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FORECASTING INDIHOME USERS BY USING TRIGONOMETRICS, BOX COX, TRANSFORMATION, ARMA ERROR, TREND, AND SEASONAL (TBATS) METHODS

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ABSTRACT

The rapid growth in the use of telecommunication services, particularly IndiHome, has created a pressing need to comprehend and forecast the dynamics of user growth. The swift development of IndiHome services in Pematangsiantar underscores the importance of efficiently forecasting and managing user growth. This research aims to predict future IndiHome users using the TBATS method (Trigonometrics, Box Cox Transformation, Arma Error, Trend, and Seasonal). User data for IndiHome services were obtained from Telekomunikasi Indonesia (Telkom) Pematangsiantar. The collected data underwent analysis and interpolation using the TBATS method. The choice of the TBATS method is attributed to its capability to handle complex patterns of seasonality, trends, and variability in telecommunication service usage data. The TBATS method involves model optimization and model validation using the Mean Absolute Percentage Error (MAPE). The forecasted results for IndiHome users in the next 5 years, with the highest IndiHome users reaching 426,9432, indicate a reasonable forecasting performance. The accuracy of the forecast, as measured by the MAPE calculation, ranges around 30.5%, signifying that the TBATS method demonstrates a satisfactory forecasting capability for IndiHome user data.
Keywords: Forecasting, TBATS, MAPE, IndiHome Users

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PRELIMINARY

Forecasting originates from the word "forecast," which means an estimate regarding the likelihood of an event that will occur in the future (Sinaga & Irawati, 2018). It is a crucial tool in efficient and effective planning. Forecasting is an activity that estimates or predicts future events with the help of preparing a plan in advance, where the plan is made based on the capacity and ability of demand and production that has been carried out in the company (Lusiana & Yuliarty, 2020).

Forecasting is also an effort to project or estimate something that has not yet occurred. For example, it involves predictions related to dynamic variables such as population size, per capita income, company sales volume, consumption, and similar factors that are constantly fluctuating. These changes are complex and influenced by various factors, such as the culture of the surrounding community, family income levels, and other personal factors. Therefore, determining precise changes in these aspects becomes challenging, and that is why forecasting is necessary (Syahputra, Supriono, & Suharyono, 2018). This prediction is closely related to supervision because an action will be taken by a company if something happens outside of its target prediction (Sumarjaya, 2016). The benefits of forecasting include the ability to provide accurate predictions, thereby reducing company costs. It also empowers companies/institutions to anticipate future conditions, mitigate the risk of failure, and allows the use of forecasting in decision-making at the management level of the company/institution (Olivia, Erviana, Saumi, Elviana, & Marlinda, 2022).

Time series data is a series of observations that are sorted by time periodically (Al'afi, Widiart, Kurniasari, & Usman, 2020). Time series forecasting can be done using a forecasting model to predict the future value of a variable based on previously observed values (Ma'Fulloh & Sumarsono, 2022). Time series forecasting is a study concerning sequentially ordered data over time, with the aim of projecting data that will emerge based on previous data (Reynaldo & Palinggi, 2021). As an alternative, forecasting methods involve analyzing correlation patterns between variables to be predicted and time variables, which fall into the category of time series (Fajar & Nonalisa, 2021).

IndiHome is a Triple Play service provided by PT. Telkom Tbk, which includes Home Internet (Fixed Broadband Internet), Home Phone (Fixed Phone), and Interactive TV (UseeTV) with various pricing options. IndiHome is the latest product from PT. Telkom, introduced in conjunction with the transition of Telkom's network from copper cables to fiber optic cables. PT. Telkom faces challenges in presenting this new product to the public, both potential customers and existing ones. These challenges include meeting customer expectations and needs after purchase, assessing whether the product quality justifies its price, and evaluating whether the service quality is satisfactory or not in line with customer needs. The implementation of promotional strategies for Indihome is crucial in efforts to introduce the new product released by PT. Telekomunikasi Indonesia, especially in the Pematangsiantar region. Therefore, the forecast of the number of Indihome installations aims to determine the upcoming installation figures at Telekomunikasi Indonesia Pematangsiantar. The forecasting method employed is TBATS, assisted by the RStudio application, with a forecasting variable system based on historical time series data. This is expected to enhance services according to the needs and anticipate the upcoming number of users (Ginting, Mirza, Putri, & Brutu, 2021).

