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A COMPARATIVE STUDY BETWEEN THE HOLT-WINTERS MODEL AND FUZZY TIME SERIES IN PREDICTING MONTHLY ELECTRICITY CONSUMPTION: A CASE STUDY OF THE ZLITEN REGION

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Abstract

This study aimed to compare the performance of the Holt-Winters model and the fuzzy time series model in predicting monthly electricity consumption using monthly data for the Zliten region from January 2017 to December 2024. The study employed descriptive analysis and time series analysis methods. IBM SPSS Statistics was used to implement the Holt-Winters model, while the fuzzy time series model was implemented using fuzzy logic relationships. The efficiency of both models was evaluated using prediction accuracy measures such as MAE, RMSE, and MAPE. The results showed that both models possessed good predictive power, with the Holt-Winters additive model clearly outperforming the fuzzy time series model based on the prediction error values. The study recommended adopting the more accurate Holt-Winters additive model for forecasting future electricity consumption.

Keywords: Electricity consumption, Holt-Winters, fuzzy time series, prediction, time series.

1. Introduction

Electricity is one of the most essential resources upon which economic and social activities depend. Accurate forecasting of electricity consumption is a crucial topic that assists decision-makers in effectively planning electricity production and distribution. With the continuous increase in electricity demand, population growth, and urban expansion, the need for accurate statistical models to forecast electrical loads has become essential (Makridakis et al., 1998).

Time series models are widely used in analyzing electricity consumption data. Among the most prominent of these models is the Holt-Winters model, which is distinguished by its ability to represent general trends and seasonality in the data (Hyndman & Athanasopoulos, 2021). Fuzzy time series have also emerged as a modern method that offers high flexibility in dealing with irregular data and the ambiguity inherent in real-world phenomena (Song & Chissom, 1993).

This study aims to compare the performance of two models in forecasting monthly electricity consumption using real data for the period from 2017 to 2024.

2. Problem Statement

Electricity companies face difficulty in accurately predicting electrical loads due to seasonal variations and fluctuations in consumption rates. This can lead to poor future planning for electricity generation and distribution. Therefore, there is a need to use effective statistical models capable of improving the accuracy of electrical load prediction.

3. Objectives

This study aims to analyze the temporal behavior of electricity consumption, develop a Holt-Winters forecasting model and a fuzzy time series model, and then compare the accuracy of the two models to determine the most efficient forecasting model.

4. Hypothesis

This study hypothesizes that there are statistically significant differences in forecasting accuracy between the Holt-Winters model and the fuzzy time series model.

5. Previous Studies

Hyndman and Athanasopoulos (2021) conducted a study that examined the use of the Holt-Winters model in predicting seasonal time series. The results showed that the model has a high ability to capture the general trend and seasonality in time data, making it suitable for predicting short- and medium-term electrical loads. Song and Chissom (1993) presented the fuzzy time series model as an alternative to traditional models, explaining that this model is characterized by its ability to deal with uncertain and fluctuating data more flexibly compared to classical models. Makridakis et al. (1998) also indicated that models based on exponential smoothing are among the most widely used forecasting models in economic and energy applications due to their ease of application and acceptable accuracy. In another study, Box et al. (2015) explained that time series analysis is one of the most important statistical methods used in predicting economic and energy phenomena, especially when regular and relatively long-term time data are available.

6. Theoretical Framework

6.1 Time Series:

A time series is a collection of chronologically ordered observations. Studying time series data aims to analyze time patterns and predict future values (Box et al., 2015). A time series typically consists of a general trend, seasonal variations, periodic fluctuations, and a random component.

6.2 The Holt-Winters Model:

The Holt-Winters model is used when data exhibits a general trend and seasonal variations. It is one of the most well-known seasonal exponential smoothing models (Hyndman & Athanasopoulos, 2021) and is divided into two sub-models: the additive model and the multiplicative model.

6.3 Fuzzy Time Series:

Fussy time series emerged to address ambiguity and uncertainty in time data. They rely on transforming numerical data into fuzzy sets and then constructing fuzzy logical relationships between them (Song & Chissom, 1993). They are characterized by their ability to handle ambiguity and flexibility with fluctuating data while minimizing the impact of outliers. 7. Study Methodology

The study relied on monthly data for electricity consumption in the Zliten region during the period from January 2017 to December 2024, i.e., 96 monthly observations. Descriptive analysis of the two models was used: the Holt-Winters model and the fuzzy time series model, with calculation of prediction accuracy measures.

