Level $L_1=Z_1$ and Trend:

$$b_1 = \frac{(Z_2 - Z_1)}{(b_2 - b_1)} or \frac{(Z_4 - Z_1)}{(b_4 - b_1)}.$$

Parameter Optimization

To reduce MAPE, the golden section approach was used to optimize the parameters. MAPE was determined from Brown as well as Holt predictions as well as contrasted to actual results. The technique of golden section was used to optimize the parameters () on DES Brown, while a modified version of the method of golden section was used to optimize the parameters (∝ and β) on DES Holt.[6]

Accuracy Measures for Predicting

While choosing between various alternatives, forecasting accuracy is critical. In this context, accuracy means to predicting errors that are the difference among the actual as well as predicted values for a particular time. The forecasting error determination MAPE is utilized in this investigation (MAPE). MAPE is a measurement that reflects the proportion of average absolute error that has happened.[1,8]

This measure is given by

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{e_t}{z_t}\right| * 100 = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{z_t - \hat{z}_t}{z_t}\right| * 100 \qquad (10)$$

Where:

z_t: Actual demand for time period t

$\hat{z}_t$: Forecast demand for time period t

n: Specified number of time period

$e_t : z_t - \hat{z}_t$.

RESULTS

In this part, we apply the previously discussed exponential smoothing methods to analyses time series for Generating Electrical Energies utilizing Brown's and Holt's DES for the for casting applicable Generation Electrical Energies in Kurdistan area for (132) months from 2010 to 2020.

Trend of the Generation Electrical Energies

Data on generation electrical energies were received and then plotted onto the graph to identify the data patterns (look Figure 1). According to the time series plot, a (Generation Electrical Energies) data are now on the long-term secular decrease, though at the some point the period of enhance was not important at times. A rise in certain times could be considered non-seasonal since it did not occur at the same time each month. For Generation Electrical Energies, this method creates different Table 2 and charts. The data cover 132 time periods.

Estimated Partial Autocorrelations and Partial Auto Correlation Function (ACF) for Generation Electrical Energies

Estimated autocorrelations for generation electrical energies

The measured autocorrelations among residuals at different lags are shown in this Table 2. A lag k autocorrelation coefficient assesses a relationship among residuals for time t and time t-k. The 95.0% probability limit about 0 is also indicated. Unless the probability limit at a given lag does not include the calculated coefficient, there really was the statistically important correlation at a certain lag at the 95.0% level of confidence. In these situation, six of the 24 autocorrelation coefficients were statistically important at the 95.0% confidence level, suggesting that now the residuals are not entirely random (white noise). We could illustrate the autocorrelation coefficients by choosing Residual Autocorrelation Function from of the selection of Graphical Choices. By using ACF, a connection of a time - series data through the time series itself should be computed to detect data patterns. Figure 2 shows an ACF plot based on the data.

Estimated autocorrelations for generation electrical energies

The measured partial autocorrelations among the residuals for several lags are shown in this Table 3. A lag k partial autocorrelation coefficient assesses the relationship among the residuals at time t and time t+k once all lower lags have been taken into consideration. It could be used to determine the order in which an autoregressive model should be constructed to match the data. The 95.0% probability limits about 0 are also indicated. Unless the probability limit at a given lag does