Hasanah (2019) utilized the TBATS method to estimate the number of passengers at Juanda International Airport with sample data from the years 2012-2015. This research indicated that the TBATS method performed exceptionally well, with routes having the highest passenger numbers being arrivals from Denpasar, Balikpapan, Singapore, and departures to Denpasar, Balikpapan, Kupang, as well as Taipei. Subsequently, further research was conducted by Fajar & Nonalisa (2021) to forecast chili prices at the Kramajati Wholesale Market. The findings of this study demonstrated that the TBATS method is highly effective in predicting chili prices.

The use of the TBATS method has become a common approach frequently employed in forecasting time series data to make predictions for the future. Generally, this technique is applied in forecasting economic daily sales to understand daily seasonality and generate more accurate sales forecasts to optimize inventory and demand. However, this research extends that concept by applying forecasting to an object in the telecommunications industry, namely, IndiHome users. This creates new opportunities to apply this method in a different context, such as focusing on the telecommunications sector and forecasting objectives specifically centered around IndiHome users based on monthly seasonality.

METHODS

Data Source

In this study, the data used is quantitative data. Quantitative research is an approach used to address research questions that involve numerical data and employ statistical tools. (Ali, Hariyati, Pratiwi, & Afifah, 2022). This study obtained data in the form of data on the number of IndiHome users and the period of IndiHome users in the city of Pematangsiantar. The data used in this study uses monthly data on the number of IndiHome users in Pematangsiantar for 5 years starting from August 2018 to July 2023. This forecasting is conducted to determine the number of Indihome users for the next 60 months (Novita Sari & Purnama Sari, 2021).

Transformation Box-Cox

The Box-Cox transformation estimates the value of ω that minimizes the standard deviation of observations (y_t) or can be referred to as standardization transformation. The result of this transformation is $y_t^{(\omega)}$ when ω is not equal to zero and $In\ y_t$ when ω is equal to zero. Therefore, to find the optimal ω value, the Box-Cox transformation modifies the original data using the following formula:

$$y_t^{(\omega)} = \begin{cases} \frac{y_t^{\omega}-1}{\omega} & jika\ \omega \neq 0 \\ In\ y_t & jika\ \omega = 0 \end{cases} \quad (1)$$

where:

y_t = original data with t = 1, 2, ..., n

ω = estimated value of *Box-Cox* transformation

n = number of observations

ARMA Model

The ARMA (p, q) model is a forecasting model that falls under the linear category and is applied to time series data with constant mean and variance. The ARMA model in time series analysis involves two processes: the moving average (MA) process and the autoregressive (AR) process (Abotaleb et al., 2022). The terminology for the MA process is based on the fact that observations are obtained by specifying weights of $1, -\theta_{1,} - \theta_{2,} \dots, -\theta_{q,}$ on the variables $\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}$, then moving these weights and applying them to $\varepsilon_{t+1}, \varepsilon_t, \varepsilon_{t-1}, \dots, \varepsilon_{q+1}$ to determine y_{t-1} and so on. The AR process can be interpreted as a regression relationship within the observations. The current value in the observation (y_t) is a linear combination of p previous time observations added to ε_t, which is the information from the time series at time t that cannot be explained by previous observations. Statistically, the ARMA (p, q) model can be written as follows:

$$y_t = \sum_{i=1}^{p} \varphi_i d_{t-1} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad (2)$$

where:

$\varphi_p(B) = 1 - \varphi_1 B - \dots - \varphi_p B^p$

$\theta_q(B) = 1 - \theta_1 B - \dots - \theta_q B^q$

$\varphi_p(B)$ = component coefficient of order p

$\theta_q(B)$ = component coefficient of order q

ε_t = residual

TBATS Model

The TBATS model is a specialized type of time series model designed to handle complex seasonal patterns. This model belongs to the family of exponential smoothing models, allowing automatic transformations using the Box-Cox method and incorporating ARMA error components. The acronym TBATS refers to the combination of key elements in this model, namely Trigonometry, Box-Cox, ARMA, Trend, and Seasonality. In comparison, the BATS model is similar, but TBATS distinguishes itself by excluding trigonometric regressors and maintaining a focus on addressing complex seasonality (Tamatta, 2018). The TBATS model accommodates seasonal components with integer and non-integer periods, whether they are double or single seasonal or semi-seasonal (Hasanah, 2019).

The equation of the TBATS model is as follows:

$$y_t^{(\omega)} = \begin{cases} \frac{y_t^{\omega}-1}{\omega} & jika\ \omega \neq 0 \\ In\ y_t & jika\ \omega = 0 \end{cases} \quad (3)$$

$$y_t^{(\omega)} = l_{t-1} + \varphi b_{t-1} + \sum_{i=1}^{M} s_{t-mi}^{(i)} + d_t \quad (4)$$

$$l_t = l_{t-1} + \varphi b_{t-1} + \alpha d_t \quad (5)$$

$$b_t = (1-\varphi)b + \varphi b_{t-1} + \beta d_t \quad (6)$$

$$d_t = \sum_{i=1}^{p} \varphi_i d_{t-1} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (7)$$

$$s_t^{(i)} = \sum_{j=1}^{M} s_{j,t}^{(i)} \quad (8)$$

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos \lambda_j^{(i)} + s{*}_{j,t-1}^{(i)} \cos \lambda_j^{(i)} + \gamma_1^{(i)} d_t \quad (9)$$

$$s{*}_{j,t}^{(i)} = -s_{j,t-1}^{(i)} \cos \lambda_j^{(i)} + s{*}_{j,t-1}^{(i)} \cos \lambda_j^{(i)} + \gamma_2^{(i)} d_t \quad (10)$$

Where:

$y_t^{(\omega)}$ = *TBATS* forecast value

y_t = original data with t = 1, 2, ..., n

ω = estimated value of *Box-Cox* transformation

$\varphi_p(B) = 1 - \varphi_1 B - \cdots - \varphi_p B^p$

$\theta_q(B) = 1 - \theta_1 B - \cdots - \theta_q B^q$

$\varphi_p(B)$ = component coefficient of order p

$\theta_q(B)$ = component coefficient of order q

ε_t = residual

m = seasonal period

l_t = level index at time t

b_t = trend index at time t

s_t = seasonal index at time t

α = level smoothing parameter

β = trend smoothing parameter

γ = seasonal smoothing parameter

Furthermore, equation (1) is the Box-Cox transformation, equation (2) represents the seasonal pattern, equations (3) and (4) are the global trend and local trend, equation (5) is the error modeled by ARMA, and equations (7) and (8) are the seasonal pattern modeled by the Fourier model where this model provides frequency information from a time series data and models the seasonal pattern in time series data using a combination of sine (sin) and cosine (cos) functions (Ray et al., 2022).

