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# A Novel Approach for Forecasting Tourist Arrivals Using Web Search Data and Artificial Intelligence

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## Abstract

The development of economic activity has been matched by growth in the tourism industry. According to information, the tourism industry is growing and both the number of domestic and international tourists visiting each year is expanding. Because of this quick expansion, there are now critical complications with the management of tourism, such as predicting the arrivals for travel, particularly when a lot of people are visiting appealing locations for particular periods. The proposed Artificial Fish Swarm Optimized Dynamic Gated Recurrent Unit (AFSO-DGRU) approach transforms the forecasting of demand for tourism by utilizing intelligence from swarms to improve forecasts and strategically adapting to fluctuating visitor structures. It ensures accurate and dynamic responses even during times of uncertainty when demand is high. The study used Google Trends to collect data from searches on the web and examine trends in tourist's interest and demand for travel. By combining innovative artificial intelligence (AI) algorithms with real-time online search data, this study presents a novel way to improve the accuracy of visitor arrival predictions. The proposed method performs better than the existing methods to utilize the parameters such as mean absolute deviation called MAE (42.01), mean square error denoted by MSE (3059.85), mean absolute percentage error defined MAPE (1.34), and RMSPE or root mean square percentage error (1.43). This research utilizes web search data and AI to improve the accuracy of forecasting tourist arrivals, offering valuable insights for understanding tourism trends.

## Keywords

Tourism industry; economic activity; Google Trends; Web search; AFSO-DGRU

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## Introduction

The tourism and travel industry depends heavily on demand for tourism prediction, which has significant consequences for both tourism professionals and location authorities. Tourism administration, operation, and planning all depend on the ability to forecast visitor arrivals (Höpken et al. 2021). In particular, precise forecasting of tourist demand might enhance the creation of brief to sustained development strategies and plans, price guidelines, marketing and tourist strategies, and the distribution of scarce resources (Li and Law 2020).

Accurate and timely forecasting of tourist demand has grown in popularity in theoretical studies due to its significance. Conventional demand for tourism forecasting is based on government-published, standardized statistical information (Filieri et al. 2021). Unfortunately, forecasting was naturally constrained by the sluggish and irregular availability of such information, leading to inaccurate forecasts. Large amounts of information on the internet have a significant possibility to improve forecasting precision and give timely demand for tourism forecasts (Knani et al. 2021).

The comprehension, clarification, and prediction of demand from tourists has been a significant field of scientific study and application. It remains a pertinent field in the context of modern studies on tourism (Ma et al. 2024).

In the tourist industry, predicting demand is essential for risk justification since the industry's service product is perishable, its production and consumption processes are interdependent, they rely on additional services, and they are highly vulnerable to crises (Chen and Wei 2024).

For managing destinations and the many tourist providers, forecasting in the tourism industry means showing the course of future demand and, therefore, offers useful information. Many metrics are used in tourism demand prediction and modeling. however, visitor arrivals are a frequently used metric (Ma 2024).

Accurate predictions of upcoming events and shifts in demand for tourism are of importance to managers because they show how much can be done to control demand impacts, prepare ahead for future events, and keep an eye on swings in demand for the availability of resources. As a result, the capacity to forecast traveler demand is critical to the success of tourist enterprises (Chen et al. 2024).

Unfortunately, forecasting has the unintended consequence of causing ineffective marketing, wasteful resource usage, and degradation of durability. Precisely estimating the need for tourists is a challenging mixture of science and art. No one model regularly beats alternatives in every circumstance, as there are many different approaches employed in predicting and forecasting tourism demand (Li et al. 2024). Obtaining timely and affordable data is another difficulty in demand forecasting. Demand volatility and the absence of previous time series information are two further major obstacles. Large amounts of information appear to have the promising potential to address the challenges of novel sources of information and modeling methodologies, which are critical difficulties in modern tourist research (Han et al. 2024).

Li et al. (2020) forecasted the number of tourists visiting Mount Siguniang, China. The main findings of the research indicated that increasing the prediction effectiveness of tourist demand might be achieved by using online large amounts of information from internet search engines in conjunction with social media platforms. Demand prediction using single-source search engine data was not as successful as demand forecasting using multisource large-scale data from online review sites and engines of search.