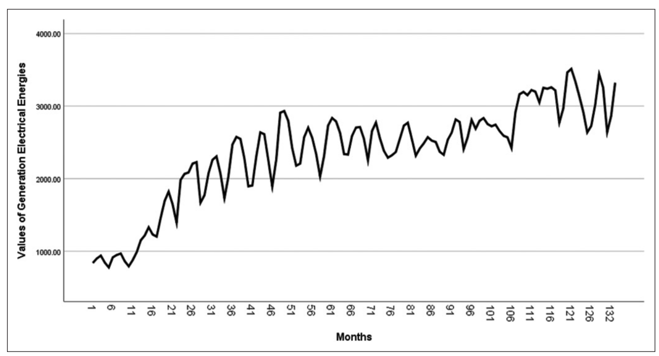


Figure 1: Plot a data Generation Electrical Energies from (132) months

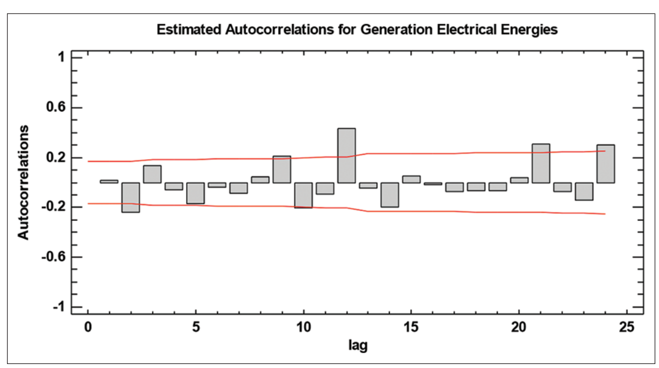


Figure 2: Auto correlation Function for Generation Electrical Energies

Table 2: Estimated autocorrelations for generation electrical energies

Lag	Autocorrelation	Stnd. error	Lower 95.0% Prob. limit	Upper 95.0% Prob. limit
1	0.0167213	0.0873704	-0.171243	0.171243
2	−0.241384	0.0873948	−0.171291	0.171291
3	0.135039	0.092344	−0.180991	0.180991
4	−0.0592817	0.0938394	−0.183922	0.183922
5	−0.171542	0.0941248	−0.184482	0.184482
6	−0.0408148	0.0964818	−0.189101	0.189101
7	−0.0877073	0.0966135	−0.189359	0.189359
8	0.0443452	0.0972194	−0.190547	0.190547
9	0.210737	0.0973737	−0.190849	0.190849
10	−0.201387	0.100795	−0.197555	0.197555
11	−0.0940386	0.103821	−0.203486	0.203486
12	0.434518	0.104469	−0.204757	0.204757
13	−0.0416651	0.117458	−0.230214	0.230214
14	−0.19711	0.117571	−0.230435	0.230435
15	0.0534731	0.120067	−0.235327	0.235327
16	−0.0195178	0.120249	−0.235683	0.235683
17	−0.0703227	0.120273	−0.235731	0.235731
18	−0.0649174	0.120586	−0.236345	0.236345
19	−0.066637	0.120853	−0.236867	0.236867
20	0.0365189	0.121133	−0.237417	0.237417
21	0.308873	0.121217	−0.237581	0.237581
22	−0.073339	0.127083	−0.249078	0.249078
23	−0.142081	0.127406	−0.249711	0.249711
24	0.300656	0.128609	−0.25207	0.25207

not include the predicted coefficient, there seems to be a statistically important connection at which lag at the 95.0% confidence level. At the 95.0% confidence level, four of the —24 partial autocorrelation coefficients were statistically important. You could plot the partial autocorrelation coefficients via choosing Partial Autocorrelation Function from of the listing of Graphical Choices. Moreover, to use the PACF, a correlation of the time - series data through the time series itself would be calculated in order to discover data patterns. Depending on the PACF diagram is shown in Figure 3.

