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An Analysis and Forecasting of Electricity Demand Using the Triple Exponential Smoothing Method

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Abstract

Electricity is a basic necessity required in daily life that supports various activities, including economic development. The continuous increase in electricity demand necessitates reliable and efficient power system planning and management. Forecasting electricity demand is essential due to its fluctuating nature and seasonal patterns. This study aims to forecast electricity demand using the Triple Exponential Smoothing method, utilizing data from the Australian Energy Market Operator (AEMO) for the New South Wales region, Australia, covering the period from January 2015 to February 2025. This method was selected because it effectively handles time series patterns consisting of level, trend, and seasonality components. The forecasting results indicated that the method closely followed the actual data patterns and produces a Mean Absolute Percentage Error (MAPE) of 2.89%, which was categorized as highly accurate. This model was expected to serve as a basis for decision-making in anticipating future fluctuations in electricity demand.

Keywords: *Electricity Demand; AEMO; Triple Exponential Smoothing, MAPE*

Abstrak

Listrik merupakan kebutuhan dasar yang diperlukan dalam kehidupan sehari-hari yang mendukung berbagai aktivitas, termasuk pembangunan ekonomi. Permintaan listrik yang terus meningkat membutuhkan peencanaan dan pengelolaan sistem kelistrikan yang andal dan efisien. Peramalan permintaan Listrik menjadi penting karena sifatnya yang fluktuatif dan mengikuti pola musiman. Penelitian ini bertujuan untuk meramalkan permintaan listrik menggunakan metode Triple Exponential Smoothing dengan menggunakan data dari Australian Energy Market Operator (AEMO) untuk wilayah New South Wales, Australia, selama periode Janurari 2015 hingga Februari 2025. Metode ini dipilih karena mampu menangani pola time series yang terdiri dari level, tren, dan seasonal. Hasil peramalan menunjukkan bahwa metode ini mampu mengikuti pola data actual dengan baik dan menghasilkan nilai Mean Absolute Percentage Error (MAPE) senilai 2,89% dimana hasil peramalan sangat baik. Model ini diaharapkan dapat giunakan sebagai dasar dalam pengambilan keputusan untuk mengantisipasi fluktuasi permintaanlListrik di masa mendatang.

***Kata-kata kunci**: Permintaan Listrik; AEMO; Triple Exponential Smoothing; MAPE*

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1. Introduction

Electricity is a basic necessity needed in daily life that supports various activities, including economic development [1]. The availability of reliable and sustainable electricity is a major factor in supporting industrial, household, and other sector activities. The increasing demand for electricity is an important aspect in electricity system planning because it has a direct effect on supply stability and efficient and quality energy management in supporting the reliability of the electric power system [2]. Accurate forecasting is essential to ensure energy reliability, particularly due to seasonal fluctuations in electricity demand that influence prediction accuracy [3]. Proper forecasting also helps ensure that electricity capacity planning runs efficiently so that the increased needs due to population growth and electricity demand can be met [4]. Electricity demand data from the Australian Energy Market Operator (AEMO) is the main source of information for analyzing fluctuations and forecast electricity demand more precisely [5]. The seasonal fluctuations of electricity demand can be seen in **Figure 1**.

