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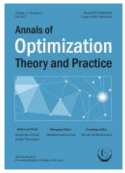

Estimation of electrical energy consumption in Tamil Nadu using univariate time-series analysis

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Abstract Demand estimation for power utilization might be a key achievement factor for the occasion of any nation. This might be accomplished if the requirement is estimated precisely. In this paper, Distinctive Univariate methods of forecasting Autoregressive Integrated Moving Average (ARIMA), ETS, Holt's model, Holt Winter's Additive model, Simple exponential model was used to figure forecast models of the power consumption in Tamil Nadu. The goal is to look at the presentation of these five methodologies and the experimental information utilized in this investigation was data from previous years for the monthly power consumption in Tamil Nadu from 2012 to 2020. The outcomes show that the ARIMA model diminished the MAPE value to 5.9097%, while those of ETS, Holt's Model, Holt winter's technique, SES is 6.3451%, 9.7708%, 7.3439%, and 9.5305% separately. Depend on the outcomes, we conclude that the ARIMA approach beat the ETS and Holt winter's techniques in this situation.

Keywords Autoregressive integrated moving average (ARIMA); Electricity demand; Univariate time series analysis; Forecasting

1. Introduction

Electricity might be a huge drive for a monetary turn of events, while the efficiency of forecasting of demand is a pivotal element bringing about the accomplishment of proficiency arranging. Hence, energy examiners need a proposal to raised pick the premier fitting estimating methods to flexibly precise conjectures of power utilization patterns. Nonetheless, numerous strategies add to the future power prediction. In this examination, Distinctive Univariate estimating procedures were used to conjecture the power consumption in Tamil Nadu and a correlation of these strategies were directed to pick the best methodology in this circumstance.

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2. Literature review

S. Edigera Volkan *et al.*,(2007) used the traditional models for estimating energy demand. Bashirahamad ,(2017) concludes Time-series models are exceptionally proficient when contrasted with auxiliary models since demonstrating and forecasts can be easily done.

In Kandananond, (2011), compared the three different forecast models which are ARIMA, ANN, and MLR. These models are used to prepare estimation models of power consumption in Thailand. In Zeynep andCan Ganiz, (2017), Machine Learning Based Model is applied to figure power utilization of Turkey. Salifu Katara *et al.*,(2014) compared the ARIMA models to forecast domestic, commercial, and Industrial power consumption in Tamale. Abdel-Aal R.E *et al.*, (1997) recommended the ARIMA model for Univariate time series analysis to forecast monthly power consumption. Pappas *et. al.*,(2008) presented the traditional method, to estimate power consumption. Various ARIMA models are compared to choose the best forecasting model. James W. Taylor *et al.*,(2006) suggested six forecasting methods for estimated power consumption. Mucuk and Uysal,(2009) estimated the essential energy interest in Turkey by utilizing the univariate strategy.

The monthly data was collected from an online source[1]. Since there are no observational or definite guidelines to infer the least difficult estimating model, the suitable one was chosen by picking the model with the absolute least error. Besides, a few works have been added to coordinate to check a major distinction between the errors from every technique. The assurance of a suitable determining model depended on authentic information, while the error rules, for example, RMSE and MAPE were used as measures to find the fitted model. For confirmation purposes, the outcomes are contrasted and three other customary request determination models, in particular AICc, AIC, and BIC. In this paper, the performance of ARIMA, Holt Winter's strategy, Holt Method, ETS, Simple Exponential technique are evaluated.

3. Methodology

The examination was performed utilizing five techniques, ARIMA, ETS, Holt Winter's, Holt Model, and Simple Exponential Method.

ARIMA model

This model might be a class of measurable models for exploring and determining the data. It unequivocally takes into account a set-up of standard structures in time series information, and as such gives a straightforward yet best strategy. The request for this model is commonly distinguished within the sort of (p, d, q), where p shows the request for the autoregressive part, while d is for the hours of distinction and q for the request for the moving normal part. To perform forecasting by utilizing ARIMA Model, first, the autocorrelation function (ACF) and the Augmented Dickey-Fuller (ADF) tests were

[1] Kaggle, Data accessed: https://www.kaggle.com

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used to test the stationarity of the series. Following the stationarity test, the most fitting ARIMA model for determining was distinguished as ARIMA (1, 1, 1) (0, 1, 1) with MAPE value 5.9097%. In, **Figure 1**, the ACF and PACF of the observational data are plotted.

