Selection of the Best Newspaper Forecasting Method Using Holt-Winters and Long Short Term Memory Method

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Abstract

As a result of digitalization, demand for newspapers has become more volatile and difficult to predict. This research aims to determine the best forecasting method with the smallest error value to reduce the company's rate of newspaper returns and losses. The holt-winter and long-short term memory approaches are used to analyze the data. In addition, the results of this research's forecasts were compared to the previous research that used the ARIMA method and trend line analysis method. The forecasting method will be chosen based on the lowest Mean Absolute Percentage Error (MAPE) criteria. According to this research and the previous research, the MAPE value for the trend line analysis method is 2.94%, 3.52% for the ARIMA method, 3.87% for long short-term memory; meanwhile, the holt-winter has the lowest error rate, with a MAPE value of 2%. In conclusion, the best forecasting method for forecasting newspaper demand at PT. XYZ is the holt-winter method.

Keywords
holt-winter, long-short term memory, forecasting, newspaper industry, MAPE

1. Introduction
Due to digitalization for business players, such as PT, demand for newspapers has become more fluctuating and difficult to predict. XYZ, fluctuating demand that tends to fall is a challenge. Every day, this newspaper company ordered many newspapers from a printing company. This newspaper's distributor has several agents in the former Surakarta Residency area. Because demand is becoming more fluctuating and difficult to predict due to digitalization, newspaper companies must plan regarding newspaper returns (A'yun et al., 2021). Newspaper companies face large losses due to this high rate of returns or returns (Permatasari et al., 2018). The average return of newspapers from agents to this newspaper company is 5%. Until the year is 2017, the entire revenue for this newspaper company is estimated to be around Rp. 18,400,000,000 (Wijiyanto et al. 2012). As a result, companies require a method for forecasting the number of requests for newspapers with a small error rate in order to avoid newspaper company losses.

This problem can be solved in several ways. Starting with the supply and demand imbalance that results in high newspaper returns. Several forecasting methods have been chosen, including the ARIMA model, which has a small mean absolute percentage value (MAPE) (Permatasari et al., 2018). The trend line analysis method was also chosen because it has a small error rate (A'yun et al., 2021). The newspaper industry also conducts research on daily distribution route optimization by considering total distribution distance, time, and vehicle load using the capacitated vehicle routing problem model with sweep and clustering algorithms and the nearest neighbor approach (Saraswati et al., 2017). A problem-based learning technique can be used to design, improve, and install an integrated system for solving problems in the newspaper industry (Sutopo and Aqidawati 2019).

Calculations were conducted in this research using two alternative ways to solve the demand problem and determine the best forecasting method: the holt winter forecasting method and the long short-term memory method. The Holt winter forecasting method is a strategy for overcoming trend and seasonal effects in time series data. By giving three consecutive weighting factors in their forecasts, this method is based on three elements, namely original, trend, and seasonal data elements (Putra et al., 2019). The long-short-term memory method is suitable for generating accurate variable predictions. The most accurate forecasting is based on the level of prediction error; the smaller the error rate, the more precise a method is in predicting (Wiranda and Sadikin 2019).

The forecasting results in this study were compared to the past research that used the ARIMA method and trend line analysis method. The method for forecasting the number of newspaper requests with the lowest error rate is the best performance criterion for the problem. The Mean Absolute Percentage Error (MAPE) criteria to calculate the error rate. By using the lowest MAPE criteria, the forecasting method will be chosen. The appropriate forecasting method can lower the company's rate of return or newspaper returns while also reducing losses.

The purpose of this research is to find the best forecasting method to evaluate the company's rate of newspaper returns and the losses caused by it. This research aims to find a method with the smallest MAPE value, which indicates that the method has the lowest error value. Using the chosen method will be able to forecast demand or predict the number of newspaper requests that would not be wasted so the company's rate of newspaper returns and losses can be reduced.

2. Literature Review

2.1 Holt-Winter

The Holt-Winter method combines the hold and winter approaches. The Holt technique is recommended for forecasting trending time series data linearly, but the winter method is beneficial for explaining seasonality when time-series data has a seasonal pattern (Singh et al., 2015). Exponential smoothing is a popular time-series forecasting technique that involves pre-processing raw data to remove unpredictability and boost the value of recent data during prediction (Jiang et al. 2020). The method takes an array of data samples collected regularly as input. The result is a forecast for a future sample (Akbas et al., 2014).