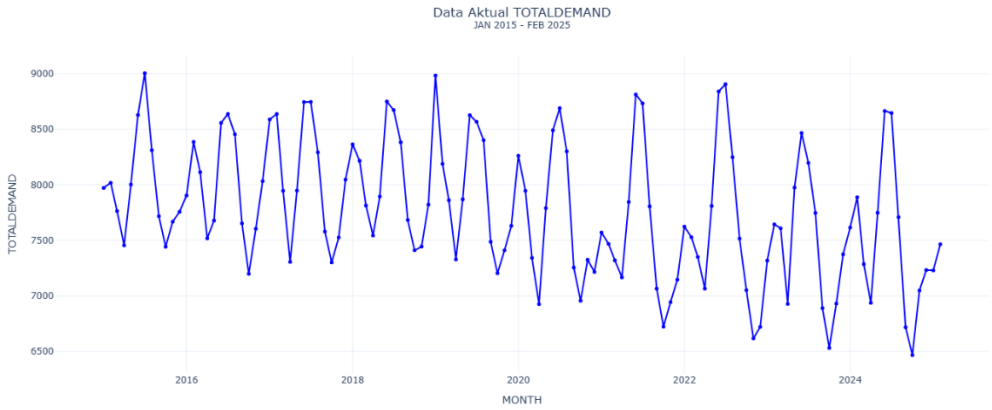

Figure 1. Seasonal Fluctuations of Electricity Demand

Various studies on electricity demand have been conducted, both using AEMO data and from other sources. Deep learning models such as CNN, LSTM and hybrid are applied to AEMO data. Meanwhile, the ARIMA and SARIMA methods are applied from different source references. Research [6] titled "Optimised Deep Learning for Time-Critical Load Forecasting Using LSTM and Modified Particle Swarm Optimization" showed that the hybrid LSTM model optimised with Modified Particle Swarm Optimization (mPSO) for short-term load forecasting on the NSW and VIC AEMO data, significantly outperformed ENN, LSTM, GA-LSTM, and PSO-LSTM. In NSW, MSE, RMSE, and MAPE fell by 91.91%, 94.89%, and 74.29%, respectively; while in VIC it decreased by 91.33%, 95.73%, and 72.06%. Research [7] entitled "Forecasting Day-Ahead

Electricity Demand in Australia Using A CNN-LSTM Model with an Attention Mechanism" proposes a hybrid CNN-LSTM model with an attention mechanism for daily electricity demand forecasting shows that the model is able to reduce MAPE to 1.69%, compared to the base CNN-LSTM model which produces a MAPE of 1.88%. Another study **[8]** titled "The Importance of Environmental Factors in Forecasting Australian Power Demand" used a hybrid SARIMA model with several environmental variables to forecast peak electricity demand resulting in a MAPE of 3.41% and an increase in accuracy of 46.3% compared to the regular SARIMA model. Research **[9]** entitled "Time Series Analysis of Electricity Consumption Forecasting Using ARIMA Model" used the ARIMA model to predict electricity consumption with parameters (p,d,q) based on ACF, and PACF plots, as well as data stationarity resulting in a MAPE value of 4.33%. Despite their accuracy, models such as CNN-LSTM often require large volumes of data and high computational resources. SARIMA applies a linear modeling approach and requires complex data preprocessing, making it less flexible in dealing with varying seasonal patterns. ARIMA shares similar limitations and does not automatically handle seasonal components, making it less suitable for data with trend and seasonal fluctuations.

Most of these studies use a machine learning or hybrid approach and not many have applied Triple Exponential Smoothing (TES) method to electricity demand. The Triple Exponential Smoothing is relatively simple, requires low computational resources, and is easier to interpret compared to deep learning or ARIMA-based models, making it a suitable choice for time series data with seasonal fluctuations such as electricity demand. The Triple Exponential Smoothing method is an effective statistical approach for modeling time series with level, trend, and seasonal patterns, providing more accurate forecasts than many other methods **[10].** Research **[11]** shows that the Triple Exponential Smoothing method produces an accuracy of 41.87% compared to the ARIMA model with a MAPE of 3220.64% in electricity consumption forecasting.

This study aims to apply the Triple Exponential Smoothing method in electricity demand forecasting using data from Australian Energy Market Operator (AEMO). The Triple Exponential Smoothing method applies using optimized parameters α = 0.002505536, β = 0, and γ = 0.729052739 which are obtained through value adjustment with a solver in Excel. This study considers the patterns of levels, trends, and seasonals in time series data and evaluates the accuracy of forecasting results using Triple Exponential Smoothing method using the Mean

Absolute Percentage Error (MAPE) value. This research is expected to produce high accuracy for electricity demand forecasting in Australia using AEMO data and be able to contribute to developing more accurate and tailored forecasting methods. The forecasting results by the triple exponential smoothing method can support AEMO allocate electricity supply across regions during peak seasons.

2. Method

This study uses a quantitative approach with a time series forecasting method. Time series data is the result of observing a periodic process in the same time span **[12].** The types of data collected are based on daily, weekly, monthly, or yearly intervals **[13].** The purpose of time series data is to identify patterns or trends in historical data in a given period, which are then used to predict future values **[14].** The quantitative approach in time series forecasting takes advantage of patterns formed in the past, so sufficient and quality historical data is essential to produce accurate predictions.