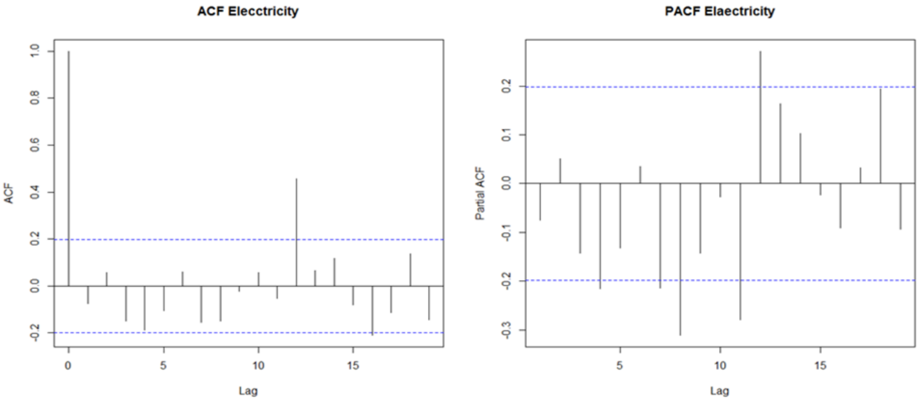

Figure 1. ACF and PACF for Observational Data

ETS

ETS is a period arrangement determining a strategy for univariate data that can be reached out to help information with a deliberate pattern or occasional part. Outstanding smoothing anticipating techniques are comparative in that an expectation is a weighted amount of past perceptions, yet the model unequivocally utilizes a dramatically diminishing load for past perceptions. In particular, past perceptions are weighted with a mathematically diminishing proportion. ETS model alluding to the unequivocal displaying of Error, Trend, and Seasonality. In this paper, we use ETS model with a multiplicative pattern to conjecture ten years of Electricity utilization with value of MAPE 6.3451%. The forecasted values are as shown in **Figure 2.**

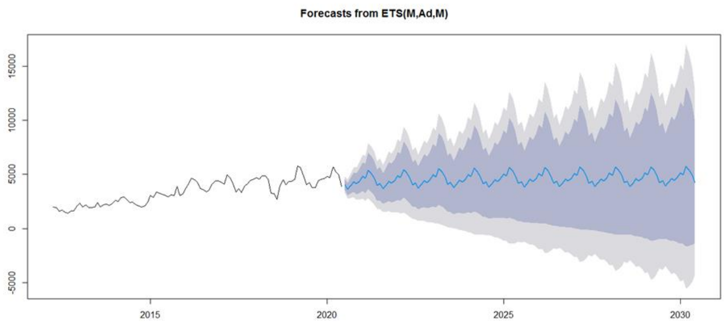

Figure 2. Forecast from ETS model.

Holt-Winters' additive model

This model is appropriate for occasional time series. Holt-Winters' determining model comprises of four conditions one-gauge condition and three smoothening conditions, one each for level, pattern, and irregularity. These four conditions are the part structure portrayal of Holt-Winters' additive model. In this paper, we use Holt-Winter's additive model to figure ten years of monthly Electricity utilization with MAPE 7.3439%. The forecasted values are as shown in **Figure 3.**

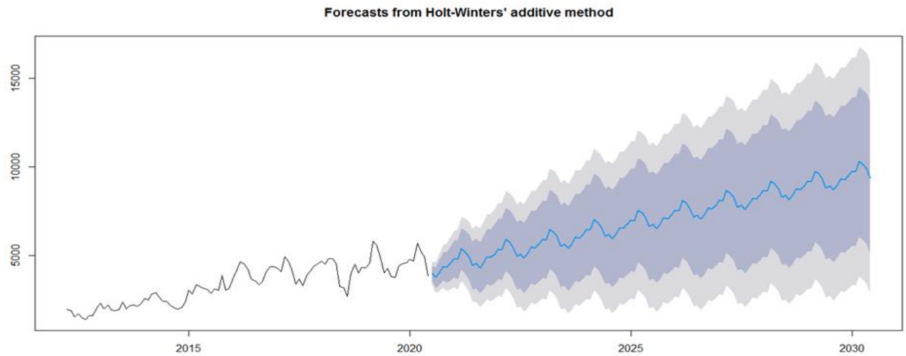

Figure 3. Holt-Winter's additive model.

