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Load forecasting analysis for estimating transformer capacity of Karangkates Substations using Holt-Winters method in Python

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ABSTRACT

In the six years from 2010 to 2015, the peak load in the East Java region increased by an average of 284 MW per year. Karangkates Substation is part of an interconnected electrical system that supplies Java Island. To ensure a high level of reliability in its service, it is necessary to prepare for load growth to make sure that it does not exceed its ideal conditions, therefore special analysis of transformer capacity is needed. Using the Holt-Winters (HW) method as a reference for processing the data can be used as a reference in planning and anticipating the growing electricity demand. The results of this study are with the accuracy of the HW method with mean absolute percentage error (MAPE) = 2.645%, while the accuracy of the fuzzy time series (FTS) method = 6.399%. A forecast result done with HW methods shows the transformer at the substation Karangkates reached its normal working capacity in March 2018 at 99.583% of installed capacity and exceeded the maximum capacity in April 2018 at 101.493% of installed capacity.

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1. INTRODUCTION

Preview study [1]-[5], peak load in the East Java region increased by an average of 284 MW per year over six years (2010-2015), according to data released by National Electricity Company (PLN) in 2016 [6], [7]. As an important component in PLN's power grid system that supplies electricity to the entire island of Java, Karangkates Substation requires reliable electrical system resilience [8]-[11]. Load development planning is essential to ensure a high level of reliability by avoiding optimal overcapacity. Due to their continuous operation, transformers have a major effect on the capacity of the electrical system. A common transformer loading limit is 80% of the installed capacity set by PLN according to its requirements [12], [13].

To maintain a reliable electrical system, load increases must be considered when evaluating transformers. Therefore, it is necessary to accurately forecast future loads [14]. Different forecasting techniques are suitable depending on the type of data used. Exponential smoothing (ES) is a commonly used method to handle load data with trends and seasonal characteristics calculation method for load capacity of Urba [4], [15]-[18]. There are several versions of this technique, including Holt-Winters (HW), multiple, and single ES. Long-term trend and seasonal data can be accurately and precisely predicted by HW [19]-[22].

The HW method, as highlighted in previous research [23]-[26], stands out as the preferred approach for long-term load growth forecasting. Its effectiveness in predicting monthly peak load growth at Karangkates

Substation is consistently affirmed in recent studies [27]-[29]. While it may exhibit less precision for short-term forecasts, its ability to provide satisfactory results for long-term planning is invaluable. Moreover, when integrated with automated data mining techniques, the HW method enables the estimation of transformer remaining life, facilitates anticipation of necessary modifications, and enhances maintenance and planning processes, ultimately ensuring the seamless continuity of energy supply.

This study compares forecasting methods for periodic data peak load at Karangkates Substation using three data: data 1 (2011-2012), data 2 (2011-2014), and data 3 (2011-2017). The HW method achieves the lowest MAPE values across all sets, notably 2.645% in Data 3. It accurately predicts the transformer's capacity exceedance in March and April 2018. HW is deemed superior for long-term forecasting due to its ability to capture seasonal patterns and trends, unlike artificial neural networks (ANN) and fuzzy time series (FTS), which, although effective, exhibit lower accuracy. These results aid PLN in transformer planning and maintenance scheduling, affirming the reliability of the HW method [30]-[40].

There are three comparative studies summarized in the comparator for this study. The first study [8], a method for 24-hour optimal scheduling of energy storage systems (ESS) in South Korea with a focus on customer benefit maximization, peak load reduction, and charge/discharge cycle minimization. The second study [1], suggested a method for forecasting photovoltaic (PV) power in the short future with the HW method that could potentially be used for energy management and power leveling facing the challenges of global warming and increasing energy demand. The third study [9], introduced a support vector machines with autoregressive integrated moving averages (ARIMA-SVM) hybrid model to improve hourly load forecasting accuracy by correcting outliers and reducing MAPE using 2014-2015 data in the southern region, which can improve the stability of the electricity system network.

This study aims to forecast recurring peak loads at the Karangkates Substation using HW method and evaluate its accuracy in comparison to alternative methods. Unlike previous studies [8], [9], [20], which addressed energy system optimization and grid stability, this study emphasizes transformer capacity planning to prevent blackouts. Notwithstanding differences in extent, both types of research play crucial roles in advancing the electricity sector.