2.1. Triple Exponential Smoothing

Triple Exponential Smoothing is a widely used time series forecasting method, which relies on three smoothing equations, namely level, trend, and seasonal smoothing to produce accurate forecasting based on historical data patterns. Each smoothing equation has different parameters **[15].** This method uses three parameters, namely α (alpha), β (beta), and γ (gamma), each of which has a value between 0 and 1 **[16].** The equation of forecasting calculations using the Triple Exponential Smoothing method is as follows **[17]:**

a. Level

Level is used to find out the most recent averages of the actual data after removing seasons and trends to obtain the exact base values. The formula for calculating the level are presented in Equation (1):

$$\boldsymbol{Lt = \alpha\left(\frac{Y_t}{S_{t-s}}\right) + (1-\alpha)(L_{t-1} + T_{t-1})} \quad (1)$$

b. Tren

Tren are formula used to model consistent changes in data over time. The formula for calculating tren are presented in Equation (2):

$$\boldsymbol{Tt = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}} \quad (2)$$

c. Seasonal

The seasonal component is important for recognizing recurring patterns in the data, thus aiding with periodic fluctuations such as daily, monthly, or yearly. The formula for the seasonal component are presented in Equation (3):

$$\boldsymbol{St = \gamma\left(\frac{Y_t}{L_t}\right) + (1-\gamma)S_{t-s}} \quad (3)$$

d. Forecast

Forecasting is used to forecast the future value of data with a combination of level, tren, and seasonal patterns, the formula for forecasting are presented in Equation (4):

$$\boldsymbol{\hat{y}t + k = (L_t + k \times T_t)S_{t+k-s}} \quad (4)$$

Where:

α = Fixed values for level smoothing.

β = Fixed values for trend pattern smoothing.

γ = Fixed values for seasonal pattern smoothing.

Yt = The actual value of the period t.

St = The value of seasonal smoothing for period t.

Lt = The value of the period level smoothing t.

Tt = The value of trend smoothing for period t.

k = The number of future periods that are the object of the forecast.

ŷt+k = The value of the forecast results for the t+k period.

The Triple Exponential Smoothing method is carried out through several systematic steps to produce accurate forecasting. First set the values of the α, β, and γ parameters. Electricity demand data is used to calculate level, trend, and seasonal components (1), (2), (3). After that, the forecasting results are calculated using these three components (4). The accuracy of the forecast was then evaluated using the MAPE error value (5). The Triple Exponential Smoothing flowchart are presented in **Figure 2.**