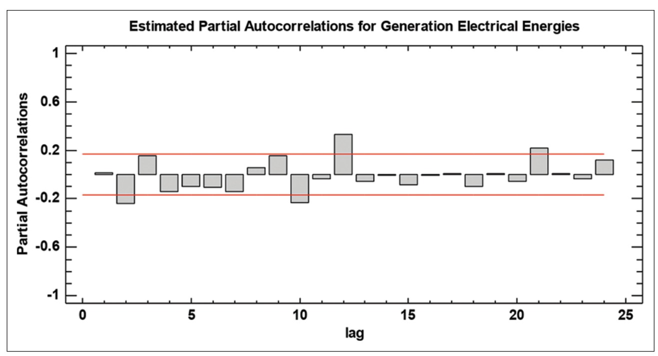


Figure 3: Partial Autocorrelations Function for Generation Electrical Energies

Application of DES Using Brown and Holt Model

Depending on data examination, it is recognized that the data has a trending pattern. DES is the time series processing approach utilized. There really are two methods to the DES technique, 1 variable linear DES from Brown as well as 2 parameter DES from Holt. A testing cases for these techniques were then evaluated utilizing parameters assigned at random. The experiment process was divided into two phases: Initialization (training) utilizing training data to achieve the constituents which will be utilized to assess the forecasting as well as experimenting to make accurate predictions relying on the value of a component parts achieved from of the initializing phase as well as comparison with data test method to evaluate the value of as well as MAE and MAPE.

Application of DES using brown

Smoothing variables (α) utilized in DES Brown testing are chosen (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9). The results of the MAPE evaluation are presented in Table 4. The outcomes of these experiments revealed that the value of $\alpha = 0.2$ caused the least error, because the (MAPE =

Table 3: Estimation partial autocorrelations for generation electrical energies

Lag	Partial Autocorrelation	Stnd. error	Lower 95.0% Prob. limit	Upper 95.0% Prob. limit
1	0.0167213	0.0873704	-0.171243	0.171243
2	−0.241732	0.0873704	−0.171243	0.171243
3	0.153079	0.0873704	−0.171243	0.171243
4	−0.140071	0.0873704	−0.171243	0.171243
5	−0.0975302	0.0873704	−0.171243	0.171243
6	−0.10485	0.0873704	−0.171243	0.171243
7	−0.139082	0.0873704	−0.171243	0.171243
8	0.0528022	0.0873704	−0.171243	0.171243
9	0.155682	0.0873704	−0.171243	0.171243
10	−0.230709	0.0873704	−0.171243	0.171243
11	−0.0358917	0.0873704	−0.171243	0.171243
12	0.333182	0.0873704	−0.171243	0.171243
13	−0.0568566	0.0873704	−0.171243	0.171243
14	−0.00962131	0.0873704	−0.171243	0.171243
15	−0.082228	0.0873704	−0.171243	0.171243
16	−0.00415532	0.0873704	−0.171243	0.171243
17	0.0103137	0.0873704	−0.171243	0.171243
18	−0.0988107	0.0873704	−0.171243	0.171243
19	0.00642562	0.0873704	−0.171243	0.171243
20	−0.0551295	0.0873704	−0.171243	0.171243
21	0.218259	0.0873704	−0.171243	0.171243
22	0.00970171	0.0873704	−0.171243	0.171243
23	−0.0380208	0.0873704	−0.171243	0.171243
24	0.117758	0.0873704	−0.171243	0.171243

Table 4: MAPE value for the DES brown

α	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
MAPE	11.2484	9.26275	9.36603	9.55898	9.67292	9.8182	9.82523	9.60284	9.4356

Table 5: MAPE value for DES holt

MAPE	β / α	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
MAPE	0.1	10.1139	9.94129	9.93563	9.96147	10.0146	10.129	10.1839	10.0151	9.91106
MAPE	0.2	9.4136	9.34794	9.39981	9.44035	9.56963	9.79795	10.0164	10.2344	10.4674
MAPE	0.3	9.09144	9.22661	9.46055	9.79021	10.0959	10.4022	10.7455	11.1267	11.5143
MAPE	0.4	9.02689	9.35794	9.72886	10.1104	10.5094	10.9138	11.3833	11.867	12.3145
MAPE	0.5	9.00694	9.43233	9.83182	10.2438	10.7197	11.1727	11.6403	12.1686	12.6818
MAPE	0.6	8.90925	9.34006	9.79061	10.2269	10.6686	11.1207	11.6528	12.1753	12.6051
MAPE	0.7	8.79654	9.2637	9.64667	10.0507	10.5156	10.9651	11.3411	11.6038	11.7229
MAPE	0.8	8.62661	9.01604	9.41114	9.83381	10.1908	10.4887	10.6578	10.6803	10.6121
MAPE	0.9	8.38666	8.77974	9.161	9.4774	9.74875	9.89043	9.90722	9.86512	9.8109

9.26275% if the $\alpha = 0.2$ which was the minimum error for forecasting, the suitable parameter in DES Brown is equal to $\alpha = 0.2$.