The daily tourist amount to tourist sites was predicted using a novel method based on long short-term memory or LSTM networks which could assemble multimodal longitudinal data, including historical traveler volume and query data from engine, and weather information recommended by Bi et al. (2020). Furthermore, there was evidence that search engine and conditions data were very important for predicting tourism volume because when past information, query information, and climate information were combined, the method's predicting ability was greater than when search engine data was absent or when engines of search and weather-related information were combined.

How AI has impacted and continues to impact the primary procedures within the tourist sector was examined by Bulchand-Gidumal (2022). After discussing AI algorithms and programs used in the travel and tourism industry, they next moved on to the data the internet, or IT, foundations of AI which were relevant to the sector.  Summarize by describing the challenges AI faces in the tourism and travel industry, suggesting a research agenda, and illustrating the future possibilities for AI in tourism.

The Least Squares Support Vector Regression called LSSVR architecture's hyper-parameters in the suggested model were tuned using Gravitational Search Algorithm (GSA) as explained by Xie et al. (2021). They found that the best predicting performance might be obtained by combining specific mobile phrases and financial indicators with LSSVR-GSA, after testing these models with different parameters. The findings showed the efficacy of the method's recommended framework and the usage of big records as predictors for estimating the need for cruise journey in China.

By the usage of AI to estimate demand for tourist points of interest, Zhang et al. (2021) aimed to develop modeling reliability. For both brief- and long-time period based on AI methods for forecasting, and employed a decomposition technique that yields notable accuracy. With no further records needed, the suggested technique successfully breaks down the statistics and improves accuracy. As a result, the work resolved the overfitting problem and made an empirical addition by putting forth a very precise deep learning (DL) technique for estimating tourism demand based on AI.

Forecasting tourist quantity was a prominent issue in the management of tourism, and DL methods were emerging as a viable tool for identifying the features of tourism volumes information was recommended by Li et al. (2023). DL approaches could increase predicting accuracy, as the research empirical verification has shown. Additionally, the suggested method outperformed standard models by a large margin.

The hourly points of interest vacationer extent prediction approach presented via Xue et al. (2023) become primarily based on spatial combination and used multimodal machine learning. The system turned into assessed the usage of a number of web sites with real-time traveller counts captured at durations of fifteen mins. Furthermore, with considerable profits at the 1% level, the findings of the Diebold-Mariano test and empirical research showed that the recommended structure might exceed existing models that have been at the cutting side.

Facebook called FB Prophet and its use to visitor call for prediction for site visitors every day in Mainland China's Jiuzhai Valley National Park and Macao turned into presented via Liu et al. (2023). The breakdown end result of Facebook Prophet tested how well it might manage the effect of trends associated with seasons and holidays. The predicting findings demonstrated that FB Prophet performs better than different approaches when taking into consideration seasonal developments, excursion impacts, and additional variables.

The goal of the study was to use an innovative technique known as the AFSO-DGRU to determine tourist demand prediction. This device uses the intelligence from swarms to enhance predictions and makes strategic adjustments to changing traveler structures. It ensures specific and flexible answers even at unpredictable instances of recognition.

The study was organized as follows, Section 2 provided an explanation of the suggested system, Section 3 detailed the outcome, and Section 4 effectively portrayed the study's conclusion.

## Methodology

This phase efficaciously outlines the data preparation procedure and introduces the proposed AFSO-DGRU approach, imparting clarity on how the informations is based for the study.

1. Data Preparation

The data collected from web searches the usage of Google Trends offers insights into consumer interest over the years, helping to perceive developments and fluctuations that correlate with tourism. It allows knowledgeable predictions about future journey patterns and preferences.

1.1. Google Trends for Tourism

The Google Trends website examines at how frequently the most common phrases for searching are used across various languages and locations. The website compares the amount of various keywords searched over time using graphs. Forecasting tourism is one of the many industries in which Google Trends has been applied.

Analysts can forecast tendencies in tourist demand by examining previous search data and spotting interest surges that could be associated with real travel developments. The application can assist in monitoring variations in the number of searches for particular terms, providing information on probable off-seasons or tourism peak levels. Using Google patterns for tourist forecasts often entails picking appropriate search phrases and monitoring their patterns as time passes. Subsequently, the data may be scrutinized to identify trends that correspond with tourist endeavors, such as heightened inquiries for accommodation, and locations. Without the requirement for sophisticated traditional methods of forecasting, this approach enables researchers to project future tourist demand and make well-informed judgments about the distribution of resources, marketing campaigns, and tourism administration approaches.