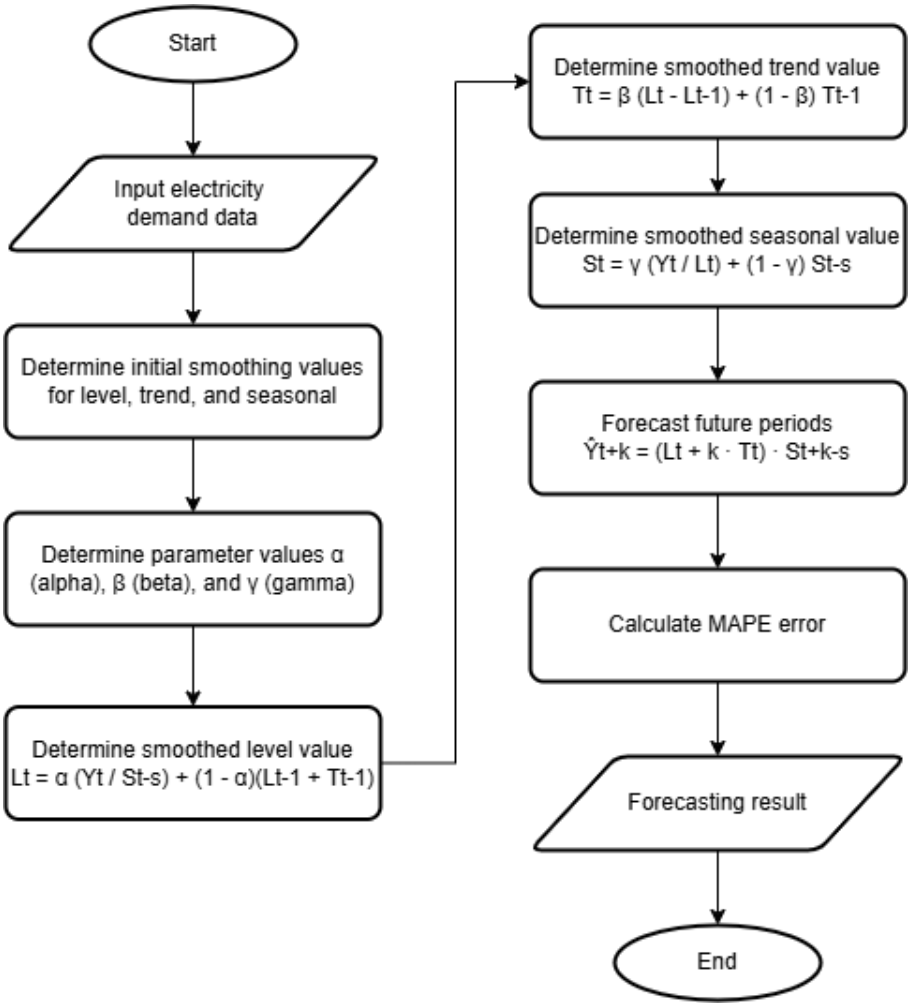

Figure 2. Flowchart of the Triple Exponential Smoothing Method

To determine the optimal values of the α, β, and γ parameters, in the Triple Exponential Smoothing method, the solver feature available in Excel is used. This feature serves to optimize parameters by minimizing the value of forecasting errors, such as Mean Absolute Percentage Error (MAPE). Using a solver, Excel automatically sets the combination of parameter values to make the forecast results accurate. This process helps the model make better predictions and demonstrates the influence of the meter on the models performance.

2.2. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) functions to calculate how much of the error percentage of the forecast results is against the actual data in a given time frame **[18].** Achieving forecasting results with a perfect level of accuracy (100%) is very difficult, so an evaluation of the error rate calculation is required [19]. The formula for the calculation of MAPE are presented in Equation (5):

$$MAPE = \left(\frac{100\%}{n}\right) \sum_{t=1}^{n} \frac{X_t - F_t}{X_t} \quad (5)$$

Where:

Xt = Actual data value of period t

Ft = Forecasting value of period t

N = The total amount of data analyzed

According to formula (5), the lower the MAPE value, the more accurate the forecast will be, because a low MAPE value means that the forecast results are closer to the actual data. The MAPE assessment criteria for the evaluation of the forecasting model are presented in **Table 1 [20].**

Table 1. MAPE Value Criteria

MAPE Value	Criteria
$< 10\%$	Very Accurate Forecasting Result
$10\% - 20\%$	Accurate Forecasting Result
$20\% - 50\%$	Less Accurate Forecasting Result
$> 50\%$	Inaccurate Forecasting Result

2.3. Data

This analysis uses electricity demand data (Total Demand) in the New South Wales, Australia region obtained from the Australian Energy Market Operator (AEMO) website. AEMO is the independent body that manages Australia's largest energy systems and markets, including the electricity and gas markets, and is responsible for ensuring a safe and reliable energy supply. The data taken covers the period from January 2015 to February 2025. Forecasting is done using a combination of Excel and Python software. Excel is used for manual calculation processes and initial visualizations, while Python is used for complex visualization and systematic validation of forecasting models.

3. Result and Discussion

Electricity demand forecasting using *the Triple Exponential Smoothing* method on a monthly basis in the New South Wales region, Australia. The data used consisted of 122 data covering the period from January 2015 to February 2025. The first step in this analysis is to input actual data in the form of a table that has two variables, namely the variable X indicating the Month and the variable Y indicating the Total Demand in that period. Actual data are presented in **Table 2.**

Table 2. Actual Data

Month	Total Demand
Jan-15	7972,91
Feb-15	8018,75
Mar-15	7764,33
Apr-15	7455,68
May-15	8002,87
Jun-15	8628,6
Jul-15	9005,77
Aug-15	8311,81
Sep-15	7717,77
Oct-15	7442,59
Nov-15	7668,17
Dec-15	7757,4
…	…
Jul-24	8646,94
Aug-24	7709,46
Sep-24	6718,53
Oct-24	6467,7
Nov-24	7048,38
Dec-24	7232,55
Jan-25	7230,12
Feb-25	7465,44

The next step is the visualization of the actual data. The visualization aims to see patterns, trends, and fluctuations of electricity demand during the period before the forecast is made. The actual data visualization are presented in **Figure 3.**