The authors in this study contributed to conducting a literature study on long-term electricity load forecasting methods, particularly the HW method. They also collected monthly peak load data for the Karangkates Substation for seven years (2011-2017), used in this study. The authors' significant contribution is in comparing the accuracy of the HW method with other forecasting methods, such as FTS, ARIMA, and ANN, for forecasting the monthly peak load at GI Karangkates. The author shows that the HW method produces the lowest mean absolute percentage error (MAPE) value compared to other methods, especially for larger data sets.

This research makes an essential contribution to education, especially in electrical engineering, by introducing a long-term electrical load forecasting method that can be integrated into the curriculum. Using the Holt-Winters (HW) method in peak load forecasting not only supports decision-making in the energy sector but also provides an opportunity for students to learn practical applications of data analysis techniques in optimizing electricity infrastructure. Overall, the authors proved that the HW method is the most suitable for long-term monthly peak load forecasting at GI Karangkates. This study's findings are expected to help PLN optimize future scheduling strategies for transformer replacement and maintenance.

2. METHOD

Electricity load refers to the total demand placed on a power plant. The classification of load is based on the type of electricity usage [41], [42]. Maintaining the distribution system's capacity is essential to ensuring dependable and ongoing service. Planning of the distribution system is necessary to accommodate the growing load and ensure technical and economic feasibility. The complexity of the system determines the selection of equipment to handle different alternatives effectively. This enables the distribution system to handle the load from secondary conveyors through substations, maintaining its reliability [10].

Transformers operate based on the electromagnetic principles of amperes and Faraday's induction. Variations in current or electric fields produce magnetic fields, which in turn generate induced voltages. The percentage of transformer loading can be determined using (1).

$$\%load = \frac{s_t}{K_{trafo}} \times 100\% \tag{1}$$

s_t is transformer load at time t, K_{trafo} is transformer capacity.

Similar to reading a speedometer, exponential smoothing (ES) is a time-series forecasting technique that makes use of past data to anticipate future values [43], [44]. It assists in detecting recurrent trends and growth rates as well as mitigating random data variations. However, its basic form lacks components for handling trend or seasonality complexities. To overcome this, Holt proposed the double exponential smoothing method, which enhances forecasting capabilities by incorporating data trends.

The Holt-Winters (HW) method [3], also called the triple ES method, introduces components for seasonality and trends. It extends traditional smoothing to account for seasonal variations, ensuring that seasonal patterns are accurately captured. By smoothing across seasons, the method incorporates historical data from previous and preceding seasons to forecast the current season's component. This integration of seasonal patterns enhances the accuracy of the forecasting process. The equation for HW exponential smoothing is as (2)-(5).

$$level = 1_t = \alpha.(X_t - m_t) + (1-\alpha).(1_{t-1} - 1_{n-1}) \quad (2)$$

$$tren = b_t = \beta.(1_t - 1_{t-1}) + (1-\beta).b_{t-1} \quad (3)$$

$$season = m_t = \gamma.(X_t - 1_t) + (1-\gamma).m_{t-L} \quad (4)$$

$$forcast = S_{t+n} = 1_t + nb_t + m_{t-L+1(n-1)modL} \quad (5)$$

Where bt is the trend component at time t, It is the level component at time t, mt is the seasonal component at time t, α is the level smoothing factor ($0 < \alpha < 1$), β is the trend smoothing factor ($0 < \beta < 1$), γ is the seasonal smoothing factor ($0 < \gamma < 1$), Xt is the actual value at time t, n is the number of periods to forecast, L is the length of a season, and mod L represents the remainder when divided by L.

This study takes into consideration different ways for comparison in addition to the ES method. These methods include FTS, autoregression (AR), moving average (MA), ARIMA, and ANN. Shown as follows:

- FTS includes creating rules, defuzzifying sets [40], figuring out membership functions, and fuzzifying sets. using the mean-max method.
- AR explores [41] the relationship between a variable's values in consecutive periods and measures the effect size and strength using the autocorrelation coefficient with the same variable as both independent and dependent variables.
- The simple moving average (SMA) is a time series calculation that helps filter out noise and reveal data patterns by averaging past data [42]. It smooths out short-term fluctuations and provides insights into trends or cycles in the data. It also allows for distinguishing between short-term and long-term behavior. SMA is commonly employed in financial analysis, including stock market analysis, exchange rates, and sales volume.
- ARIMA (Box-Jenkins method) [43] is a powerful time series forecasting technique, excelling in short-term forecasting by solely using past and current values of the dependent variable, but accuracy diminishes for long term. ARIMA is effective when observations in the time series exhibit statistical dependence.
- ANNs [44] emulate the human brain's information-processing capabilities through interconnected neurons that process information for tasks like classification and prediction. They adapt to various applications through a versatile architecture. ANNs resemble human learning through supervised learning from data examples and patterns.
- Time-series neural networks comprise two main model types: nonlinear autoregressive (NAR) and nonlinear auto-regression exogenous (NARX), which are two types of autoregression [44]. NARX models are autoregressive models that consider external inputs alongside their own time-series data, enabling the output to be influenced by both past data values and external factors. NAR models, on the other hand, base their modeling exclusively on historical time-series data.

Common methods for measuring forecast accuracy include mean squared error (MSE) and MAPE. These indicators are as (6).

$$SSE = \sum_{I=1}^{N} (X_i - S_i)^2 \quad (6)$$

Xi represents the observed or true value at the specific time point i, while Si denotes the predicted or forecasted value corresponding to that same time point I, as in (7).

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{X_i - S_i}{X_i} \right| X\ 100\% \quad (7)$$

Let n be the number of observations, Xi be the actual value at time i, and Si be the forecast value at time i. The optimal parameter values for α, β, and γ are determined using the sum of squared errors (SSE) method, which measures the difference between the true values and the predicted values of the statistical model during analysis and forecasting. The overall forecasting accuracy is evaluated using the mean absolute percentage error (MAPE), which quantifies the forecasting error relative to the observed data and indicates how well the statistical models can forecast given the available data.

2.1. Data set and pre-processing

The study utilizes 7 years (2011-2017) of monthly peak load data from the Karangkates Substation. The data consists of monthly readings for active power (P) and reactive power (Q), converted to VA units. The data is arranged in a time series format. Three data sets are used for forecasting evaluation: Data 1 (2011-2012) with a 10-month forecast, Data 2 (2011-2014) with a 10-month forecast, and Data 3 (2011-2017) with a 10-month forecast, including forecasts for 2018 and beyond until exceeding the transformer's maximum capacity.

Figure 1 shows a plot of the monthly peak loads from 2011 to 2017. The x-axis represents the years, while the y-axis shows the peak load values in VA units. The plot displays a generally increasing trend in peak loads over the 7-year period.

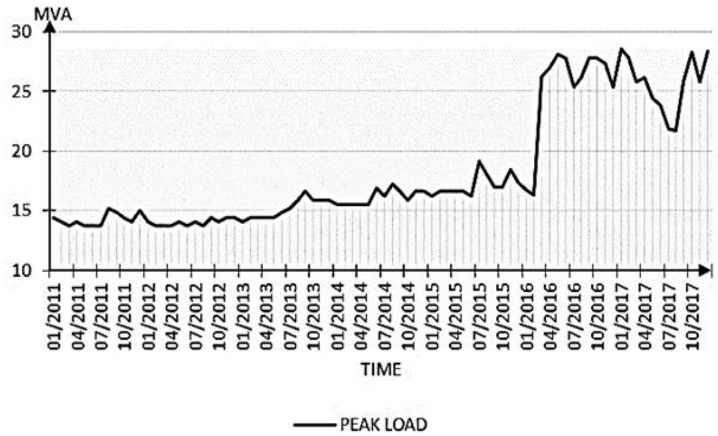

Figure 1. Monthly peak loads 2011-2017

2.2. Holt-Winters

By including seasonal elements into the forecasting trend, Holt-Winter (HW), also known as Triple Exponential Smoothing with seasonal components, is one kind of approach that makes use of seasonal additions. The additive HW method's seasonal component revolves around zero. An alternative approach is the multiplicative Holt-Winters method, which involves expressing the seasonal component in relative terms and multiplying it by the components of level and trend. The (8)-(11) represents the seasonal component of the additive Holt-Winters method.

