Forecasting demand factors of tourist arrivals in Indonesia’s tourism industry using recurrent neural network

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Abstract. Tourism is one of the sectors that have contributed to a wide variety, not just economically, but also socially political, culturally, regionally and environmentally. In Indonesia, the tourism sector has an important role in contributing to economic growth, especially in foreign exchange earnings. Therefore, it is very important to maintain and encourage the growth of tourism in Indonesia with the need for a model of forecasting the arrival of foreign tourists to Indonesia to assist the government in developing a tourism plan strategy. There are factors in demand forecasting which affect a demand in the tourism sector. In this study data in the form of fuel prices, exchange rates, per capita GDP, and the volume of bilateral trade from five countries over the span of January 2012 to December 2019 are used as variables that affect the arrival of foreign tourists. The method used to create a forecasting model is one of recurrent neural network architectures namely long short-term memory (LSTM). Three models are put in test and each model uses four types of parameters that are look-back value, hidden layer, number of epochs, and batch size. The first prediction model gives 97.21% of the highest accuracy. The second predictive model provides 99.17% of the highest accuracy. Lastly, the third prediction model provides 99.21% of the highest accuracy.  
Keywords: Forecasting, Tourism, Demand, Recurrent Neural Network, LSTM.

1. Introduction
Indonesia is well known as a country in which nature, culture and historical heritage have a range of beauty. Such circumstances indicate there are high potentials for Indonesia in tourism [1]. Indonesia's tourism industry has become a significant part of national growth because it can hold a lot of human resources, boost the local economy, and state income [2]. In Indonesia's economic development, tourism has become a GDP main contributor. It is expected to be one of the critical drivers of accelerating economic growth in Indonesia by creating jobs and businesses, export revenues and improving infrastructure [22]. In developing international tourism, to increase the flow of foreign visitors, it is essential to undertake programs that are targeted and relevant. Tourism's contribution has a broad dimension, not only in economic terms but also in social-political, cultural and regional conditions. Economically, the tourism sector contributes significantly to the foreign exchange earnings of the state, local own-source revenue and also community revenue generated from tourism businesses that are built and open up several job opportunities and great employment opportunities [1]. The number of foreign tourists can increase the foreign exchange of the country. It is because of the high foreign currency exchange against the local currency [23]. Additionally, Noersasongko et al. (2016) point out increasing the number of foreign tourists is one of the ways to improve the currency value.
The government can prepare strategic steps to build the tourism industry with the knowledge of the number of tourists coming.

As a leading sector, tourism is identified as an essential sector to develop in synergy. Through a sustainable tourism approach, efforts to conserve nature and culture and their legacies need to be synergized to support the acceleration of national development [3]. The factor tourist arrivals are still the most widely held indicator of tourism demand over the past few years [4]. According to Filippini and Hunt (2011), the need for precise tourism forecasts is therefore particularly important because of the significant contribution of the industry to the economy. To reduce the uncertainty in the decision-making process, preparation relies heavily on reliable forecasts [5]. Any data about potential tourist traffic volumes and trends is vital for hoteliers, tour operators and other tourism and transportation-related industries to prepare their investment and marketing strategies. Government institutions also need precise demand forecasts for tourism to plan and provide the necessary tourism infrastructure, such as accommodation site planning and development of transportation, among other needs. The tourist arrivals and demand forecast help the company to plan better. Long-term and short-term projections serve multiple roles, ranging from personnel and other resources to public infrastructure or equipment investments [24].

Recent studies (e.g. [6], [2], and [7]) have shown such tourism forecasting was carried out by the researchers with different methods. Similarly, Alamsyah and Friscintia (2019) [6] reviewed tourism demand forecasting as well as its determinant factors from 5 major Indonesia tourist markets by artificial neural network model. Vahikan et al. (2017) [2] used three different factors of foreign tourist arrivals from ten countries to Bali using recurrent neural network backpropagation through time. The research conducted by comparing two forecasting methods of RNN-BPTT with single moving average (SMA). It is proven that RNN-BPTT outstanding the SMA accuracy. Furthermore, Balli et al. (2018) [7] adapted and applied SARIMAX/(E)GARCH volatility models to forecast visitor arrivals by air from its eight main tourist source markets to New Zealand, and to monitor macroeconomic factors along with global and regional structural changes.