The Holt-Winter exponential smoothing method is a method that can overcome trend and seasonal factors that appear simultaneously in time series data. This method is based on three elements, namely the original data elements, trends, and seasonality. There are two types of the Holt-Winter exponential smoothing method: additive and multiplicative models. If the original data plot shows relatively steady (constant) seasonal fluctuations, the additive model is employed; however, the multiplicative model is used if the original data plot shows seasonal fluctuations that fluctuate. (Putra et al. 2019)

The equations used in the additive model are:

a. Exponential smoothing

$Lt : \alpha(Xt - St{-}S) + (1 - \alpha)(Lt{-}1 + Tt{-}1).$ (1)

b. Trend pattern smoothing

$Tt : \beta(Lt - Lt{-}1) + (1 - \beta)(Tt{-}1).$ (2)

c. Seasonal smoothing

$St : \gamma(Xt - Lt) + (1 - \gamma)(St{-}S).$ (3)

d. Forecasting period ahead

$\hat{X}t{+}p : Lt + pTt + St{-}S{+}p.$ (4)

with,

St = seasonal smoothing value at time t,

γ = smoothing constant for seasonal patterns $0 < \gamma < 1$.

S = seasonal period.

The equations used in the multiplicative model are:

a. Exponential smoothing
$Lt : \alpha(Xt/St-S) + (1 - \alpha)(Lt-1 + Tt-1).$ (5)

b. Trend pattern smoothing
$Tt : \beta(Lt - Lt-1) + (1 - \beta)(Tt-1).$ (6)

c. Seasonal smoothing
$St : \gamma(Xt\ Lt) + (1 - \gamma)(St-S).$ (7)

d. Forecasting period ahead
$\hat{X}t+p : (Lt + pTt)St-S+p.$ (8)

2.2 Long Short Term Memory

Long Short-Term Memory (LSTM) is a sort of artificial Recurrent Neural Network (RNN) architecture used in deep learning to model time-series information (Benchaji et al., 2021). Many applications of Recurrent Neural Network (RNN), such as Long Short Term Memory (LSTM), provide high accuracy in forecasting and outperform most statistical and traditional ML methods (Dudek et al., 2021). Long Short-Term Memory (LSTM) is a recurrent neural network that has successfully overcome the typical recurrent neural network's vanishing gradient problem, making it impossible to detect valuable features occurring early in input sequences (Lee et al. 2018). LSTM has a memory block that will determine which value to choose as output relevant to the input is given (Wiranda and Sadikin 2019). It accepts long-term, short-term, and input sequences at a particular time step. It generates new long-term memory, short-term memory, and an output sequence simultaneously (ArunKumar et al., 2021). The stages used in this method consist of 3 main stages: 1) Data Preprocessing; 2) Modeling through the training process LSTM network; 3) performing a test on data testing.

2.3 RMSE and MAPE

The model's performance in this study can be evaluated using the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Root Mean Square Error (RMSE) is a method for evaluating forecasts technique used to measure the level of accuracy of the estimated results of a model (Abdillah and Suharjito 2019). Root Mean Square Error (RMSE) is a method used to measure accuracy between the forecasting results and validation dataset (Jiang et al. 2020). Meanwhile, the Mean Absolute Percentage Error (MAPE) is a percentage-based measure for determining the accuracy of a forecast (Singh et al. 2015). This MAPE value interpretation can be seen on Table 1 below. According to Vroman (1998), they employ the RMSE and MAPE criteria to anticipate quality.

The equations used in the root mean square error (RMSE) are:

$$RMSE : \sqrt{\sum_{i=1}^{n} \frac{(\widehat{yi}-yi)^2}{n}} \quad (9)$$

with,
$\underline{yi}$ = forecasted value
yi = actual value
n = number of data

The equations used in the mean absolute percentage error (MAPE) are:

$$MAPE : \sum_{i=1}^{n} \left| \frac{yi - \widehat{yi}}{\widehat{yi}} \right| x\ 100\% \quad (10)$$

with,
$\underline{yi}$ = forecasted value
yi = actual value
n = number of data

According to Lewis (1982), there are several interpretations of MAPE values in forecasting:

Table 1. Interpretation of MAPE Value

MAPE	Interpretation
less than 10%	High degree of accuracy forecasting

10% to 20 %	Good accuracy rate forecasting
20% to 50%	Reasonable forecasting
more than 50%	Inaccurate forecasting

2.4 Google Collaboratory
Applications used to perform data processing are Minitab 18 and Google Collaboratory. Minitab 18 is used as a medium for collecting datasets in the form of historical data on the number of newspaper sales; then, the data files will be inputted for processing into the Google Collaboratory. Google Collaboratory is a tool developed by Google related to Artificial Intelligence to run and execute Python code in the browser (Putra 2020). Google Collaboratory can be accessed via Google Drive, where the file is in the form of .ipynb which is then inputted with text and python code to be executed.