Application of DES using Holt model

Smoothing parameters (α,β) used in DES Holt testing are selected (0.1, 0.1), (0.1, 0.2)...... (0.1, 0.9), (0.2, 0.1), (0.2, 0.2),…… (0.2, 0.9),……. (0.9, 0.9). The MAPE calculating outcomes are presented in Table 5. The findings of all these trials revealed which the value of (α = 0.1 and β = 0.9) produced the smallest error. Because the (MAPE = 8.38666% if the (α = 0.1 and β = 0.9) which was the minimum error for forecasting, the suitable parameter in DES Holt is equal to (α = 0.1 and β = 0.9).

According to Table 6 above, the Holt's DES technique has the lower MAPE score of around 8.38666% As a result, DES Holt's could well be classified as a good forecasting approach. As a result, using Holt's DES as a predicting approach for the following prediction will be more appropriate.

Parameter optimization results for des brown

Parameters for optimization α DES Brown used the golden section approach, as well as the findings could well be found in Table 7. According to the outcomes of the optimization, α = 0.22 through a MAPE optimal value of 9.23616%. While = 0.22, the DES Brown technique could be regarded to be good for prediction. The best value of MAPE was determined relying on the optimization outcomes.

DES Holt's parameter optimization outcomes

The parameters optimization α and β on DES Holt were optimized utilizing a modified golden section technique. The outcomes of parameter optimization for DES Holt are presented in Table 8. Relying on the optimization findings, the best value of was determined α=0.95 and β=0.05 with MAPE optimum value of 8.08586%. As a result, the DES Holt technique could be considered to be good at prediction.

DISCUSSION

It is shown in Table 9 shows the comparison between Brown's as well as Holt's DES for forecasting applied Generation Electrical Energies used in this study. Furthermore, this technique will predict future Generation Electrical Energies values. The data cover a period of (132) months. Brown's one-parameter linear exponential smoothing method is presently being used. The best prediction for future data, according to this approach, is a linear trend calculated by exponentially weighing whole past data values. Even before models is fit as well as Holt's two-parameter linear exponential smoothing method was chosen, every value of Generation Electrical Energies was changed as follows. The best prediction for future data, according to this

Table 6: The result of MAPE score

Method	MAPE (%)
DES Brown's	9.26275
DES Holt's	8.38666

Table 7: DES brown's parameter optimization outcomes

α	0.15	0.16	0.17	0.18	0.19	0.2	0.21	0.22	0.23	0.24	0.25
MAPE	9.77084	9.59147	9.45939	9.3768	9.31287	9.26275	9.23656	9.23616	9.25097	9.26356	9.28123

Table 8: DES Holt's parameter optimization outcomes

	MAPE										
β / α	0.05	0.06	0.07	0.08	0.09	0.1	0.11	0.12	0.13	0.14	0.15
0.85	8.31223	8.35224	8.39135	8.42957	8.46679	8.50296	8.53965	8.57689	8.61677	8.6565	8.69609
0.86	8.28947	8.32858	8.36675	8.404	8.44023	8.47538	8.51364	8.55456	8.59434	8.63298	8.67083
0.87	8.26557	8.30375	8.34097	8.37777	8.4153	8.45283	8.49215	8.53183	8.57054	8.60807	8.64593
0.88	8.242	8.28048	8.3184	8.35572	8.39245	8.43171	8.47005	8.5078	8.54588	8.58339	8.62155
0.89	8.22163	8.25912	8.29615	8.33255	8.37105	8.40933	8.44705	8.48398	8.52058	8.55875	8.59577
0.9	8.20099	8.23723	8.27313	8.31057	8.34901	8.38666	8.42346	8.45936	8.49604	8.53278	8.5736
0.91	8.17931	8.21468	8.25059	8.28874	8.32622	8.36288	8.39866	8.43469	8.47076	8.51242	8.55396
0.92	8.15662	8.19111	8.22857	8.26578	8.30228	8.33793	8.37328	8.41065	8.45232	8.49412	8.53502
0.93	8.13297	8.16867	8.20548	8.24172	8.27723	8.31264	8.35077	8.39256	8.43426	8.47501	8.51483
0.94	8.10912	8.14547	8.18134	8.217	8.25359	8.29134	8.33257	8.37418	8.41484	8.45497	8.49577
0.95	8.08586	8.12153	8.15834	8.19464	8.23179	8.27237	8.31392	8.35451	8.39493	8.43563	8.47533

