Foreign Tourist Resurgence Post Covid-19 Analysis with Naïve, Exponential Smoothing, Time Series Regression, ARIMA, and Neural Network

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*Abstract*— The tourism sector is a crucial foundation for economic growth. The interconnectedness of regions amplifies tourism's role in boosting local economies and generating job opportunities. Data collected from the Bureau of Statistics Indonesia counts the amount of inbound tourist from foreign countries to Indonesia. This study focuses on the resurgence and the recovery of the tourism sector by looking at the number of tourists coming into Indonesia on a monthly basis from April 2020 to March 2024. The data will be processed using time series models such as Naive, Holt-Winters Exponential Smoothing, Time Series Regression, ARIMA, and Neural Network. The Naive and the Exponential Smoothing although unlikely to accurately forecast, proved useful as a base model. The ARIMA model and the Time Series Regression was the more ideal model for forecasting, but both fell short of fulfilling their required assumptions thus deemed unusable. Comparing all evaluation metrics of this study, the Neural Network model provides the best balance between error minimization and model accuracy. Applying the Neural Network will need consideration of either maximizing region profit or maintaining region sustainability when handling inbound tourists.

Keywords—Time Series, Tourism, ARIMA, Neural Network, Naïve, Exponential Smoothing.

# Introduction

As a developing country, one of Indonesia’s main outlets for increasing the local economy is tourism. An increase in the number of tourist, the value-added benefits from tourism, and government spending affects the regional economic growth positively[1]. Inspecting the underlying data, the total number of income generated by tourism in Indonesia is 16 Million US dollars in 2019 [2]. An increase of importance of this sector leads to it getting hit the hardest by the COVID-19 Pandemic. Policymakers scrambled to ensure the health and safety of their citizens by shutting down Indonesia’s border for all incoming flights in March of 2020. Tourism itself isn’t tied to one form, tourism for small islands in Indonesia were also impacted negatively by the borders closing [3]. Tourism is also not a single entity within its economic sector. Industries such as hospitality, travel agencies, and transportation were also negatively impacted by the pandemic [4].

Restrictions towards tourism also exasperated other issues in Indonesia, such as poverty. Tourism creates job opportunities and increases investment that will increase household income thus reducing poverty [5]. The reduction of inbound tourism reduces growth and increases poverty significantly [5]. Tourism is also not centralized towards one region, but rather multiple regions that play their own role. Reducing the inbound tourist of one region will in turn, effect the regions that supply tourist activities [5]. Regions that don’t interact directly with tourist activities are indirectly affected by the reduction in inbound tourist by either the loss of demand from neighbouring tourist dependent regions; or the reduction in investment due to the decrease in profit [5]. In summary, tourism is a lifeline for dependent and non-tourist dependant areas. It has a crucial role to play in alleviating the impacts of poverty across multiple regions.

Throughout the lockdown period, the focus of economic growth was second to the health and safety of all countries in the world, including Indonesia. As of 2022 and 2023, border restrictions have loosened up, and created an avenue for international tourism to enter back into Indonesia. the goals of the present study were: i) Understanding the resurgence of the tourism sector in Indonesia; and ii) Forecasting the influx return of tourists to Indonesia.

# Methodology

## Naïve Method

The Naïve forecast method is one of the simplest forecasting methods. Its simplicity came from the ability to be adapted into all types of time series data. Naïve forecast observes a particular value of time before analyzing it as a current time model. Due to its simplicity as well, Naïve works quite well for time series where pattern of the data is hard to recognize and predict. The Naïve forecast can produce the last observed value and the amount of change over time is set to be the average change seen in historical data, therefore it can increase or decrease over time. The simple Naïve method follows the equation as written below:

(1)

Whereas is the actual data happening at period t. We can conclude that the forecast value of the next data in the future is the same as the last actual data [6]. If the time series data contains a seasonality pattern, then some variations will have to be taken into consideration and the Naïve forecast will be referred to as Seasonal Naïve [7]. In such case, the forecast will be based on the same observed value from a previous point with a different range according to the period of the season. The seasonal Naïve will then have an equation as:

(2)

With the value of *s* denoting the seasonal period from the data [8].

## Holt-Winters Exponential Smoothing

The Holt-Winters method is developed by Holt (1957) and Winters (1960) designed to implement the exponential smoothing method for trend or seasonality data [9]. It works by using three smoothing equations, one for the level designated by , next is for the trend represented by , and last one is to accommodate for the seasonal component represented by . Each of these equations are corresponded by [10]. As mentioned, the addition of three equations makes this method much more adept for tracking and forecasting time series that contains trend, seasonality, or even a mix of both compared to a simple exponential smoothing.