3. Methods
The procedure used by researchers to explain, process, and interpret research objects is called research methodology. The methods for analyzing the data on the number of daily subscriptions distributed to the regions by PT. XYZ is using the Holt Winter and Long-Short Term Memory (LSTM). Newspaper sales data are used to generate different forecasting models. The performance of different forecasting techniques was compared with the help of RMSE and MAPE values. The forecasting technique with the smallest error value will be chosen as a suitable forecasting method. The analytical steps used are as follows:

- Conduct an analysis of the number of daily newspaper sales data in the regions by PT. XYZ using plot diagrams and descriptive analysis.
- Forecast the available data.
- Compare actual demand with forecasted demand.
- Calculates MAPE values and compares MAPE values between models.
- After selecting the best model, future forecasting is carried out for one month.

Figure 1 illustrates the flowchart based on the analysis steps that have been described. The flowchart of this problem analysis can be seen below.

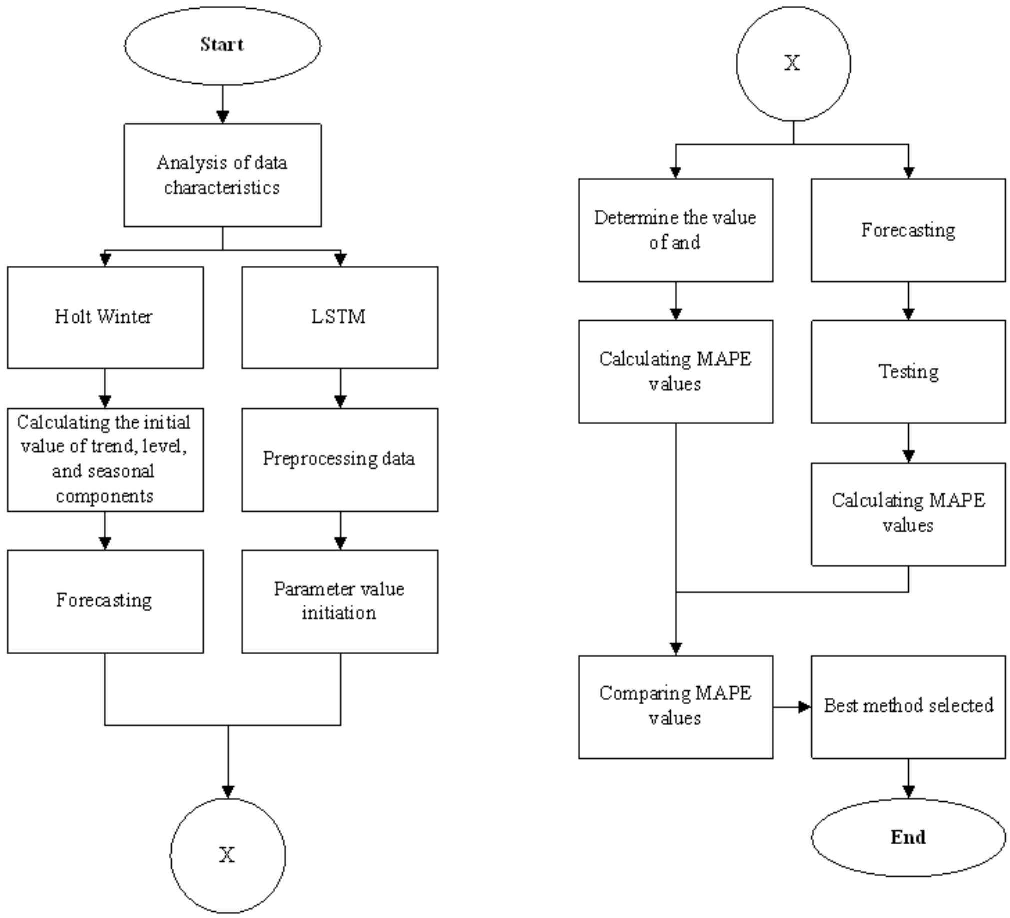

Figure 1. Research flowchart

4. Data Collection

The data used in this study is actual demand data sourced from newspaper sales by PT. XYZ for the period of January 2016 to March 2017. The data is secondary data from newspaper sales sourced from previous research by A'yun et al. (2021). The data used in this study can be seen in Table 2 below.