Table 9: The result of the MAPE Score of Parameter Optimization for DES BROWN and Holt's

Criteria	DES Brown	DES Holt's
	α=0.22	α=0.95 and β=0.05
	Period	Period
MAPE	9.23616	8.08586

Forecast Summary. *Brown's linear exp. smoothing was used as the prediction models α=0.22. *The forecast model has been chosen: Holt's linear exp. smoothing through α=0.95 and β=0.05

Table 10: Forecasting by using DES BROWN and Holt methods

Years	Months	DES Brown	DES Holt's	Years	Months	DES Brown	DES Holt's
2021	1	3063.27	3316.63	2024	1	3109.59	3971.89
	2	3064.55	3334.83		2	3110.87	3990.09
	3	3065.84	3353.03		3	3112.16	4008.29
	4	3067.13	3371.23		4	3113.45	4026.49
	5	3068.41	3389.43		5	3114.73	4044.69
	6	3069.7	3407.64		6	3116.02	4062.9
	7	3070.99	3425.84		7	3117.31	4081.1
	8	3072.27	3444.04		8	3118.59	4099.3
	9	3073.56	3462.24		9	3119.88	4117.5
	10	3074.85	3480.44		10	3121.17	4135.7
	11	3076.13	3498.64		11	3122.45	4153.9
	12	3077.42	3516.85		12	3123.74	4172.11
	1	3078.71	3535.05	2025	1	3125.03	4190.31
2022	2	3079.99	3553.25		2	3126.31	4208.51
	3	3081.28	3571.45		3	3127.6	4226.71
	4	3082.57	3589.65		4	3128.89	4244.91
	5	3083.85	3607.85		5	3130.17	4263.11
	6	3085.14	3626.06		6	3131.46	4281.32
	7	3086.43	3644.26		7	3132.75	4299.52
	8	3087.71	3662.46		8	3134.03	4317.72
	9	3089.0	3680.66		9	3135.32	4335.92
	10	3090.29	3698.86		10	3136.61	4354.12
	11	3091.57	3717.06		11	3137.89	4372.32
	12	3092.86	3735.27		12	3139.18	4390.53
	1	3094.15	3753.47				
2023	2	3095.43	3771.67				
	3	3096.72	3789.87				
	4	3098.01	3808.07				
	5	3099.29	3826.27				
	6	3100.58	3844.48				
	7	3101.87	3862.68				
	8	3103.15	3880.88				
	9	3104.44	3899.08				
	10	3105.73	3917.28				
	11	3107.01	3935.48				
	12	3108.3	3953.69				