The recurrent neural network approach is appropriate to resolve the problem of time-series prediction. RNN can overcome the non-linear problem prediction. The RNN model is a forecasting model that utilizes past values to predict future values of time-series data [8]. The application of the RNN method in forecasting is expected to produce figures that close to the actual data, so that, the results can be used as decision-making material to take action in minimize the decline occurs in foreign tourist arrivals in Indonesia [9].

2. Literature review
There are some literatures review in which became a highlight in this study.

2.1. Forecasting the demand factors in tourism industry
Tourism is made up of ideas and opinions held by people who form their decisions about going on a trip, where to go or where not to go, and what to do or not to do, how to relate to other visitors, locals and services personnel [10]. In principle, tourism can cover all kinds of trips, as long as it is both sightseeing and recreation. Tourism as a trip that takes place for a while, organized from one place to another, with the aim not to do business or to make a living in the places visited, but solely to enjoy a trip for sightseeing and recreation or to fulfil diverse desires [11]. Almost every organization, large and small, private and public, make explicit and implicit assumptions because an organization should plan to meet the potential conditions that have imperfect knowledge. Furthermore, modern tools for forecasting, together with computer capabilities, have become essential for organizations operating in the modern world [12]. Demand, in this case, more generally referred to as market demand, implies there is a demand on the market for certain goods at a certain price and at some time in any event [13]. Forecasting is very important for the tourism industry. Accurate forecasting provides direct assistance to government and industry stakeholders to help them make important decisions, prevent waste and inefficiency of tourism capital while reducing risk and uncertainty [14], [15]. The determinant of
macroeconomic factors such as GDP, bilateral trade volumes, fuel prices, and exchange rate can be used as a guideline if it becomes a supporting variable for coming to a certain country [7].

2.2. Forecasting tourism demand with recurrent neural network architecture

A neural network is a pattern classifier that, in some ways, behaves like a human mind. A neural network consists of artificial neurons linked by the edges, organized in a collection of layers. The number of layers and neurons per layer determines the strength of the classifier and the number of fine-grain patterns that can be identified. Each edge that connects a node (neuron) has a weight. It is the value of these weights, modified for each pattern that stimulates the process of recognition within the neural network [16]. Deep learning is a method of learning which uses multi-layered neural artificial networks. Such artificial neural networks are made identical to the human brain, in which neurons are attached to form a very complicated neuron network [17]. Jeff Elman developed the first Recurrent Neural Network (RNN) in 1990. The use of a recurrent neural network is due to the improved adaptability of this type of network to processing sequences of time data compared to other types of neural networks [18],[19]. Allows the network to map to each output from all previous inputs [20]. The LSTM is a specific form of RNN capable of learning long term dependencies. It is specifically designed to prevent the gradient problem from vanishing / exploding. An LSTM is well suited for classifying and/or predicting data from the time series. There are several LSTM-unit architectures. A common architecture consists of a memory cell, an input gate, an output gate and a gate to forget gate [25], [26]. Moreover, each LSTM cell is calculating new hidden state and cell state values. The figure 1 below [2], [18] illustrates the RNN being unrolled (or unfolded) in a full network when a previous time step is needed to determine the current time step which is shown as t-1 and t respectively.