There are two variations from the method-the additive and multiplicative Holt-Winters [9]. The component for the additive method is:

(3) (4) (5) (6)

The multiplicative method for Holt-Winters is:

(7) (8) (9) (10)

For both methods, the value of is between 0 and 1. The variabel *p* represents the seasonality period or the period length. For a monthly data, the value of *p* would be 12 and quarterly data would be 4. The forecast of is always one step forward using the last value available from . To forecast more into the future up to K number ahead, then the equation for forecast will both be changed from the variations by:

(11) (12)

Where:

(13)

## Autoregressive Integrated Moving Average (ARIMA)

There are many time series analysis models separated into two categories, namely stationary and nonstationary models. Classic regression models are sometimes insufficient to generate full explanation of a time series data, for example some structures from ACF of the regression residual are not captured correctly. With this being the situation, correlation that is created by lagged linear relations introduces *autoregressive* (AR) and *autoregressive* *moving* *average* (ARMA). This development is then increased by adding nonstationary models, therefore creating the *autoregressive integrated moving average* (ARIMA) [11].

ARIMA can be further explained as a method to forecast time series data when it is not stationary. The base of this model relies on the usual ARMA, however ARMA requires the data to be stationary [12]. When faced with non-stationary data however, differencing is required to help convert it into stationary data, with how many times it takes until it is stationary. The full model ARIMA will have an order of (p, *d,* q), where *p* represents the value of the *autoregressive* (AR) process, *d* represents the number of differences done to the data (I), and *q* is the value of the *Moving Average* (MA)process.

We define as a process of ARIMA (*p, d,q*) with the variable fits a stationary ARMA(*p,q*) model. If we implement differencing, with *d* acting as the order and a non-negative integer then we will obtain an AR model with differencing such as:

If *d* = 1:

(14)

If *d* = 2:

(15)

The process of *moving average* is similar to the process of *autoregressive,* although not as useful compared to the *autoregressive* models. A variable is an MA(*q*) model if:

(16)

The MA model specifies that at at a point of time *t* is in fact a linear combination of past noise components and present ones, opposite of the AR model that suggests is a linear combination of past values, plus noise.

Despite this, combining both models will obtain the ARIMA model as ARIMA (*p, d, q*) and written as such:

(17)

Both and acts as “stationary and invertible” operators where all bases of the characteristic equations lie outside the unit circle. Keep in mind that the left side of the ARIMA equation represents the *autoregressive* part [9].

ARIMA models can be varied to better complement the data available, as such with the seasonal data. In this context, ARIMA would be called SARIMA or Seasonal ARIMA model as part of an extension from its base form [10]. Reference [13] suggested that seasonal ARIMA includes *autoregressive* and *moving* *average* terms defined at lag or period *s*.

The seasonal ARIMA are a combination of equations between periods relationship represented with an ARIMA model below:

(18)

Where both are polynomials in B*s* that contains no root formulated as:

(19)

And

(20)

And the basic ARIMA model, thus creating a seasonal ARIMA (*p, d, q*) (*P, D, Q*) *s* with *s* acting as a subindex to refer the seasonal period as:

(21)

To not confuse the variables, and is often called the regular autoregressive and moving average factors and are called the seasonal autoregressive and moving average factors respectively [14].

## Time Series Regression

Keep in mind that time series data is known to differ from static data used in processing methods due to the importance of implementing ordering for its data points. Regression methods are used to predict continuous value and to project the relationship between a set of predictors (features) with a target variable into a straight line. However, features for regression are often static and do not have any correlation towards time, for example a given case of predicting house prices can be done with number of bedrooms, crime rate in area, air quality, and many others. Features such as those are not dependent on time and less likely to change over time.

Therefore, if we try to implement time series regression towards that case, then the value of those features will not be stuck in a single value, but we try to correlate them with time, for example daily air quality and daily crime rate can be a good change for the features. Another alternative would be to use features that are recorded within a certain period. Regression, in the sense of time series forecasting, is used to fit autoregressive models on recent or seasonal data of the past and then predict future value for a decided range of time [15].