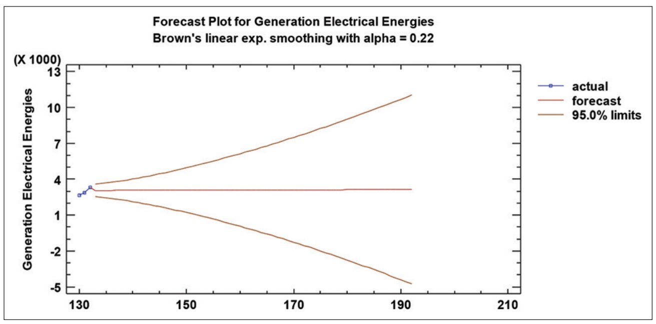
approach, is a linear trend calculated by exponentially weighing whole past data values. Before fitting the model, each value of the Generation Electrical Energies was modified as follows. As a consequence, DES Holt's approach could be considered to be good at forecasting. DES Holt's is chosen as the strongest forecasting model. Depending on the optimization outcomes, achieved optimal value of (α=0.95 and β=0.05) through MAPE optimum value of 8.08586% in DES Holt's technique. However, depending on the optimization outcomes in the DES Brown's technique, an optimal value of α=0.22 was found, with a MAPE ideal value of 9.23616%. Then, Holt's technique could be considered to be the most suited way for forecasting Generation Electrical Energies data since the value of MAPE in DES Holt's method was less than the value of MAPE in the DES Brown's method.

$$\text{MAPE}_{\text{(DES Brown method)}} = 9.23616\% > \text{MAPE}_{\text{(DES Holt's method)}} = 8.08586\%$$

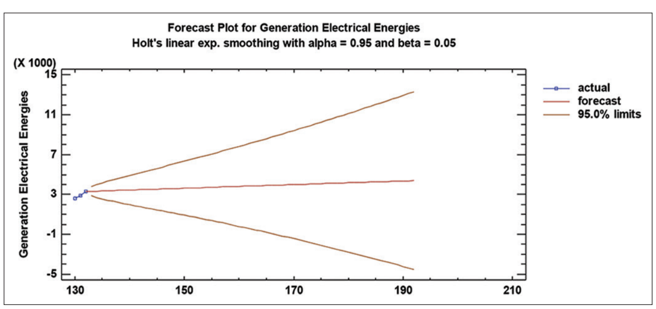
CONCLUSION AND RECOMMENDATION

The contrast among Brown's and Holt's DES could be established depending on the criterion of MAPE for determining the optimum data technique. With using MAPE as performance measurements, we concluded that the Holt's DES Technique is the ideal technique since the values of MAPE in the Holt's DES would be less than the values of MAPE in the Brown's DES. Furthermore, depending on the optimization has been done α and β the optimal values achieved for DES Holt's are (optimal values of $\alpha = 0.95$ and β optimal value of 0.05) having MAPE optimal value of 8.08586%, as well as for DES Brown's is (optimum value of $\alpha = 0.22$ via MAPE optimal value of 9.23616%). A MAPE of the DES Holt's approach was lower than that of MAPE DES Brown's technique. Future research are planned to optimize the parameters utilizing various non-linear programming approaches or to optimize by making changes to the initialization method

Prediction: Forecasting using Optimum Parameter for the DES Brown and DES Holt methods



This Table 10 illustrates the expected values for the Generation Electrical Energies. Throughout the period while true data is obtainable; this also shows the forecasted values from either the fitting model as well as the residuals (data-forecast). It indicates 95.0% forecast limits for predictions for time period beyond the ending of a series. Those limits represent where a actual data values at the chosen future time was expected to be through 95.0% confidence, providing the fitted model is adequate for the data. You could plot the predictions by choosing Prediction Plot from the listing of graphical choices. You could modify the level of confidence when reviewing the plot using the alternative mouse button as well as selecting Pane Options. Choose Model Comparisons from of the list of Tabular Options to evaluate if the model appropriately matches the data.



That table illustrates the predicted values for the Generation Electrical Energies. Throughout the period when real data are obtainable, this also shows the projected value from of the fitted models as well as the residuals (data-forecast). It indicates 95.0% forecast limits for predictions for periods of time well beyond ending of the series. These limits represent where the real data value is expected to be through 95.0% confidence at a given future time, providing the fitted model was adequate for the data. You could plot the predictions by choosing Prediction Plot from of the list of graphical choices. You could modify the level of confidence when examining the plot by using the alternative mouse button as well as selecting Pane Options. Choose Model Comparisons from of the listing of Tabular Options to see if the model matches the data well.

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