![RNN structure](image)

**Figure 1. RNN structure.**

3. Methodology

The data containing five main variables in which the explanatory variables or independent variable was determined from previous research about tourism industry as well. In this study, the data used is secondary data because the required data is available for public and can be retrieved from the government or institutional site. The data and its source for this research are listed as follows:

1) Tourist arrivals data was obtained from the site of statistic bureau of Indonesia
2) Per capita GDP data was obtained from Imf.org
3) Bilateral trade volume data was obtained from the site of statistic bureau of Indonesia
4) Fuel price data was obtained from Bloomberg.com
5) Exchange rate data was obtained from exchangerates.org.uk

The four determinant of macroeconomic factors such as per capita GDP, bilateral trade volumes, fuel prices, and exchange rate are believed to be useful as a guideline if it becomes a supporting variable for coming to a certain country as can be seen in table 1 [7]. Distribution of training data and testing data is divided into 80:20, where the split was done with the help of python script.

3.1. Data pre-processing

The pre-processing step is required before to make a forecast. Data Pre-processing is the stage in which the data is transformed or encoded to get to such a state that it can be easily parsed by the
machine. In other words, the data characteristics can be readily interpreted by the algorithm [21]. These steps include:

1. Interpolation is intended for transforming the data from quarterly to monthly data.
2. Data normalization using MinMaxScaler in python programming language to normalize data distribution by rescale the range of data to (0, 1).
3. Success condition obtained after the pre-processing phases where the data can be processed easily by the machine.

### Table 1. Data characteristics

| No. | Data                      | The amount of data | Indicator                                                                 |
|-----|---------------------------|--------------------|---------------------------------------------------------------------------|
| 1.  | Visitor Arrivals          | 480 data           | The response variable or the variable that might affected by the explanatory variable. |
| 2.  | Per capita GDP            | 480 data           | The 1st explanatory variable that affect the response variable.            |
| 3.  | Exchange Rate             | 480 data           | The 2nd explanatory variable that affect the response variable.            |
| 4.  | Fuel Price                | 480 data           | The 3rd explanatory variable that affect the response variable.            |
| 5.  | Bilateral Trade Volume    | 960 data           | The 4th explanatory variable that affect the response variable.            |
|     | TOTAL DATA                | 2,880 data         |                                                                           |

#### 3.2. Model building

The model of this research requires parameters such as shown in table 2. The look-back determine the number of past data taken for predicting the future value. Hidden layer for the layer needed for the model. The number of hidden layer is actually free to determine on how many layer needed but the average number of hidden layer that are often used starts from 1 at least and 4 layers at most. Epochs for number of iteration and batch size for number of batch in the model.

### Table 2. Parameters for model building

| No. | Parameters | Values               |
|-----|------------|----------------------|
| 1.  | Look-back  | 7, 14, and 21        |
| 2.  | Hidden layer | 4                   |
| 3.  | Epochs     | 200, 300, and 400    |
| 4.  | Batch size | 1 and 3              |

The number of hidden layer consisting only one value was because the author previously made an attempt to run on 4 different hidden layers (1, 2, 3, and 4 hidden layer) and turned out using 4 hidden layers in several attempts yield a good result in accuracy. This condition applied to batch size as well from attempted using 3 different kinds of batch size (1, 3, and 7). This was done because if attempting to try for more numbers for testing then there will be many combinations of model and therefore, took longer time to process. Each parameters will be tested based on a predetermined value which then will be combined with the values of other parameters. The combination of each parameters is shown in table 3.

From the table above, several combinations of parameters have been obtained. For this study, the author decided to take 3 optimal model (those with low loss value) determined from all the
parameters, especially based on number of iteration (epoch) in case one model is not suitable for particular dataset. The combinations that have been obtained will then be used as a model for forecasting the arrival of foreign tourists to Indonesia along with forecasting other variables that affect the arrivals. The 1st model has configuration of 21 look-back, 300 epochs, 4 hidden layers, and 3 batch size. Then 2nd model has combination of 21 look-back, 400 epochs, 4 hidden layers, and 1 batch size. Lastly the 3rd model with a configuration of 21 look-back, 400 epochs, 4 hidden layers, and 3 batch size.