$$\hat{y}_{t+h|t} = l_t + hb_t + s_{t+h-m(k+1)} \tag{8}$$

$$l_t = \alpha.(y_t - s_{t-m}) + (1-\alpha).(l_{t-1} + b_{t-1}) \tag{9}$$

$$b_t = \beta^*.(l_t - l_{t-1}) + (1-\beta^*).b_{t-1} \tag{10}$$

$$s_t = \gamma.(y_t - l_{t-1} - b_{t-1}) + (1-\gamma).s_{t-m} \tag{11}$$

Multiplicative HW is a different kind of HW method where the seasonal component is specified in or according to the seasonal period and is expressed in relative terms.

$$\hat{y}_{t+h|t} = (l_t + hb_t).s_{t+h-m(k+1)} \tag{12}$$

$$l_t = \alpha.\frac{y_t}{s_{t-m}} + (1-\alpha).(l_{t-1} + b_{t-1}) \tag{13}$$

$$b_t = \beta^*.(l_t - l_{t-1}) + (1-\beta^*).b_{t-1} \tag{14}$$

$$s_t = \gamma.\frac{y_t}{l_{t-1+}b_{t-1}} + (1-\gamma).s_{t-m} \tag{15}$$

Also known as triple exponential, HW by including seasonal elements in the predicting trend, a sort of technique known as seasonal additives can be used. There is hardly no seasonal component. There are three smoothing equations based on the HW additive equation [19], which are level lt, trend bt, and seasonality St. When predicting $\hat{y}_{t+h|t}$, for the seasonal period m, the number of periods h is given by an integer $\frac{y_t}{s_{t-m}}$ that is used to guarantee that When the most recent sample, which was the observation, was taken, the sample's seasonal index was in force γ that shows the passage of time t. Based on the lowest error value, the related smoothing parameters β, α, γ have a value between 0 and 1.

3. RESULT AND DISCUSSION

3.1. Data 1

Figures 2 and 3 analyze and visualize forecasting results for data 1. Figure 2 shows graphical representations of load prediction outcomes. Figure 3(a) breaks down the results of Holt-Winters (HW) and single exponential smoothing (SES) models. Figure 3(b) examines autoregressive (AR) and simple moving average (SMA) model results. These figures provide a multi-faceted view of different models' performance in predicting data 1 load patterns.