Using the knowledge of nonstationary ARIMA and its seasonal counterpart SARIMA, a sample equation of the time series regression implementing the simple linear regression (SLR) can be seen below:

(22)

Where here is a zero-mean stationary process. Assuming that is in fact stationary, this regression model would then be called a *regression model with correlated errors. [textbook]*

As said before, Time Series Regression accepts seasonal time series data as well [14]. An additive seasonal time series can be written as the following regression equation:

(23)

Where and are the trend-cycle variables. with acting as the seasonal variables. The component can also be described as a linear combination of seasonal dummy (indicator) variables. For example, the seasonal period *s* can be written as

(24)

Combining all three would then create a time series regression equation such as:

(25)

## Neural Network

Neural Network and Deep Learning are deeply connected to the point where most researchers concluded that Neural Network is essentially what makes Deep Learning. Seeing its importance, it is worth explaining how Neural Network is able to perform predictions based on an input. The main component of Neural Network is a lot of loosely connected *neurons* interacting with each other. A neuron receives input from each other or from the initial data, starts calculating based on parameters such as its *activation* *function*, and then returns an output sent to another neuron, a different layer, or straight to the output dataset. The parameters mentioned before can be external factors, such as the *weight* of a neuron explaining its relevance in the network, or maybe *bias* that will affect the *activation function* therefore affecting the output. The result will then be compared against an expected value from the input, giving out variance that would help adjust the *weight* and *bias* in the next run. This makes the neurons learn from their error in the next process [16].

A diagram of a mathematical equation

Description automatically generated

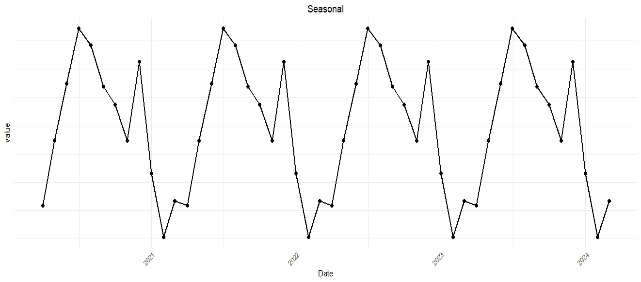
## **Fig 1.** Neural Network

Given its simplicity, Neural Network has improved over the course of time, thus resulting in derivatives and increased depth of its variations. An example of this is the Artificial Neural Network (ANN). ANNs are universally known due to their inspiration from the way neurons interact with each other to recognize patterns. ANNs can amaze researchers at its development in 1943 and improvement for the future, such as its ability to accept time series data. ANN has the capability to read nonlinear time series and create a model for prediction at the end because of its nonlinear mapping from the input neurons to the output. ANN has also gained more notoriety by being able to recognize and predict seasonal patterns of time series data. With this, a new structure of ANN is obtained, known as Seasonal ANN (SANN) that would determine the number of input and output neurons in accordance with the seasonal period of the series. Research using SANN shows that it outperforms other statistical models and feedforward ANN [17].

# Result and Discussion

## A graph showing a line Description automatically generated **Fig 2.** Yearly Tourist Arrival

Before using models to predict the number of tourist arrivals, we first need to identify the type of time series plot the data categorizes in. **Fig 2.** is a general plot used to look at the type of time series. Considering the data was collected post covid, the plot is difficult to concretely identify. Further analysis uses a decomposition method to refine the identification process.



## **Fig 3.** Seasonal Plot

**Fig 3 and Fig 4** are the result from the decomposition function. This study found that the yearly intake of foreign tourists is both a trend and a seasonal data. Seasonality occurs per 12-month interval that spikes in month 7. The result from the decomposition, specifically in **Fig 3**, is good starting indicator for the resurgence of tourist in Indonesia.

A graph with a line

Description automatically generated

## **Fig 4.** Trend Plot

## Naïve Model

The naive method does not require parameter estimation or complex configuration. The forecast for the next period is simply the value of the last observed period plus the seasonality. This approach is used as a benchmark to evaluate the performance of more sophisticated time series models.

## Triple Exponential Smoothing

To initiate the Holt-Winter method, the process involves three smoothing equations, each with a corresponding smoothing parameter:

1. Level smoothing (α): This preserves the series' baseline value.
2. The trend or long-term direction of the series is captured by trend smoothing (β).
3. Seasonal smoothing (γ): Captures the series' seasonal variations.

The values for all the parameters are in the range of , several models can be created by adjusting the level of influence from each parameter. Table I are the results from creating the models.

1. TES Train Results

|  |  |
| --- | --- |
| Models | RMSE |
| 0.5,0.5,0.5 | 89061 |
| 0.2,0.8,0.3 | 137038 |
| 0.8,0.2,0.3 | 84670 |
| 0.9,0.9,0.9 | 108530 |

## Time Series Regression

Configuring a time series regression involves creating a base model using the periods first as an identification process for significant lags. the base model identified the periods () as being statistically significant towards predictions. This conclusion coincides with the use of the lagged period to further refine the model.