7. Practical Evaluation

7.1 Descriptive Analysis of Electricity Consumption Data:

Monthly electricity consumption data was entered into IBM SPSS Statistics software, where the first variable represents time and the second variable represents electricity consumption values. The arithmetic mean, standard deviation, and minimum and maximum values of the study data were calculated to determine its characteristics. The results are shown in the following table:

Table 1. Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	C.V
Consumption	96	52533	149518	96425.21	21397.84	22.19%

Table (1) presents the descriptive statistics for electricity consumption from January 2017 to December 2024. The average monthly electricity consumption was 96,425.21 units, while the standard deviation was 21,397.84 units, indicating significant variation in consumption levels during the study period.

The lowest consumption value was 52,533 units, while the highest was 149,518 units, reflecting a wide range of changes in electricity consumption over time. These results suggest the possibility of temporal trends or seasonal effects that warrant further analysis using time series models.

The coefficient of variation was approximately 22.19%, indicating a moderate degree of dispersion in the electricity consumption data compared to the overall average consumption. This reflects relative stability in the time series, despite the presence of seasonal fluctuations and temporal trends that necessitate the use of appropriate predictive models.

7.2 Time Series Analysis:

Figure 1 shows the time series of electricity consumption during the period from January 2017 to December 2024.

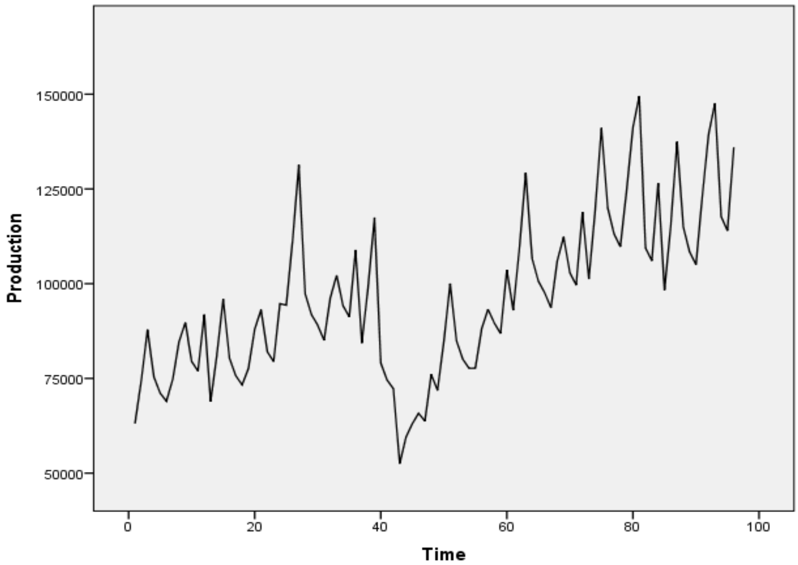

Fig.1. Time series of electricity consumption for the study period.

Figure 1 reveals a general upward trend in electricity consumption levels over time, with recent years showing higher values compared to earlier years. A clear seasonal pattern is also evident, characterized by the recurring peaks and troughs in a nearly regular cycle, indicating an annual seasonal influence on the data. Furthermore, some sharp declines were observed during specific periods, which may reflect the impact of temporary operational or technical factors. These results suggest the suitability of using seasonal forecasting models, such as the Holt-Winters model, for analyzing this time series and predicting future values.

7.3 Holt-Winters Additive and Multiplicative Models and Selection of the Best Model:

The Holt-Winters additive and multiplicative models were applied to electricity consumption data with the aim of identifying the most efficient model for representing the time series and predicting its future values.

Table 2. Comparison of conformity quality indicators between the Holt-Winters additive and multiplicative models

Index	Winters Additive	Winters Multiplicative
R^2	0.909	0.901
RMSE	6526.210	6813.824
MAE	3899.746	3926.810
MAPE (%)	4.402	4.263
Normalized BIC	17.710	17.796
Ljung-Box Sig.	0.278	0.001

Table 2 shows that both models achieved a high level of predictive accuracy, with the coefficient of determination (CID) exceeding 90% in both models. This indicates a high capacity to explain changes in electricity consumption during the study period.