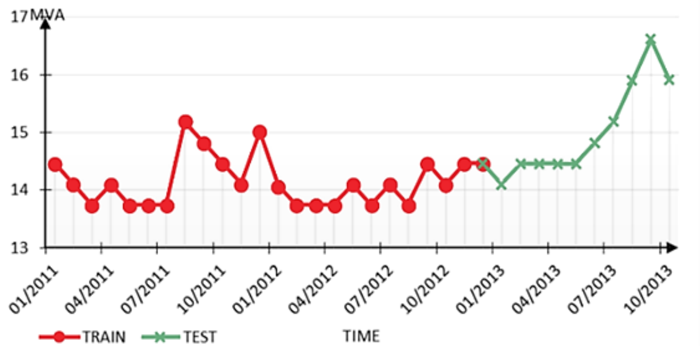

Figure 2. Data 1

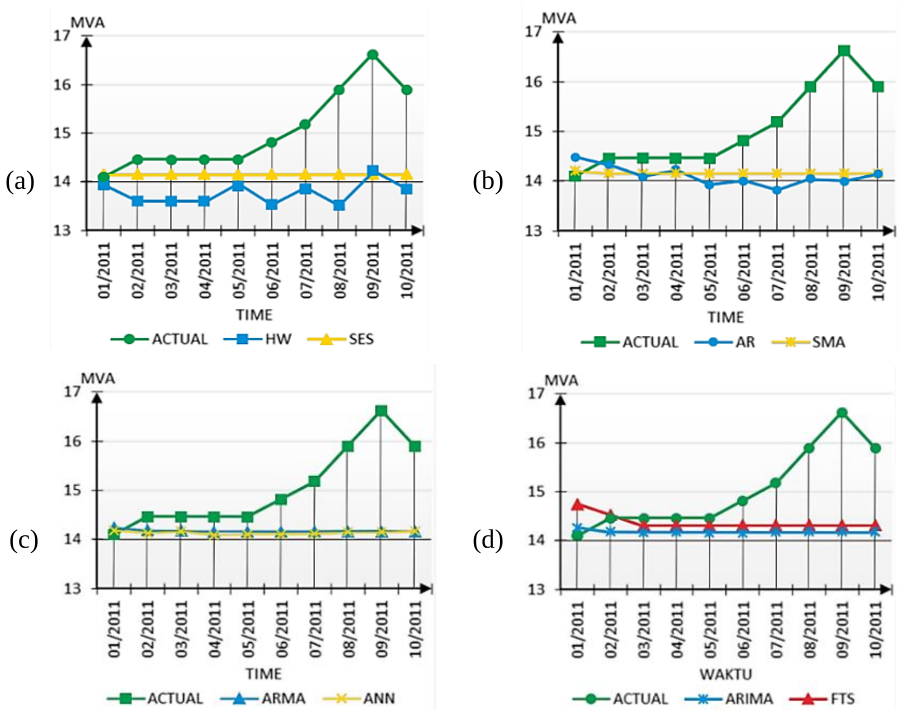

Figure 3. Displays forecast results: (a) HW and SES, (b) AR and SMA, (c) ARMA and ANN, and (d) ARIMA and FTS

Figure 3(c) presents the load forecasting results using ARMA and ANN models. Figure 3(d) displays the outcomes using ARIMA and FTS models. Table 1 summarizes the results from all forecasting models, while Table 2 displays the MAPE figures determined for the various models under consideration.

In general, the chart patterns of the forecasting models exhibit a linear shape. However, the Holt-Winters model stands out with a distinct seasonal pattern depicted on the resulting graph. This can be attributed to the limited size of the data, which restricts the ability of other models to accurately predict future changes. Unlike other models, the Holt-Winters model directly incorporates seasonality data, enabling it to capture and incorporate recurring trend changes within the model.

Table 1. Forecast results and actual value

No.	Actual (MVA)	Forecasting method (MVA)							
		HW	SES	AR	SMA	ARMA	ANN	ARIMA	FTS
1	14.098	13.943	14.150	14.480	14.205	14.241	14.199	14.256	14.747
2	14.459	13.616	14.150	14.327	14.155	14.185	14.137	14.192	14.531
3	14.459	13.605	14.150	14.103	14.155	14.167	14.168	14.172	14.314
4	14.459	13.603	14.150	14.226	14.155	14.162	14.103	14.166	14.314
5	14.459	13.931	14.150	13.931	14.155	14.160	14.108	14.165	14.314
6	14.819	13.545	14.150	13.998	14.155	14.160	14.106	14.165	14.314
7	15.179	13.858	14.150	13.826	14.155	14.160	14.117	14.166	14.314
8	15.900	13.513	14.150	14.043	14.155	14.159	14.151	14.167	14.314
9	16.621	14.221	14.150	14.002	14.155	14.159	14.152	14.168	14.314
10	15.900	13.863	14.150	14.136	14.155	14.159	14.169	14.169	14.314

Table 2. MAPE value

No.	Forecasting method	MAPE (%)	No.	Forecasting method	MAPE (%)
1	AR	6.4	5	SES	5.7
2	MA	5.7	6	FTS	5.1
3	ARMA	5.7	7	ANN	5.8
4	ARIMA	5.7	8	HW	8.2

3.2. Data 2

Data 2 is visualized in Figure 4. The forecasting results for data 2 are illustrated in Figure 5. A comprehensive summary of the forecasting results from all models can be found in Table 3. Furthermore, Table 4 provides the calculated MAPE values for each forecasting model. From Table 4, most models have MAPE below 10%, except SMA. Comparing Data 1 and 2, there is overall accuracy improvement. HW MAPE dropped significantly from 8.1% to 4.6%. ANN decreased from 5.8% to 3.9%. AR went from 6.4% to 3.9%. ARMA decreased from 5.7% to 4.9%. ARIMA improved markedly from 5.7% to 2.6%. SES dropped from 5.7% to 3.1%. FTS decreased from 5.1% to 3.8%.