Forecasting Ability

Forecasting error is the difference between the actual value of observed data and the forecasted value for the same period. In measuring forecasting error, various metrics are utilized, and one of them is the Mean Absolute Percentage Error (MAPE) (Yustiani, Wahyuningsih, & Siringoringo, 2023). MAPE is a metric used to assess the effectiveness of a forecasting method by calculating the average error rate of the method (Ma'ruf & Narendra, 2022). The MAPE value shows the accuracy of the predicted value of time series data in the form of a percentage formulated by the following equation:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - F_t}{Y_t}\right| \times 100\%, \quad t = 1,2,3,\dots,n \qquad (11)$$

Where:

Y_t = observation value at time t

F_t = forecasting value at time t

n = number of observations

$n = 1,2,3,\dots,n$

To evaluate forecasting results with MAPE, there is a certain significance range that indicates how good the forecasting results are. MAPE percentage $< 10\%$ percentage indicates the level of significance of the forecasting results is very good. MAPE percentage $10\% - 20\%$ percentage indicates good forecasting results, while $20\% - 50\%$ the significance level of the forecasting results is quite good. MAPE percentage $> 50\%$ percentage indicates poor forecasting results (Astuti & Bakri, 2021). Therefore, the smaller the MAPE value, the more accurate the forecasting technique used, and the larger the MAPE value, the less accurate the forecasting technique used (Tobing, 2022).

This research uses the help of RStudio software. The research procedures carried out in this study in order to achieve the research objectives are as follows:

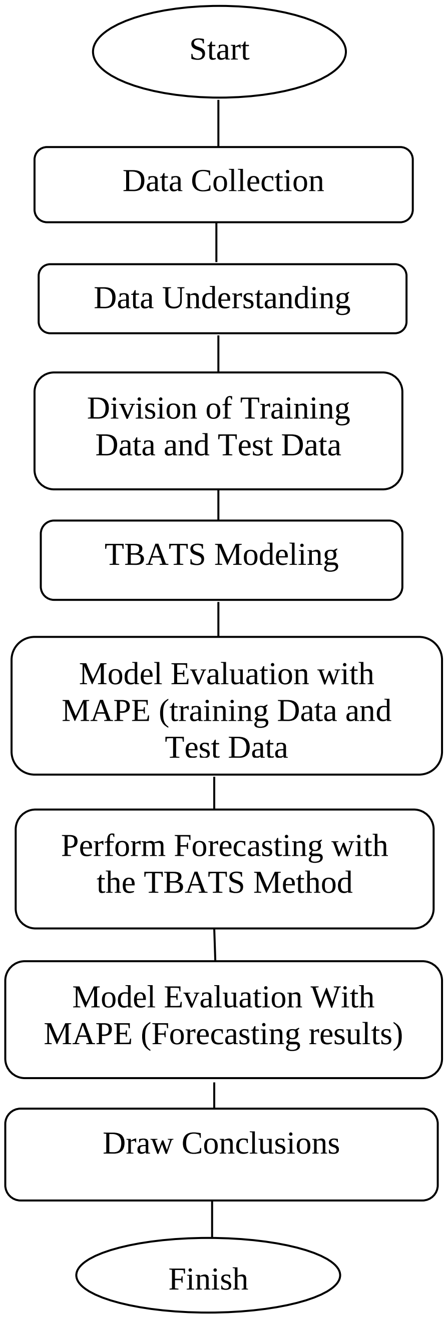

Figure 1. TBATS *Flowchart*

The Research Procedure

The first step undertaken in this research is to collect the acquired data and comprehend it to avoid errors in data analysis. Subsequently, the data is divided into training and testing sets to train and test the model. Next, TBATS modeling is performed to obtain parameter values supporting the model. With the obtained parameter values, model evaluation is carried out using Mean Absolute Percentage Error (MAPE) on both the testing and training data to assess the accuracy of the model in prediction. Following that, forecasting for future periods is conducted using the TBATS method. With the forecast results in hand, model evaluation tests can be performed to measure the accuracy of the model or demonstrate how well the model performs in forecasting. The final step involves drawing conclusions from the research findings.