| No. | Look-back | Epochs | Hidden Layer | Batch Size | Loss   |
|-----|-----------|--------|--------------|------------|--------|
| 1.  | 7         | 200    | 4            | 1          | 0.0019 |
| 2.  | 7         | 200    | 4            | 3          | 0.0010 |
| 3.  | 7         | 300    | 4            | 1          | 0.000753 |
| 4.  | 7         | 300    | 4            | 3          | 0.000689 |
| 5.  | 7         | 400    | 4            | 1          | 0.000586 |
| 6.  | 7         | 400    | 4            | 3          | 0.000527 |
| 7.  | 14        | 200    | 4            | 1          | 0.0011 |
| 8.  | 14        | 200    | 4            | 3          | 0.000920 |
| 9.  | 14        | 300    | 4            | 1          | 0.000623 |
| 10. | 14        | 300    | 4            | 3          | 0.000851 |
| 11. | 14        | 400    | 4            | 1          | 0.000897 |
| 12. | 14        | 400    | 4            | 3          | 0.000629 |
| 13. | 21        | 200    | 4            | 1          | 0.0015 |
| 14. | 21        | 200    | 4            | 3          | 0.0011 |
| 15. | 21        | 300    | 4            | 1          | 0.000613 |
| 16. | 21        | 300    | 4            | 3          | 0.000349 |
| 17. | 21        | 400    | 4            | 1          | 0.000502 |
| 18. | 21        | 400    | 4            | 3          | 0.000292 |

Table 3. Testing results.

Table 4. Prediction performance measurement.

| Number of arrivals | China | Malaysia | Singapore | Australia | Japan |
|--------------------|-------|----------|-----------|-----------|-------|
| RMSE:24,943.66     | RMSE:22,604.23 | RMSE:23,119.53 | RMSE:9,867.22 | RMSE:6,398.90 |
| MAPE:11.24%        | MAPE:7.86%     | MAPE:14.70%   | MAPE:7.15%   | MAPE:8.72%   |
| Per capita GDP     | RMSE:0.340     | RMSE:0.245    | RMSE:0.699   | RMSE:0.408   | RMSE:1.111 |
| MAPE:2.33%         | MAPE:2.88%     | MAPE:8.3%     | MAPE:8.0%    | MAPE:1.70%   | MAPE:0.185 |
| Fuel price         | RMSE:0.178     | RMSE:0.111    | RMSE:0.429   | RMSE:0.215   | RMSE:0.85 |
| MAPE:2.89%         | MAPE:3.52%     | MAPE:3.15%    | MAPE:3.70%   | MAPE:2.33%   | MAPE:2.33% |
| Exchange rate      | RMSE:0.004     | RMSE:0.00525  | RMSE:0.00788 | RMSE:0.0432  | RMSE:0.000148 |
| MAPE:2.29%         | MAPE:2.80%     | MAPE:1.15%    | MAPE:3.09%   | MAPE:1.17%   | MAPE:1.17% |
| Bilateral trade    | RMSE:467,121,825.77 | RMSE:75,277,362.56 | RMSE:193,241,143.37 | RMSE:93,884,751.20 | RMSE:146,125,505.08 |
| volume (import)    | MAPE:10.01%    | MAPE:10.01%   | MAPE:8.03%   | MAPE:9.69%   | MAPE:7.27%   |
| Bilateral trade    | RMSE:293,566,690.52 | RMSE:75,277,362.56 | RMSE:171,394,218.64 | RMSE:38,390,112.46 | RMSE:86,513,049.89 |
| volume (export)    | MAPE:6.76%     | MAPE:11.08%   | MAPE:9.33%   | MAPE:13.96%  | MAPE:6.83%   |

4. Result and discussion
The prediction of number of arrivals showing quite similar graphic trend for China, Singapore, and Japan as shown in figure 2. The prediction model between predicted data and actual data does not
make a big difference for any of the countries. It was known that Australia have the lowest MAPE with 7.15% or equal to 92.85% accuracy of prediction from configuration model of 21 look-back, 4 hidden layer, 400 epochs, and one batch size.