Table 2. Actual demand

Period	Demand	Period	Demand
2016-01	68217	2016-09	618726
2016-02	643154	2016-10	645388
2016-03	651105	2016-11	633852
2016-04	669641	2016-12	612400
2016-05	600311	2017-01	599835
2016-06	639149	2017-02	562901
2016-07	594268	2017-03	615615

2016-08	643260		

5. Results and Discussion

This section presents the graphical and numerical results of the performance measures for each forecasting method used, namely holt winter and long short term memory. Each picture shows the results of forecasting using each method with different settings. The actual demand data in Figure 2 is the sales data of PT. XYZ script in the period January 2016 to March 2017. The results of the descriptive analysis of newspaper sales data are presented in Table 3. The actual demand pattern data based on Figure 2 shows the long-term upward and downward trend in the data. Also, for the Figure 3, the magnitude of the seasonal effect that varies from period to period affects the shape model used, namely the multiplicative model.

Table 3. Results of descriptive analysis of actual demand

Variable	N	N*	CumN	Percent	CumPct	Mean	SE Mean	StDev	Sum of Squares	Min
Demand	15	0	15	100	100	627452	8030	31099	5,91898E+12	562901

Variable	Q1	Median	Q3	Maximum	Mode	N for Mode
Demand	600311	633852	645388	682177	*	0