Holt's model

Holt's model is a famous smoothing model to estimate the information with the pattern. It has three conditions that cooperate to produce the last conjecture. The first is a fundamental condition that straightforwardly changes the last period's pattern. It refreshed after some time during that time condition. certainly, the last condition is utilized to produce the last pattern. Also, the general smoothing and the pattern smoothing conditions are used in this model. The model is additionally called the double smoothing model. In this paper, we utilize Holt's technique to estimate ten years of Electricity utilization with the value of MAPE 9.7708%. The forecasted values are as shown in **Figure 4.**

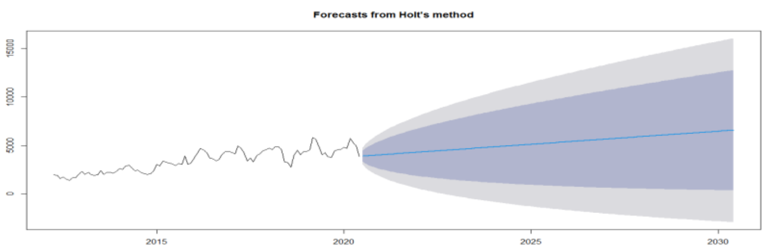

Figure 4. Forecasts from Holt’s model.

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Simple exponential model

This model is a popular assessing procedure for univariate data without an example or abnormality. It requires a limit. This limit controls the effect of the recognitions at prior time steps decays exponentially. the coefficient is as often as possible set to a motivator someplace in the scope of 0 and 1. Tremendous characteristics infer that the model spotlights primarily on the most recent past discernments, however more humble characteristics mean a more prominent measure of the arrangement of encounters is viewed as when making a desire. In this paper, we use SES to predict ten years of Electricity usage with MAPE 9.5305%. The forecasted values are as shown in **Figure 5.**

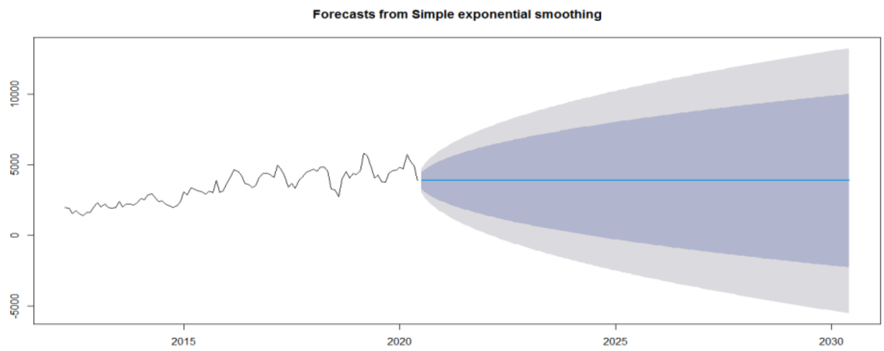

Figure 5. Forecasts from simple exponential model.

4. Results

The MAPE, RMSE, AIC, AICc, and BIC from the over five techniques are thought about in **Table 1**. The outcomes demonstrated that the mistake minimization ability of the ARIMA model with MAPE 5.9097% outflanked the other four methodologies, ETS model with MAPE 6.3451%, Holt-Winter's additive model 7.3439%, Holt's technique 9.7708%, and SES 9.5305% separately. The proposed ARIMA model for electric demand is selected from the above results. It can be supposed to be the best regarding prediction for power consumption in Tamil Nadu.

Table 1. The Comparison of Errors from Five Different Models

	MAPE	**RMSE**	**AIC**	**AICc**	**BIC**
ARIMA	5.9097	292.6657	1246.48	1246.97	1256.29
ETS	6.3451	270.821	1602.544	1611.094	1649.256
Holt-Winter's additive model	7.3439	293.048	1613.623	1621.179	1657.741
Holt's method	9.7708	433.4146	1667.112	1667.758	1680.088
SES	9.5305	432.6054	1662.742	1662.995	1670.528

Table 2, shows the forecasted value from July 2020 to Jun 2030 of monthly electricity

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consumption in Tamil Nadu. From, the above-tabulated value we clearly see that ARIMA model has the lowest MAPE value 5.9097, RMSE value 292.6657, AIC value 1246.48, AICc value 1246.97, and BIC value 1256.29.