### 1.2. Searches By Tourism Destinations

The destination-based data is also divided out by Google Trends. Everyone can look at the fundamentals of location data using Google Trends and comprehend the underlying statistics in the following section.

Step 1: Once the Google Trends query has been completed, scroll below to view interest in searches by the tourism destinations. Inevitably will see Interests by area if have chosen. Higher levels of interest in searches are found.

Step 2: The map perspective on the information will be immediately shown by Trends Explore. Using the button with three stacking straight lines located at the upper right corner of the visualization to switch between the map and list views. Both perspectives will be displayed right at once if the window is large enough.

Step 3: Google Trends information categorized by area, and city is available for viewing. One can additionally browse search results by metropolitan area. Use the menu located in the upper right corner of the map to choose any division like.

Step 4: As with other Trends data, it provides an integrated search interest number while hovering over a realm or utilizing a list view. The place with the greatest standardized interest in the subject is assigned a value, and the remaining values are indexed correspondingly.

## 2. Enhancing Tourism Demand Forecasting with AFSO-DGRU

The dynamic nature of the tourism industry necessitates accurate forecasting methods to control traveler to manage visitor flow and optimize resource allocation. The proposed AFSO-DGRU approach addresses this challenge by means of integrating swarm intelligence with advanced recurrent neural network (RNN) structure. By making use of net search records from structures like Google Trends, the AFSO-DGRU model captures real-time traits and patterns in tourist interest, permitting it to respond dynamically to fluctuations in tourism.

### 2.1. DGRU

Automated translation and signal identification are only two examples of the many application tasks on which RNN architectures including LSTM and gated recurrent unit have been showing outstanding results. Particularly, as an enhanced version of LSTM, multiple investigations have shown that GRU performed better than LSTM in numerous cases because the triple gate mechanism in LSTM has been shortened to two gate processes in the DGRU memory unit, such as resetting gate $y_s$ and updating gate $q_s$.

The following describes the topological components for the data retention unit and gateways at step $s$ in the DGRU, It uses online search data to increase the precision of predicting the number of tourists arriving.

$$y_s = \sigma\,(x_y w_s + v_y g_{s-1} + a_y) \qquad (1)$$

$$q_s = \sigma\,(x_q\, w_s + v_q g_{s-1} + a_q) \qquad (2)$$

$$d_s = \tanh\,(x_d w_s + v_d q_s g_{s-1} + a_d) \qquad (3)$$

$$g_s = (1 - y_s) \cdot g_{s-1} + y_s \cdot d_s \qquad (4)$$

Where the model's inputs, concealed state, and storage unit condition are represented by the variables $w_s$, $g_s$, and $d_s$. The weight matrices and biased vectors are $x_y$, $x_q$, $x_d$, $v_y$, $v_q$, $v_d$, and $a_y$, $a_q$, $a_d$ . $\sigma$ Stands for the sigmoid function are utilized in (1) to (4). It is not possible to completely extract a range of characteristics using the naïve DGRU model as visualizations of features and just one path are required for additional processing.

Feature presentations from both directions of motion are modeled as a way to build the DGRU structure and alleviate the aforementioned difficulties, leading to significant improvements in forecasting accuracy for tourist arrivals by effectively utilizing web search data and adapting to fluctuating patterns. The following (5) and (6), are the topological structures of each direction in DGRU.

$$\overrightarrow{g_s} = \overrightarrow{GRU}(w_s, g_{s-1}) \qquad (5)$$

$$\overleftarrow{g_s} = \overleftarrow{GRU}\,(w_s, g_{s+1}) \qquad (6)$$

The DGRU network's outputs can be combined in the processes shown in (7).

$$P_s = \overrightarrow{g_s} + \overleftarrow{g_s} \qquad (7)$$

Since data on features fusing from both forward and backward orientations solely depends on an easy addition or concatenated method, recent investigations have demonstrated that there is a problem with information duplication in DGRU. The DGRU structure was illustrated in the Figure 1.

$$G_s = \eta\overrightarrow{g_s} + (1 - \eta)\overleftarrow{g_s} \qquad (8)$$

Where the scale variable, represented by $\eta$, controls how features are represented in both directions. It functions as a naïve DGRU network when $\eta$ = 0 or 1 shown in (8). By effectively turning this scale variable, the model aims to optimize feature representation, ultimately enhancing the accuracy of identifying tourist arrivals and improving the overall prediction efficiency of the DGRU architecture.