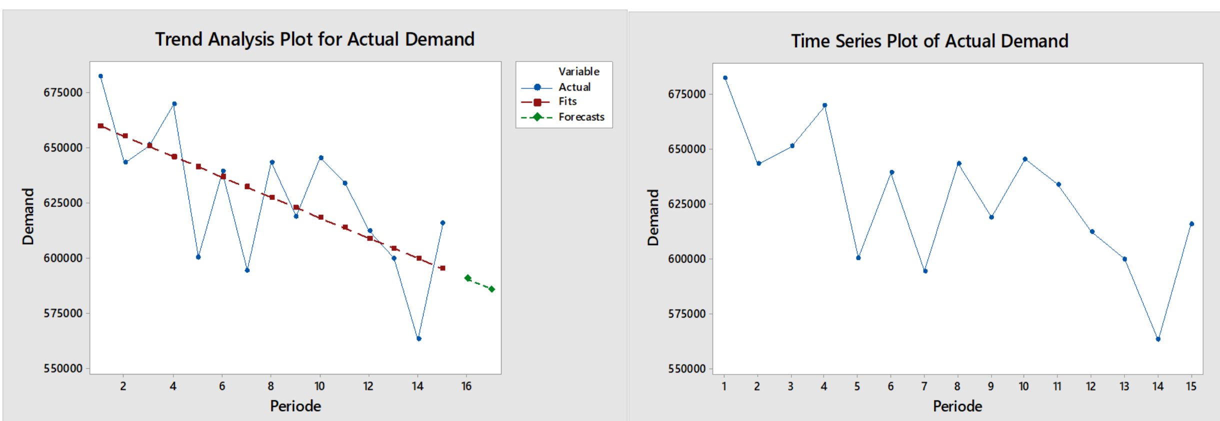

Figure 2. Preliminary data from actual demand

5.1 Holt-Winters

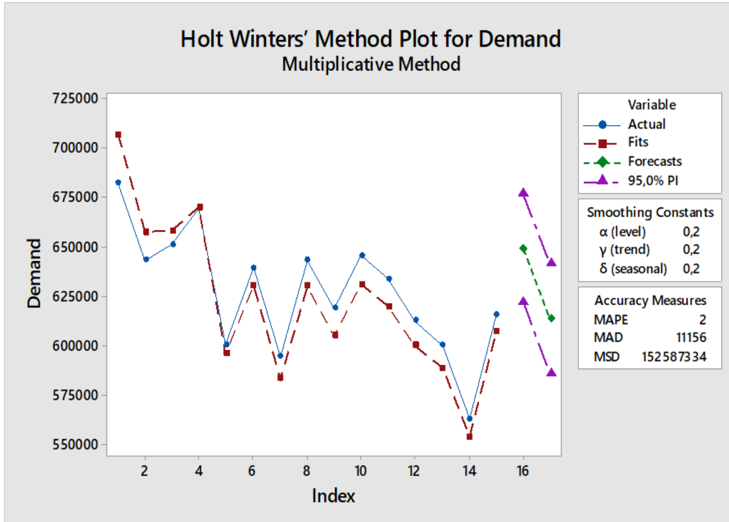

Figure 3. Result of calculation using holt winters method

Table 4. Results of next month forecast

Period	Forecast	Lower	Upper
16	649137	621806	676469
17	613127	585367	640886

The Holt-Winters in this research use the smoothing constant α=0,2, β=0,2, and γ=0,2. Based on the results shown in Figure 3, the forecast is in the cycle. The Winter is used for calculation because there is a trend in demand for newspaper sales. Forecasting results for next month show an increase in the request number in the 16th period and a decrease in the number of requests in the 17th period as presented in Table 4. Based on the forecasting results with the Holt-Winter method having a MAPE value of 2%, these results indicate that the forecasting method used is excellent and has a high level of model accuracy because the MAPE value is in the range of 0-10%.

5.2 Long Short Term Memory

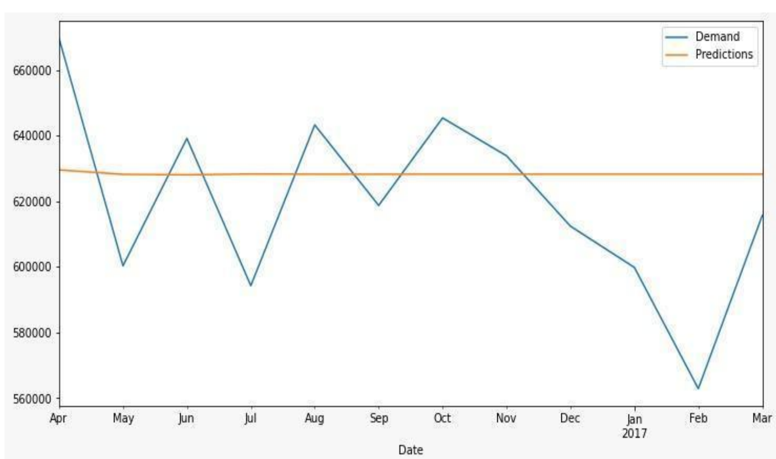

Figure 4. Result of calculation using long short term memory method

This research examines 15 months of newspaper demand data. Training and testing data are used in the Long short term memory method. The data used is 80% training data and 20% test data. This composition is used because the learning machine is better educated to examine models with a more extensive amount of training data. With this combination, it is expected that the resulting model will provide better data forecasting tests. The number of trained data is 12, with data from the first 12 months being used. This figure represents 80% of the entire quantity of demand data provided. The number of data being tested is three, using the data from the last three months.

A graph with two blue and red lines is obtained based on the processing results. The blue line shows the pattern formed by the existing demand data, while the red line shows the prediction results of demand based on the existing demand data. Then to get the MAPE value, data processing is carried out on the google collaboratory, which results in the MAPE value for predicting demand for the next period based on existing demand data. The MAPE value is 3.8 percent based on data processing with the long short - term memory method.

5.3 Comparison with the Previous Research

In addition, the results of this research's forecasts were compared to the previous research that used the ARIMA method and trend line analysis method. The forecasting method will be chosen based on the smallest Mean Absolute Percentage Error (MAPE) criteria. According to this research and the previous research, the trend line analysis method has a MAPE value of 2,94%, and the ARIMA method has a MAPE value of 3,52%. Meanwhile, the long short-term memory has a MAPE value of 3,87%, and the holt-winter has the lowest error rate, with a MAPE value of 2%.

6. Conclusion

Based on the results of this research, the holt-winter method had an error rate of 2%, and the long short term memory method had an error rate of 3,6%. Then, previous research with the ARIMA method had an error rate of 3,52%, and trend line analysis had 2,94%. It can be seen that the optimal forecasting method is the holt-winter method because it has the lowest error rate of all the alternatives. So, the company can use the holt-winter forecasting method to predict the number of requests for newspapers in the future to reduce the rate of returns and losses experienced by the company.

The limitation of this research is focused on forecasting the secondary data sourced from the previous research. However, the latest actual demand and sales data are not collected, so we cannot see the actual prediction. So, future research can be conducted by collecting the latest sales data and comparing the holt-winter method with other forecasting methods, especially using Machine Learning. Later, the result can be compared with this research and analyzed further.

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