![Figure 2. The results of the predictions.](image)

When the prediction was done, it was expected to have an output of model performance in the form of RMSE value and MAPE value as can be seen in table 4. Root Mean Square Error (RMSE) is commonly used in many recommendation systems for calculating the difference between the expected scores (the real data) and the actual scores (the predicted data). While MAPE indicates how many errors in prediction (In percentage) relative to the real value [27], [28]. Each variable represents the performance of each country with their optimal combination model. After predicting all visitor countries and getting numeral from the results of the predictions then the next thing is to make regression and its analysis of the economic variables towards the number of tourist visits to Indonesia. Regression is conducted with the objective of seeing how variables such as per capita GDP, fuel price, exchange rate, and bilateral trade volume influence each country towards the number of international tourist arrivals to Indonesia.
Furthermore, can be seen in table 5. The regression result of per capita GDP variable shows a positive effect for China and Malaysia. This means per capita GDP has positive correlation on increasing those two countries visitor arrivals to Indonesia. This finding indicates that China's and Malaysia’s per capita GDP growth increased the monthly arrivals of visitors to Indonesia. However, the insignificant positive growth coefficient of per capita GDP, shows in Australia, Singapore, and Japan. The potential interpretation of this negative per capita GDP correlation factor would be that these countries are classified as the top tourist source markets that are comparatively richer concerning their actual per capita GDP making the number of arrivals to Indonesia not affected by the variable.

**Table 5. Regression coefficient results.**

|                      | China   | Malaysia | Singapore | Australia | Japan   |
|----------------------|---------|----------|-----------|-----------|---------|
| Per capita GDP       | 53,906.52 | 75,850.60 | -7,919.24 | -3,621.84 | -1,158.67 |
| Fuel price           | -36,362.05 | -19,763.21 | 45,780.49 | -14,639.10 | -4,298.26 |
| Exchange rate        | 335,162.78 | -568,330.02 | -206,814.47 | 784,404.05 | 7,202,231.84 |
| Bilateral trade      |         |          |           |           |         |
| volume (import)      | -0.0000565 | -0.0000307 | 0.0000137 | -0.0000532 | 0.0000297 |
| Bilateral trade      | 0.0000430 | 0.0000776 | -0.0000199 | 0.00000332 | -0.0000273 |
| volume (export)      |         |          |           |           |         |

The impact of fuel price showing positive coefficients for Singapore. This probably due to changes in fuel price affecting the transportation ticket price (for instance, like airfares) in which Singapore’s visitor arrivals to Indonesia heavily affected by. Meanwhile, the rest of the countries such as China, Malaysia, Australia, and Japan were negatively affected by the changes in fuel prices. There were two countries presented negative parameters for the change in the exchange rate variable. These countries are Malaysia and Singapore. The reason may arises from factors beyond the macroeconomic determinants that cause the negative effect of the monthly visitor arrivals of Malaysia and from Singapore to Indonesia, such as closer proximity and flying distances for both countries to Indonesia. On the other hand, China, Australia, and Japan showing a positive coefficient. This indicating that as the exchange rate relative to these countries’ currency against US dollar increase, the number of arrivals variable tends to increase too.

The bilateral trade volume for import was found to have negative effect, reducing the number of visitor arrivals from three countries that are China, Malaysia, and Australia at the moment when import was increase. Still with the same variable, Singapore and Japan had a positive coefficient in increasing visitor arrivals to Indonesia. Last variable to evaluate is bilateral trade volume for export. Three countries (China, Malaysia, and Australia) were positively affected by the variable. Indicating visitor arrival from these three countries are expected to increase when export was increase. Meanwhile, the negative impact was found for Singapore and Japan as well. It can be assumed when the export variable decreased, the number of arrivals from Singapore and Japan were increasing.