1. Lagged-1 Regression Results

|  |  |
| --- | --- |
| **Variables** | **P-value** |
| (Intercept) | 0.00197 |
| April | 0.0994 |
| August | 0.05483 |
| December | 0.00144 |
| February | 0.45466 |
| July | 0.00579 |
| June | 0.00528 |
| March | 0.01846 |
| May | 0.0039 |
| November | 0.17019 |
| October | 0.0402 |
| September | 0.06649 |
| t | 0.02118 |
| lagged 1 | 1.77E-14 |

Significance testing using the p-value of the time series lagged-1 regression results in the lagged period being statistically significant for predictions. Furthermore, analysis using the lagged-2 regression results in the lagged-2 period being less statistically significant. The comparison between these 3 models lead to the conclusion that the model using lagged-1 is better suited for predictions. This is especially evident in value being . Assumptions for regression are made to further solidify the fit of the model towards the data. The assumptions are autocorrelation, homoscedasticity, and normally distributed. The results are shown in Table II. Each test uses the p-value as a metric for comparison towards of . the hypotheses in order are:

1. Autocorrelation  
    : There is no autocorrelation in the data  
    : There is autocorrelation in the data
2. Homoscedastic  
    : The data exhibits homoscedasticity  
    : The data exhibits heteroscedasticity
3. Normally Distributed  
    : The data is distributed normally  
    : The data is not distributed normally
4. Regression Testing

|  |  |
| --- | --- |
| Parameters | p-value |
| Autocorrelation | 0.611176 |
| homoscedasticity | 0.040606 |
| Normally Dist | 0.275541 |

Comparing all the s in Table III with an of lead to the conclusion that although the data is normally distributed and has no autocorrelation, the problem lies with the heteroscedasticity of the data. This indicates that the variance of the residuals is not constant across all levels. This implies that the Time Series Regression is not sufficient to forecast this data and a more complex model is needed.

## Seasonal Autoregressive Integrated Moving Averarge

Using the SARIMA requires the conditions that the time series data is both stationary towards the mean and the variance. Stationarity is integral for time series analysis and cannot be ignored [18]. To identify these conditions, first evaluate the conditions towards the variance. Stationary towards variance is crucial in identifying the need for transformation for the data. Using a test with lambda, with the hypothesis test of: : Stationary towards variance; : Not Stationary towards variance. With the being valued at , it can be concluded that the data is stationary towards the variance and does not need to be transformed.

Secondly, we need to identify the data’s stationarity towards the means. The hypothesis test: : Not Stationary towards means; : Stationary towards means. Using the Augmented Dickey-Fuller (ADF) test, the statistical value using the data without differencing is , because this value is significantly higher than of , the null hypothesis is accepted. This conclusion is not sufficient for a an ARIMA modeling. Differencing is needed for further testing. Stationarity towards the mean was achieved using a differencing of with the being significantly lower then . with the result from this test, we can use an ARIMA with the order due to the result of the differencing.

A graph of a graph

Description automatically generated with medium confidence

**Fig 5.** ACF and PACF

To help identify the other orders of ARIMA, particularly the order for AR and MA, the PACF and ACF plots are used respectively. Based on **Fig.5,** there are several orders for both the AR and the MA. Multiple models need to be created to determine the most fitting model.

1. SARIMA RESULTS 12 PERIODS

|  |  |  |
| --- | --- | --- |
| SARIMA | Seasonal | AIC |
| 2,0,1 | 1,1,1 | 697.02 |
| 2,0,1 | 0,1,0 | 693.75 |
| 0,2,1 | 1,0,0 | 934.53 |
| 1,2,1 | 1,0,0 | 936.09 |

based on the results from table IV, the better model comparatively is the ARIMA (2,0,1) (0,1,0)12. the resulting model is as follows:

(26)

Using the ARIMA model also requires rigorous testing to identify the fit of the model towards the data. Tests are done on the residuals of the model to ensure independence (White Noise) and normally distributed. The hypotheses are as follows: for white noise, : The residuals are white noise; : The residuals are not white noise. For normal distribution, : The residuals are normally distributed.; : The residuals are not normally distributed.

1. Arima Testing

|  |  |
| --- | --- |
| Parameters | p-value |
| white Noise | 0.8123 |
| normally dsitributed | 1.758e-05 |

Results in Table V when compared to an of implies that the errors produced by the SARIMA model are independent of each other but are not normally distributed. Inferring from the results of the testing, a more comprehensive model is needed to better fit the data.