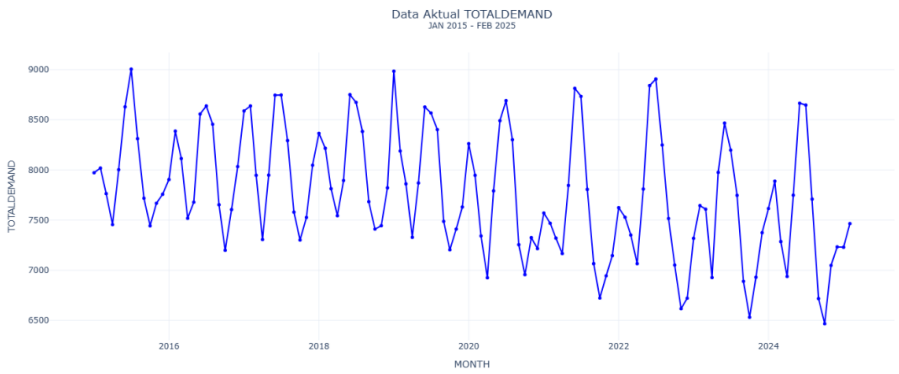

Figure 3. Visualization of Actual Data

The next stage is to determine the initial value of smoothing level, tren, and seasonal as the first step before forecasting. Level values are calculated as the average of the initial data. Tren as the average difference between periods, and seasonal as the difference between the actual value

and the level in the same period. The determination of the initial value of smoothing are presented in **Table 3.**

Table 3. Starting Value of Smoothing

Month	Total Demand	Level	Tren	Seasonal
Jan-15	7972,91			1,00
Feb-15	8018,75			1,00
Mar-15	7764,33			0,97
Apr-15	7455,68			0,93
May-15	8002,87			1,00
Jun-15	8628,6			1,08
Jul-15	9005,77			1,13
Aug-15	8311,81			1,04
Sep-15	7717,77			0,97
Oct-15	7442,59			0,93
Nov-15	7668,17			0,96
Dec-15	7757,44	7978,89	-0,02	0,97

After the level, tren, and seasonal values are determined, forecasting is carried out using the parameters α = 0.002505536, β = 0, and γ = 0.729052739 which are obtained through value adjustment with *a solver* in Excel. The forecasting process is conducted using the Triple Exponential Smoothing method by updating the levels, trends, and seasons for each period. The comparison between the actual data and the forecast including the error, absolute error, squared error, and absolute percentage error is used to evaluate the accuracy of the model. The forecasting result using the Triple Exponential Smoothing method are presented in **Table 4.**

Table 4. Forecasting Triple Exponential Smoothing Method

Month	Total Demand	Forecast	Error	Absolute Error	Squared Error	Absolute % Error
Jan-16	7904,28	7972,89	-68,61	68,61	4707,03	0,868
Feb-16	8386,25	8018,53	367,72	367,72	135216,20	4,385
Mar-16	8114,21	7764,99	349,22	349,22	121954,73	4,304
Apr-16	7518,53	7457,13	61,40	61,40	3769,59	0,817
May-16	7678,15	8004,57	-326,42	326,42	106551,65	4,251
Jun-16	8558,16	8629,53	-71,37	71,37	5093,64	0,834
Jul-16	8637,35	9006,53	-369,18	369,18	136292,91	4,274
Aug-16	8454,79	8311,63	143,16	143,16	20493,82	1,693
Sep-16	7653,54	7717,92	-64,38	64,38	4144,47	0,841
Oct-16	7198,82	7442,56	-243,74	243,74	59407,24	3,386
Nov-16	7605,24	7667,48	-62,24	62,24	3874,37	0,818
Dec-16	8034,13	7756,53	277,60	277,60	77063,39	3,455
Jan-17	…	…	…	…	…	…

Month	Total Demand	Forecast	Error	Absolute Error	Squared Error	Absolute % Error
Feb-17	…	…	…	…	…	…
Jan-24	7615,99	7423,97	192,02	192,02	36869,82	2,521
Feb-24	7887,81	7628,75	259,06	259,06	67112,80	3,284
Mar-24	7286,91	7549,45	-262,54	262,54	68927,60	3,603
Apr-24	6937,51	6979,29	-41,78	41,78	1745,65	0,602
May-24	7748,96	7943,00	-194,04	194,04	37651,44	2,504
Jun-24	8665,71	8572,33	93,38	93,38	8720,30	1,078
Jul-24	8646,94	8387,30	259,64	259,64	67413,25	3,003
Aug-24	7709,46	7872,24	-162,78	162,78	26495,79	2,111
Sep-24	6718,53	7043,24	-324,71	324,71	105438,00	4,833
Oct-24	6467,7	6666,03	-198,33	198,33	39334,10	3,066
Nov-24	7048,38	6889,90	158,48	158,48	25115,39	2,248
Dec-24	7232,55	7244,80	-12,25	12,25	150,08	0,169
Jan-25	7230,12	7573,32	-343,20	343,20	117789,64	4,747
Feb-25	7465,44	7826,81	-361,37	361,37	130591,07	4,841