Besides regression coefficient, P-value is also evaluated in this study to determine whether a variable from each country is significant or not significant to the number of tourist arrivals. The results can be seen in table 6. The confident level was set to 95% with 5% of significance level. The P-value of per capita GDP variable was found significant on Malaysia meanwhile the rest of countries (China, Australia, Singapore, and Japan) was found to be insignificant. The variable of fuel price was not found to be significant for all the countries, indicating there is insufficient evidence to say that there exists a non-zero correlation. For exchange rate variable, it was reported to have significant on Australia only and insignificant for four countries proving there is insufficient evidence of a correlation exists. Japan was founded to be significant on bilateral trade volume for import variable. Showing there is sufficient evidence that a non-zero correlation exists. However, four other countries
(China, Malaysia, Singapore, and Australia) founded to be insignificant for the variable. Last variable, bilateral trade volume for export, were reported to have significant on Japan and China while the rest of the countries reported to have insignificant.

Table 6. P-value results.

|                           | China          | Malaysia       | Singapore      | Australia      | Japan          |
|---------------------------|----------------|----------------|----------------|----------------|----------------|
| Per capita GDP            | 0.0536201      | 0.0000013      | 0.240166       | 0.056733       | 0.635532       |
| Fuel price                | 0.3410368      | 0.6105161      | 0.115543       | 0.15802        | 0.347144       |
| Exchange rate             | 0.8103558      | 0.3175477      | 0.484417       | 0.01213        | 0.081532       |
| Bilateral trade volume (import) | 0.0695099 | 0.7583385      | 0.597859       | 0.852451       | 0.001794       |
| Bilateral trade volume (export) | 0.0379312 | 0.3760957      | 0.57907        | 0.952242       | 0.005488       |

5. Conclusion

The preceding chapter has been used to forecast the number of foreign tourist arrivals to Indonesia and their economic variables, followed by a regression analysis of the results of the forecast to see the relationship between dependent variables and independent variables. The conclusion of the research that has been carried out is the prediction performance measurement from model 1 with weight configuration of 21 look-back, 4 hidden layers, 300 epochs, and 3 batch size generates the lowest error value (MAPE) of 2.795%, providing 97.21% predictability. The model 2, comprises a weight combination of 21 look-back, 4 hidden layers, 400 epochs, and 1 batch size. The model yields the lowest error value (MAPE) of 0.832%, thus providing 99.17% predictability. And last with model 3 consisting a combination of 21 look-back, 4 hidden layers, 400 epochs, and 3 batch size. The model eventually success to generates the lowest error value (MAPE) of 0.795% making of 99.21% predictability.

The study's primary research findings have many important consequences for policy-makers strategic decision-making and policies, such as identifying the best strategies and solutions based on reliable tourism demand forecasting for Indonesia from its main tourism source markets. The forecasting of visitor arrivals finding would be useful in a way government as policy-maker establish policies in maintaining the tourism sector. Suggestions can be more directed towards strategic decision-making about an action that needs to be taken or prevented when an increase or decrease in tourist numbers happened. Utilization by the government can be done in the form of scheduling repair and maintenance of a city's infrastructure or any public facilities (like ATM and money changer) to avoid inconvenience for the tourist. The government can also pay attention to several economic variables are having a certain impact on several countries that visit Indonesia, especially from those 5 major tourist market.

The study’s suggestion for tourism related operators would be providing a useful insight on how tourism demand from perspective of economic variables affecting Indonesia’s visitor arrivals. Thus, to overcome the demand a forecasting model were build. The industry related to tourism then could have made an improvement in such sector as necessary. Examples on how to leverage the tourism sector from this visitor arrivals would be creating a strategic decision to utilize or marketing a potential tourist destination. Tourism operators could also enhance the industry throughout promotion on tourist destination or in the form of airline fares.

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