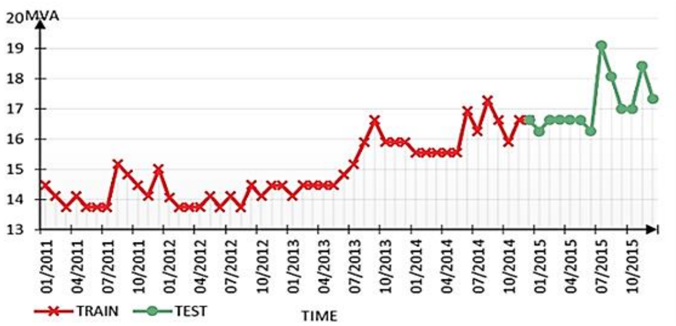

Figure 4. Data 2

Table 3. Forecast results and actual value

No.	Actual (MVA)	Forecasting method (MVA)							
		HW	ANN	AR	MA	ARMA	ARIMA	SES	FTS
1	16.260	16.192	16.595	16.393	15.507	16.464	16.560	16.565	16.356
2	16.621	16.199	16.486	16.394	14.918	16.393	16.544	16.565	17.354
3	16.621	16.112	16.357	17.233	14.918	16.326	16.555	16.565	16.689
4	16.621	16.014	16.391	16.835	14.918	16.262	16.584	16.565	16.356
5	16.621	15.952	16.348	17.624	14.918	16.202	16.623	16.565	17.354
6	16.260	16.811	16.452	17.433	14.918	16.145	16.669	16.565	16.689
7	19.091	16.155	16.378	17.281	14.918	16.091	16.720	16.565	16.356
8	18.062	16.957	16.383	17.624	14.918	16.041	16.773	16.565	17.354
9	16.981	16.616	16.401	17.676	14.918	15.992	16.828	16.565	16.689
10	16.981	16.098	16.391	17.522	14.918	15.947	16.884	16.565	16.356

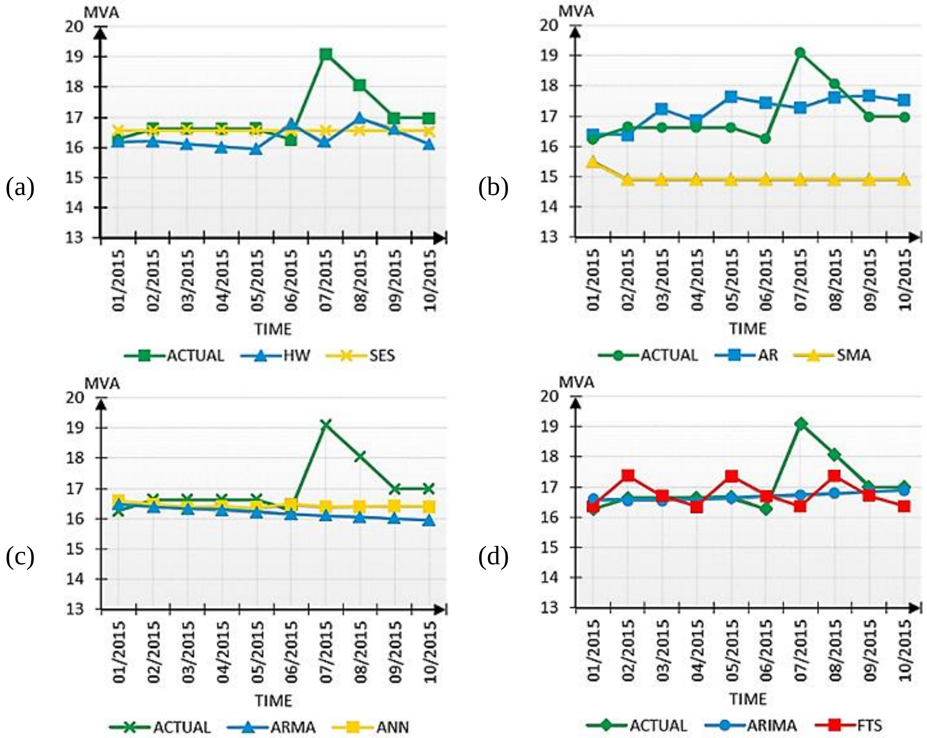

Figure 5. Displays forecast results: (a) HW and SES, (b) AR and SMA, (c) ARMA and ANN, and (d) ARIMA and FTS

Table 4. MAPE value

No.	Forecasting method	MAPE (%)	No.	Forecasting method	MAPE (%)
1	AR	3.9	5	SES	3.1
2	MA	1.7	6	FTS	3.8
3	ARMA	4.9	7	ANN	3.9
4	ARIMA	2.6	8	HW	4.6

3.3. Data 3

Figure 6 displays Data 3. Figure 7 shows the forecasting results for Data set 3. Table 5 provides a comprehensive summary of results from all models. Table 6 includes the calculated MAPE values for each model. Among the models, only HW, FTS, and ANN exhibit a MAPE below 10%, with HW having the lowest MAPE of 2.6%, followed by ANN at 3.7% and FTS at 6.4%.