RESULT AND DISCUSSION

Data Description

In this study, data on the number of IndiHome users in the city of Pematangsiantar for 5 years were utilized, resulting in a total of 60 data points as follows:

Table 1. IndiHome User Data Pematangsiantar City

Year	User
2018	2.908
2019	8.124
2020	8.923
2021	5.100
2022	5.220
2023	2.940

Based on table 1, a graph of IndiHome user data patterns in Pematangsiantar City can be seen in figure 2 as follows:

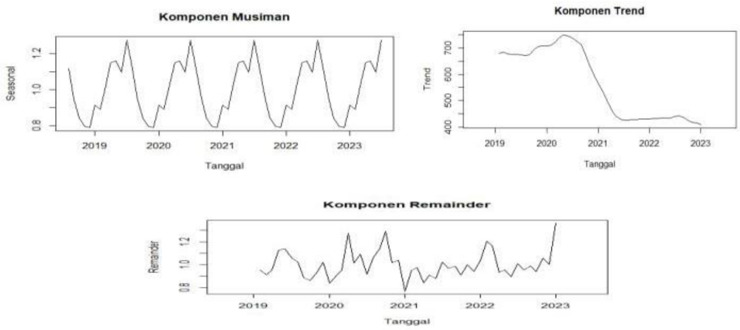

Figure 2. User Data Pattern Graph

From the graph, it can be seen that IndiHome users in Pematangsiantar City have seasonal and trend patterns.

Division of Training Data and Testing Data

Training data and testing data are two sets of data that are commonly used in the process of developing forecasting models or prediction models. Training data aims to teach or train the model so that it can make accurate predictions. Meanwhile, testing data aims to evaluate or test the performance of the model and identify whether the model can make good predictions in the future. Furthermore, it is done by dividing the dataset into 80% data for training and 20% data for testing.

The following is the calculation of the proportion of training data and testing data:

Table 2. Proportion of Training and Testing Data

	Training	Testing	Total
Ratio	80%	20%	100%
Total	48	12	60

It is known that the research data is 60 data, where the data is divided into 48 training data and 12 testing data. The use of training and testing data can help in ensuring that the forecasting model not only memorizes the training data (overfitting), but is also able to make predictions that are outside the data. By measuring the performance of the model on the testing data, it can decide whether the model is good enough or needs to be adjusted to improve its accuracy.

TBATS Modeling

Before forecasting, it is necessary to train the TBATS method using training data. To do TBATS modeling, it is assisted by using Rstudio software with a library (forecast):

```
library(forecast)
jumlah_data <- nrow(data_pengguna_indihome1)
jumlah_pelatihan <- round(0.8 * jumlah_data)
data_pelatihan <- data_pengguna_indihome1[1:jumlah_pelatihan, ]
data_uji <- data_pengguna_indihome1[(jumlah_pelatihan + 1):jumlah_data, ]
model_tbats <- tbats(data_pelatihan$Jumlah_Pengguna)
print(model_tbats)
```

The result of the output is the result of modeling with the TBATS method on training data to show the parameters of the TBATS model that have been obtained from the training process. With this model, it can perform forecasting on test data or future data. TBATS modeling of IndiHome user data obtained results, namely TBATS (0, {0,0}, -, {12,1}).

Table 3. TBATS Model Coefficients

Parameter	Coefficient
Ω	0
Λ	0
Α	1.03762
Γ	0
Β	0
AIC	620.8723
Sigma	0.1540148

Based on the results obtained, it shows that the TBATS model is relatively better in modeling IndiHome user data because the smaller the AIC value, the better the model is relatively in explaining the data.

Model Evaluation

After modeling TBATS, using Rstudio software, we can evaluate the performance of the model using Mean Absolute Percentage Error (MAPE) on training data and testing data. Based on the output results with the TBATS method in forecasting IndiHome user data, the calculation of MAPE data training of 12.27538 shows that the performance ability of TBATS in forecasting IndiHome users is good. Meanwhile, based on the output results obtained with the TBATS method in forecasting IndiHome user data obtained MAPE calculation of data test of 51.08017 indicate that the performance ability of TBATS in forecasting IndiHome users is poor.