Regarding the mean squared error (MAPE), the multiplicative model achieved a value of 263.4% compared to 402.4% for the additive model. This very slight difference indicates a similar level of predictive accuracy between the two models. As for other error indicators, the additive model performed better, recording a lower value for the root mean squared error (RMSE = 6526.21) compared to the multiplicative model (RMSE = 6813.824). It also recorded a lower mean absolute error (MAE = 3899.746) than the multiplicative model (MAE = 3926.810).

The additive model also achieved a lower value for the Normalized BIC (Normalized BIC=17.710) compared to the multiplicative model (Normalized BIC=17.796), which reflects a higher quality for the additive model while maintaining relative simplicity.

One of the most important criteria used in evaluating time series models is the Ljung-Box test for residual independence. The statistical significance value for the summation model was 0.278, which is greater than 0.05, indicating the absence of significant autocorrelation in the residuals and that the model successfully explained most of the patterns in the data. In contrast, the significance value for the multiplicative model was 0.001, which is less than 0.05, indicating the presence of residual autocorrelation and the model's inadequacy in explaining all components of the time series.

Based on the preceding comparison, it can be concluded that the summation model is the most suitable model for electricity consumption data in Zliten, due to its superiority in most quality of fit indicators and its success in passing the residual independence test, which supports its adoption in predicting future values. After adopting the Holt-Winters collective model as the most suitable for the study data, it was used to predict the monthly electricity production in the city of Zliten during the year 2025. Table 3 shows the expected values of consumption during the months of the year.

Table 3. Projected values for monthly electricity Consumption in 2025 using the Holt-Winters additive model

Month	Expected values	Month	Expected values
JAN 2025	119579	JUL 2025	123815
FEB 2025	134553	AUG 2025	135618
MAR 2025	152777	SEP 2025	141550
APR 2025	130055	OCT 2025	127841
MAY 2025	124636	NOV 2025	124950
JUN 2025	121914	DEC 2025	142299

The forecast results in Table 3 indicate the continuation of the seasonal pattern observed in historical data, with consumption levels varying across different months of the year while maintaining a generally upward trend. March recorded the highest expected value at 152,777 units, while January recorded the lowest expected value at 119,579 units.

The results also show an expected increase in consumption during the first and third quarters of the year, with relative decreases during some summer months and the beginning of the fourth

quarter. This reflects the continued seasonal influences that characterized the time series during the study period.
These forecasts indicate that the expected demand for electricity in Zliten will remain at high levels throughout 2025, which can contribute to supporting planning, operation, and decision-making related to the management of the electricity system.

7.4 Applying the Fuzzy Time Series Model:

Fuzzy time series are a modern technique used to predict uncertain and ambiguous phenomena. These methods rely on transforming numerical values into fuzzy sets and then constructing fuzzy logical relationships used in the prediction process.
In this section, a fuzzy time series model was applied according to the methodology proposed by Chen (1996) to predict monthly electricity consumption in the Zliten region. This was done to conduct an objective quantitative comparison with the Holt-Winters summation model used in the previous section.
First, the study universe was defined based on the smallest and largest values in the data. The minimum monthly consumption was 52,533 units, while the maximum was 149,518 units. To simplify the division process, the following universe was a adopted: [U = [52,000, 150,000]. The universe was then divided into seven equal intervals of 14,000 units each, as shown in Table 4.

Table 4. Division of the study range into fuzzy periods

Fuzzy set	Domain (Range)	Midpoint	Fuzzy set	Domain (Range)	Midpoint
A1	52000, 66000	59000	A5	108000, 1122000	115000
A2	66000, 80000	73000	A6	122000, 136000	129000
A3	80000, 94000	87000	A7	136000, 150000	143000
A4	94000, 108000	101000			

After dividing the domain into fuzzy periods, each monthly consumption value was transformed into the fuzzy set to which it belongs according to the period it falls within, a process known as fuzzification. Table 5 shows a sample of the transformed data with a sample of actual and predicted values and errors.