The AR, MA, ARIMA, SES, and ARMA models showed high error values of 10-29%, while FTS, ANN, and HW had smaller MAPE, especially with larger datasets. HW demonstrated superior long-term forecasting accuracy. For Data 1, 2, and 3, HW had MAPE of 8.2%, 4.6%, and 2.6% respectively, outperforming others. HW is suitable for long-term seasonal/trendy data due to its components. FTS is good for short/medium data but struggles with non-repetitive seasons. ANN can improve with modified layers/more data. HW can improve with tuned smoothing parameters but risks overfitting. Single ES, AR, SMA, and ARIMA are unsuitable for such data.

The Karangkates Substation transformer, with a capacity of 30 MVA at 70/20 kV, exceeded its normal operating capacity from March to August 2018, peaking at 101.5% in April 2018. Although the load decreased after September 2018, it rose again from December 2018 to March 2019. Fluctuations in March-April 2016 may be attributed to PLN interconnection maneuvers and system regulation. Given the transformer's exceeding of maximum capacity in April 2018 and anticipated further increases from January 2019, PLN should promptly consider adding or replacing transformers, or implementing network maneuvers to ensure power supply stability and reliability.

In conclusion, for the monthly peak load forecast data of the Karangkates Substation, the most suitable method is the HW model. This model effectively captures the seasonal patterns and trends present in the data, enabling accurate forecasting. Moving forward, a forecast is conducted to determine the projected time when the transformer at the Karangkates Substation will reach its maximum capacity, as depicted in Figure 8.