Forecasting

After evaluating the performance of the model using Mean Absolute Percentage Error (MAPE) on training data and testing data. Furthermore, it can perform forecasting for the next 5-year period using following RStudio command formulation:

```
# Membuat data tanggal untuk 5 tahun ke depan
tanggal_ramalan <- seq(as.Date("2023-08-01"), as.Date("2028-07-01"), by = "months")
# Melakukan peramalan dengan model TBATS
hasil_peramalan <- forecast(model_tbats, h = length(tanggal_ramalan))
# Mengambil nilai peramalan dari hasil
peramalan_jumlah_pengguna <- hasil_peramalan$mean
# Membuat data frame hasil peramalan
data_peramalan <- data.frame(Tanggal = tanggal_ramalan, Jumlah_Pengguna =
peramalan_jumlah_pengguna)
# Tampilkan hasil peramalan
print(data_peramalan)
```

The results of IndiHome user forecasting for the next 60 months or 5 years can be obtained.

Table 4. Forecasting Results of IndiHome Users 5 Years in the Future

No	Date	Number of Users
1	August 2023	386,0260
2	September 2023	352,7396
3	October 2023	323,5731
.	.	.
.	.	.
.	.	.
58	May 2028	419,9887
59	June 2028	426,9432
60	July 2028	413,9671

In the given forecasting results, the highest forecast value in forecasting is in June 2024, June 2025, June 2027, June 2028 which is 426,9432 users where these four months have the highest estimated number of users. The forecasting results also show 80% and 95% confidence intervals with each row showing forecasts for specific months with the following columns:

Table 5. IndiHome User Forecasting Confidence Interval for the Next 5 Years

Lo 80	Hi 80	Lo 95	Hi 95
320,7877	464,5317	290,84200	512,3608
282,6610	440,1924	251,38937	494,9502
251,3324	416,5781	219,86907	476,1905
230,3828	403,6257	198,60574	468,2060
220,9838	407,1959	187,97584	478,6982
.	.	.	.
.	.	.	.
.	.	.	.
144,5523	911,9484	88,77528	1484,9190
156,3246	1002,1473	95,59877	1638,7248
164,5643	1071,8631	100,21540	1760,1106
165,9773	1098,2244	100,65551	1810,9305
159,6819	1073,1873	96,43858	1776,9698

Acquired, for example, on January 6th, the user forecast is 386.0260 and the forecasting result also contains two confidence intervals, namely 80% confidence interval ranging from 320.7877 to 464.5317 and 95% confidence interval ranging from 290.84200 to 512.3608. These intervals provide an approximate range of expected values with corresponding confidence levels and indicate the extent of the forecasting confidence level for that value.

Furthermore, it can evaluate the performance of the model using Mean Absolute Percentage Error (MAPE) on forecasting data to measure accuracy and can help provide an overview of the extent to which the forecasting model functions properly in predicting future data. So, it can be obtained that the calculation of the MAPE value of the data from the IndiHome user forecasting results for the next 60 months is around 30,51097495 or 30.5%, so the forecasting performance ability of the TBATS method is quite good in forecasting IndiHome user data for the next 5 years.

CONCLUSION

From the above research findings, it can be concluded that the Trigonometrics, Box Cox, ARMA error, Trend, and Seasonal (TBATS) method is quite effective in forecasting IndiHome users for the next 5 years (60 months ahead). This is evident from the Mean Absolute Percentage Error (MAPE) calculations, which are around 30.5%. In conclusion, the forecasted highest number of IndiHome users is approximately 426,943.2 users. Despite fluctuations in some periods, the number of users tends to remain relatively high. This indicates that, despite monthly variations in the number of users, the overall trend remains positive with a fairly stable usage rate.

With this research, it is hoped to contribute to improving services and formulating strategies to prevent unforeseen events. Suggestions for further research include enhancing forecasting methods by combining different methods and types of data, as well as adding more sample data to produce more accurate predictive values.

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