## Neural Network

**Fig.5** shows that the ACF and PACF identified the significant lags being lag 1 and lag 2. Using these lags we can create several models for comparison.

1. Lag 1 NN

|  |  |
| --- | --- |
| Model | RMSE |
| 5,0 | 58.282 |
| 9,0 | 58.103 |
| 9,2 | 56.293 |
| 9,5 | 56.190 |
| 11,7 | 57.157 |
| 14,9 | 58.215 |

Based on Table VI, the model with the smallest RMSE uses lag-1 and has (9,5) hidden layers. There are 9 nodes in the input layer and 5 in the hidden layer.

## Model Comparison

1. Comparisons Table For Training Set

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Models | MSE | RMSE | MAPE | MPE |
| naïve | 33152811824 | 182079.1362 | 49.06 | 36.698 |
| TES | 7169086981 | 84670.46109 | 18.59 | 10.466 |
| NN | 3129585643 | 56190.44 | 11.61 | -1.958 |

This study’s main goal is to predict the resurgence of foreign tourist in Indonesia post Covid-19. The useability of certain models heavily relies on the assumption test being sufficient. The Time Series Regression fails in the assumption of Homoscedasticity. This infers that the variance of errors created are not constant, therefore forecasting using this model will rely on a skewed interpretation. The ARIMA model also fails in the assumption of normality. The errors created by the ARIMA are not distributed in a fashion for modeling.

This study identified three possible models for time series forecasting and evaluated them based metrics in Table VII and Table VIII. The metrics for each model can be interpreted as:

1. Root Mean Square Error (RMSE): in the context of foreign tourist resurgence, RMSE defines the precision of the forecast.
2. Mean Absolute Percentage Error (MAPE): in the context of foreign tourist resurgence, MAPE explains the accuracy of the forecast.
3. Mean Percentage Error (MPE): in the context of foreign tourist resurgence, MPE is the directional bias of the forecast obtained from a model. A positive MPE indicates an underestimation of the forecast, whereas the negative MPE indicates an overestimation of the forecast.
4. Comparisons Table For Testing Set

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Models | MSE | RMSE | MAPE | MPE |
| naïve | 96,553,616,724 | 310730.7785 | 27.08 | -27.09 |
| TES | 26,522,155,811 | 162856.2428 | 13.72 | 11.47 |
| NN | 16,781,128,768 | 129542 | 9.91 | 5.563 |

This study will focus more on the testing set of the data for foreign tourist resurgence, which starts in July of 2023. This is due to the lack of relevance of the training data in 2024. The training data starts in early April of 2020 where Covid-19 was at its highest point up until its decrease in June 2023. It can be inferred that the test data would be more suitable for model identification and predicting future forecasts.

Based on the metrics of the testing dataset, the model with the lowest MSE and RMSE score is the Time Series Regression model with Neural Network model following behind. This result can be obtained due to the Regression model’s robustness towards small sample sizes of the data. The lowest MAPE and MPE score of each model can be seen obtained by the Neural Network model with Time series regression following suit. Neural Network in general is more adaptive to different patterns given on the data compared to other models due to its nature of learning from errors, therefore providing it the ability to accept seasonal data that is highly dynamic and changing as time goes on. However, keep in mind that the Time Series Regression fails to fulfill the assumption of homoscedasticity, therefore it will not be valid to be used as a predicting model.

# Conclusion

Results in this study provide evidence on the resurgence of foreign tourist in Indonesia. Using time series models like Naïve, Exponential Smoothing, Regression, ARIMA, and Neural Network, this study predicts a rise in the number of inbound tourists. This is a good indicator for the recovery of the tourism sector post Covid-19.

When deciding on the best model to predict foreign tourist resurgence for future references in Indonesia, the purpose of the model needs to be decided first and foremost. With the context of foreign tourist resurgence, it is recommended to use the MPE metric for evaluation due to its use in determining the overestimating and underestimating of the forecast result. The results of the test from this study suggest that Neural Network model is the best model to be used for predicting incoming foreign tourists in the future. Due to the interdependence of regions with tourism, an accurate prediction is crucial in evaluating the need for tourism-based investments for certain regions. This study offers insight on data-driven aspects of economic investments. Regions should identify their main goal regarding tourism by applying different models in different situations. This will prove crucial in improving the economic structure of tourism and tourism-adjacent regions while also contributing to the lowering of poverty within those regions.

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