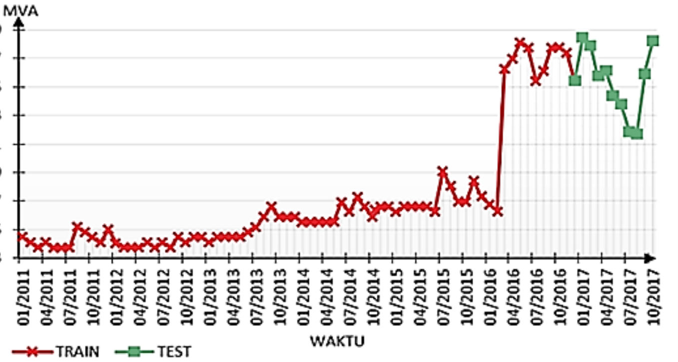

Figure 6. Data 3

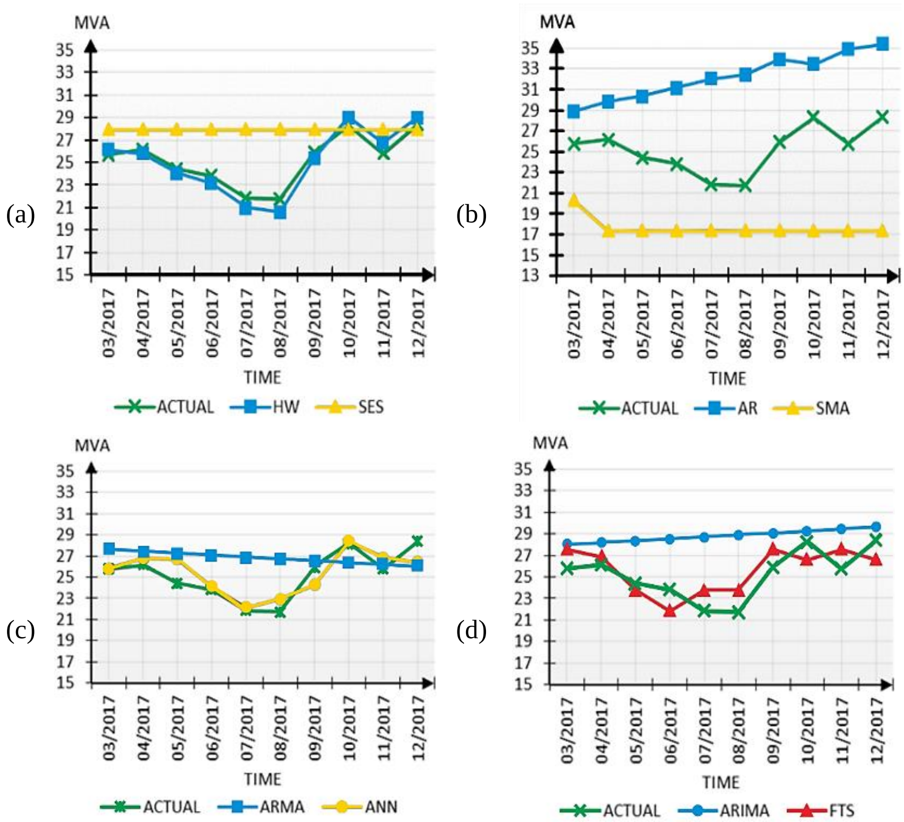

Figure 7. Displays forecast results (a) HW and SES, (b) AR and SMA, (c) ARMA and ANN, and (d) ARIMA and FTS

Table 5. Forecast results and actual value

No	Actual (MVA)	Forecasting method (MVA)						
		AR	MA	ARIMA	SES	FTS	ANN	HW
1	25.788	28.890	20.318	28.018	27.915	27.563	25.831	26.087
2	26.160	29.873	17.319	28.175	27.915	26.850	26.725	25.821
3	24.440	30.336	17.319	28.343	27.915	23.763	26.714	24.034
4	23.812	31.175	17.319	28.519	27.915	21.863	24.111	23.143
5	21.839	32.052	17.319	28.700	27.915	23.763	22.133	20.946
6	21.717	32.459	17.319	28.884	27.915	23.763	22.937	20.602
7	25.909	33.952	17.319	29.069	27.915	27.563	24.298	25.352
8	28.254	33.458	17.319	29.255	27.915	26.613	28.400	28.926
9	25.788	34.907	17.319	29.442	27.915	27.563	26.825	26.743
10	28.375	35.439	17.319	29.630	27.915	26.613	26.439	28.965

Table 6. MAPE value

No.	Forecasting method	MAPE (%)
1	AR	28.7
2	MA	29.6
3	ARMA	15.1
4	ARIMA	10.1
5	SES	12.2
6	FTS	6.4
7	ANN	3.7
8	HW	2.6

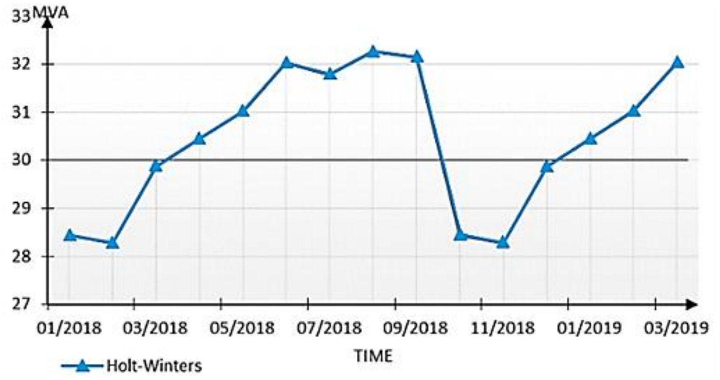

Figure 8. Peak load forecast of Karangkates Substation

4. CONCLUSION

This study verifies that, in the long term, the Holt-Winters (HW) method is the best choice for predicting the monthly peak load at Karangkates Substation. Although its accuracy may not be as accurate as for short-term estimation, it routinely provides sufficient results. The method is effective in estimating the remaining life of transformers and determining the optimal time for upgrades, especially when paired with automated data mining tools. The implementation of an integrated strategy facilitates planning and maintenance, guarantees optimal transformer operation, and prevents interruptions to the power supply. The findings establish the HW approach as the industry standard for long-term load growth projections at Karangkates Substation.

Using this method, PLN can plan transformer capacity more precisely, reducing the risk of under or overcapacity that could jeopardize energy availability. The HW method helps PLN plan transformer maintenance schedules and choose the right time to replace, repair or upgrade components without disrupting energy flow. Careful long-term planning also lowers the likelihood of unplanned power interruptions, improving customer service dependability. Precise predictions help simplify budget administration for transformer maintenance and upgrades, and maximize expenditure while reducing resource wastage. The findings are expected to drive the development of more advanced forecasting technologies in the future, enabling real-time monitoring of transformers and strengthening power system reliability.

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