Table 5. Sample of actual values, fuzzy variables, expectations, and errors

Time (t)	Month/Year	Actual value	F(t-1)	F(t)	Expected value	Absolute error	MAPE
1	01/2017	63086	-	A1	-	-	-
2	02/2017	74351	A1	A2	63667	10684	14.37%
3	03/2017	87871	A2	A3	78895	8976	10.22%
9	09/2017	89730	A3	A3	89435	295	0.33%
39	03/2020	117446	A5	A5	115000	2446	2.08%
95	11/2024	114000	A5	A5	115000	1000	0.88%
96	12/2024	136000	A5	A7	115000	21000	15.44%

Table 5 shows that the model exhibited high accuracy in stable months (t=9, t=95), while recording high errors during exceptional periods of decline (such as July 2020, associated with the COVID-19 pandemic) due to the model's reliance on fixed averages.

After completing the fuzzy transformation, all first-order reversal relationships were extracted using the formula F(t-1) → F(t) for observations from t=2 to t=96. These relationships were then grouped according to the previous case. Table 6 shows the integration of these grouped relationships with the final forecasting rules, where the forecast value was calculated as the arithmetic mean of the midpoints of all subsequent cases for each previous case.

Table 6: Combined fuzzy reflection relationships and prediction rules (Chen, 1996(

Previous case	**Subsequent cases (frequency)**	**Prediction rule** $\hat{y}(t)$
A1	A2(2), A1(4)	63667
A2	A3(7), A2(10), A4(1), A1(1)	78895
A3	A2(6), A3(9), A4(6), A5(2)	89435
A4	A3(6), A4(6), A5(6), A6(2)	103800
A5	A6(3), A3(1), A2(1), A4(4), A7(3), A5(4)	115000
A6	A4(3), A7(2)	117800
A7	A5(4), A7(2)	124333

The prediction rules were applied to the entire period (95 predictions) and the overall accuracy criteria for the fuzzy model and the Holt-Winters additive model were calculated for the same period to make a fair comparison, as shown in Table 6.

Table (7): Comparison of accuracy criteria between the Holt-Winters additive and fuzzy time series models

Index	**Holt-Winters Additive Model**	**Fussy Time Series Model**
MAE	3899.75	11572.4
RMSE	6526.21	13348.1
MAPE	4.40%	11.40%

Based on the most frequent prediction rule for state A7 (which is A7 → A5 at a rate of 4 times out of 6), the fuzzy model predicted that consumption would remain at 115,000 units during most months of 2025, except for January, in which it predicted 124,333 units (because December 2024 was A7), while the Holt-Winters additive model predicted varying values according to the seasonal pattern (as in the original Table 6).

8. Results

Based on the results obtained from the descriptive analysis and the use of the Holt-Winters additive model, compared with the Chen fuzzy time series model, the study reached the following conclusions:

• The descriptive analysis results showed a clear general trend and seasonality in the electricity consumption data during the study period, which is consistent with what Box et al. (2015) indicated regarding the characteristics of energy time series.

• The Holt-Winters additive model clearly outperformed the fuzzy model, recording a MAPE of 4.40%, an RMSE of 6526.21 units, and a MAE of 3899.75, reflecting its high ability to represent the general trend and seasonality in electricity consumption data. This is consistent with the results of Hyndman and Athanasopoulos (2021), which confirmed the model's effectiveness in representing seasonality and general trends.

• The fuzzy model achieved a mean absolute error (MAPE) of 11.40%, a root mean square error (RMSE) of 13,348.1 units, and a mean absolute error (MAE) of 11,572.4 units. This performance is acceptable and consistent with the results of Song and Chissom (1993), but lower than that of the comparator model.

• Given the significant differences in accuracy measures (MAPE being approximately 7 percentage points lower in favor of the Holt-Winters model), the hypothesis that there are statistically significant differences in forecast accuracy between the two models was accepted. These differences favored the Holt-Winters additive model because it considers both the overall upward trend and the clear cyclical seasonality in the time series. In contrast, the fuzzy model used (Chen first-order) relied on fixed fuzzy periods and simple relationships that failed to capture seasonal patterns or sudden, sharp changes (such as the exceptional drop in July 2020).

9. Conclusion:

This study confirms that classical models specifically designed to fit the time series structure (trend + seasonality) still outperform simple fuzzy time series models in electricity applications when the data are regular and relatively long-term. However, fuzzy time series remain a promising alternative in cases of high uncertainty or insufficient information about the seasonal pattern.

10. Recommendations:

We recommend adopting the Holt-Winters additive model to predict monthly electricity consumption in the Zliten region, and improving the fuzzy time series model in future studies by using unequal fuzzy intervals, second- or third-order relationships, or incorporating extrinsic variables.

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