The following visualization shows a comparison between actual data and forecasting results. This graph depicts total electricity demand from January 2015 to February 2025 along with forecasts for the upcoming period from March 2025 to February 2026. The visualization between the actual data and forecasting are presented in **Figure 4.**

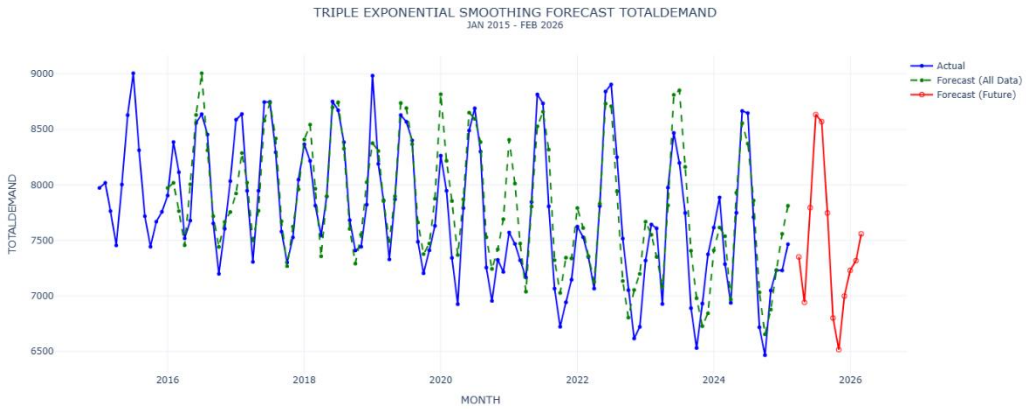

Figure 4. Visualization of Actual Data and Forecasting

Figure 3 shows the results of monthly electricity demand forecasting using the Triple Exponential Smoothing method approach from January 2015 to February 2026. On the graph, the blue line represents the actual data of electricity demand, while the dotted green line shows the model's forecasting results on historical data, and the red line depicts the predicted demand of electricity for future periods. It can be seen that both the actual data and the forecast results

follow a pattern of ups and downs that repeat every year, indicating a seasonal pattern in electricity demand. The forecast results for the upcoming period March 2025 to February 2026 are presented in **Table 5.**

Table 5. Forecasting Result fot the Upcoming Period

Month	Forecast Total Demand
Mar-25	7366,98
Apr-25	6957,38
May-25	7811,41
Jun-25	8651,24
Jul-25	8586,88
Aug-25	7762,99
Sep-25	6815,27
Oct-25	6530,20
Nov-25	7014,66
Dec-25	7245,32
Jan-26	7333,13
Feb-26	7574,30

The Mean Absolute Percentage Error (MAPE) value obtained through the Triple Exponential Smoothing method is 2.89%, which is included in the category of "Very Accurate Forecasting Result" because the value is <10% according to the MAPE assessment criteria table. This shows that electricity demand forecasting has a very high level of accuracy and is reliable in forecasting electricity demand.

4. Conclusion

Based on the results of the analysis and visualization of the Electricity demand forecast chart, it can be concluded that the electricity demand pattern in New South Wales, Australia from January 2015 to February 2026 shows consistent seasonal fluctuations every year. The Triple Exponential Smoothing model manages to follow the actual data pattern well over historical periods, as seen from the green line that almost always parallels the blue line of the actual data. For the period March 2025 to February 2026, the forecast results show a seasonal pattern similar to previous years. The Mean Absolute Percentage Error (MAPE) value of 2.89% indicates that the forecasting results are very good for the Triple Exponential Smoothing method in forecasting electricity demand. These results indicate that this method can be relied upon to assist decision-making in the electricity sector in New South Wales in particular to anticipate future fluctuations in electricity demand.

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