Table 2 .The Forecasted value of Monthly Electricity Consumption in Tamil Nadu

Month/year	Forecast	Month/year	Forecast	Month/ year	Forecast	Month/ year	Forecast
Jul 2020	4067.241	Jan 2023	5416.591	Jul 2025	5259.691	Jan 2028	6536.334
Aug 2020	3726.474	Feb 2023	5391.229	Aug 2025	4888.336	Feb 2028	6510.972
Sep 2020	4144.628	Mar 2023	6285.647	Sep 2025	5288.769	Mar 2028	7405.390
Oct 2020	4681.564	Apr 2023	6006.871	Oct 2025	5815.440	Apr 2028	7126.614
Nov 2020	4661.593	May 2023	5593.976	Nov 2025	5789.524	May 2028	6713.718
Dec 2020	4808.002	Jun 2023	4661.668	Dec 2025	5932.488	Jun 2028	5781.411
Jan 2021	4965.946	Jul 2023	4811.794	Jan 2026	6088.437	Jul 2028	5931.537
Feb 2021	4941.740	Aug 2023	4440.438	Feb 2026	6063.075	Aug 2028	5560.181
Mar 2021	5836.828	Sep 2023	4840.872	Mar 2026	6957.493	Sep 2028	5960.615
Apr 2021	5558.440	Oct 2023	5367.543	Apr 2026	6678.717	Oct 2028	6487.286
May 2021	5145.769	Nov 2023	5341.626	May 2026	6265.821	Nov 2028	6461.369
Jun 2021	4213.592	Dec 2023	5484.591	Jun 2026	5333.514	Dec 2028	6604.334
Jul 2021	4363.793	Jan 2024	5640.539	Jul 2026	5483.640	Jan 2029	6760.282
Aug 2021	3992.481	Feb 2024	5615.178	Aug 2026	5112.284	Feb 2029	6734.920
Sep 2021	4392.940	Mar 2024	6509.596	Sep 2026	5512.718	Mar 2029	7629.339
Oct 2021	4919.626	Apr 2024	6230.820	Oct 2026	6039.389	Apr 2029	7350.563
Nov 2021	4893.718	May 2024	5817.924	Nov 2026	6013.472	May 2029	6937.667
Dec 2021	5036.687	Jun 2024	4885.617	Dec 2026	6156.436	Jun 2029	6005.360
Jan 2022	5192.638	Jul 2024	5035.743	Jan 2027	6312.385	Jul 2029	6155.485
Feb 2022	5167.278	Aug 2024	4664.387	Feb 2027	6287.023	Aug 2029	5784.130
Mar 2022	6061.698	Sep 2024	5064.821	Mar 2027	7181.442	Sep 2029	6184.563
Apr 2022	5782.922	Oct 2024	5591.492	Apr 2027	6902.665	Oct 2029	6711.235
May 2022	5370.027	Nov 2024	5565.575	May 2027	6489.770	Nov 2029	6685.318
Jun 2022	4437.719	Dec 2024	5708.539	Jun 2027	5557.462	Dec 2029	6828.282
Jul 2022	4587.845	Jan 2025	5864.488	Jul 2027	5707.588	Jan 2030	6984.231
Aug 2022	4216.490	Feb 2025	5839.126	Aug 2027	5336.233	Feb 2030	6958.869
Sep 2022	4616.923	Mar 2025	6733.545	Sep 2027	5736.666	Mar 2030	7853.287
Oct 2022	5143.594	Apr 2025	6454.768	Oct 2027	6263.337	Apr 2030	7574.511
Nov 2022	5117.678	May 2025	6041.873	Nov 2027	6237.421	May 2030	7161.616
Dec 2022	5260.642	Jun 2025	5109.565	Dec 2027	6380.385	Jun 2030	6229.308

5. Conclusion

ARIMA, ETS, Holt-Winter's additive model, Holt's model, and SES, are used to forecast the monthly power consumption in Tamil Nadu dependent on the empirical data. From all the above methods we forecast the monthly power consumption from July 2020 to Jun 2030 in Tamil Nadu. In this paper, we conclude that the ARIMA (1,1,1) (0,1,1) (12) is the best model to fit the empirical data. Since this model was created with almost the least possible number of perceptions suggested.

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