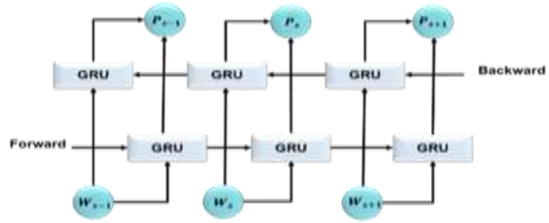


Figure 1. Structure of DGRU

2.2. AFSO

A computerized model of the collective actions of institutions of learning of fish serves as the basis for AFSO, an AI program motivated by swarm intelligence. It creates an artificial fish swarm by modeling the actions of a single artificial fish (AF).

By optimizing the forecasting accuracy in predicting fluctuating tourism demand through enhanced data-driven decision-making. With the use of knowledge shared inside its self-organizing system, each AF will seek its own local optimal before reaching the global average. Assume that the colony has $M$ fishes and that the search space is D-dimensional. An AF's present condition is represented by a vector called $W = (w_1, w_2, \dots \dots . w_n)$, where the parameter that has to be maximized is$W_j (j = 1,2, \dots . , n). Z = E(w)$, where $Z$the purpose of the operation is, represents the calorie consistency of AF in its present location.

The formula for the separation separating the $j - th$ and $i - th$ component AF is $C_{ji} = \|W_i - W_j\|$. The variable of trial number in the method's beginning state should be specified as the number of instances that AF searches for food. The next five phases outline the actions of fish swarms, optimizing the model’s ability to capture intricate patterns in tourism data for more reliable and efficient demand predictions.

- Searching Behavior

Assume that an AF's present state is $W_i$ and that a new state, $W_j$, is arbitrarily chosen to appear in its field of vision. In the following analysis, it discuss the maximum problem as an example and discuss if it moves a step in that direction in the greatest problem $W_i < W_j$. If not, choose a state $W_j$ at arbitrary after more and determine if it satisfies the forward motion circumstance.

It advances a step arbitrarily if, after a certain number of tries, it is not satisfied. The following guideline is followed when taking a step in (9), thereby enabling an iterative optimization process to enhance the precision of forecasting fluctuating tourism trends by refining each step based on real-time data.

$$\begin{cases} W_{j+1} = W_j + Step \frac{W_i - W_j}{\|W_i - W_j\|} (Z_i > Z_j) \\ W_{j+1} = W_j + Step \qquad (Z_i \le Z_j) \end{cases} \tag{9}$$

- **Swarming Conduct**

As it stands, an AF In its present surrounding ($c_{ji} <$ Visual), $W_j$ searches for the companion's quantity $ME$ and their central location $W$. If$Z_d/ME \quad > \delta Z_j$, it indicates that there is adequate food and not too much crowdedness at the very center of the fish colonies. Representation of the swarm movement computationally in (10).

This behavior is critical for optimizing the search process, as it allows the AF to efficiently navigate and exploit favorable conditions, thereby enhancing the accuracy of tourism demand forecasts through effective resource allocation.

$$\begin{cases} W_{j+1} = W_j + Step\, \frac{W_d - W_j}{\|W_d - W_j\|}\left(Z_d/ME \quad > \delta Z_j \text{ and } ME \geq 1\right) \\ W_{j+1} = Formula\ (1)\left(Z_d/ME \quad \leq \delta Z_j \text{ or } ME = 0\right) \end{cases} \tag{10}$$

- Observing Actions

Assume that $W_j$ represents the present condition of AF looking for partner $W_{max}$ in the surrounding area with $W_{max}$. If $Z_{max}/ME \quad > \delta Z_j$, it indicates that companion $W_{max}$ is not overcrowded and has a greater food consistency at this location.

The AF will advance one step in the direction of the $W_{max}$; if not, it will go on seeking. This strategic movement enhances the optimization process by allowing the AF to dynamically adjust its path based on the availability of resources, ultimately improving the precision tourism demand forecasting. The behavior described mathematically is as follows in (11)

$$\begin{cases} W_{j+1} = W_j + Step\, \frac{W_{max} - W_j}{\|W_{max} - W_j\|}\left(Z_{max}/ME \quad > \delta Z_j \text{ and } ME \geq 1\right) \\ W_{j+1} = Formula\ (1)\left(Z_{max}/ME \quad \leq \delta Z_j \text{ or } ME = 0\right) \end{cases} \tag{11}$$

- Selection of Behavior

Selecting an action to mimic, that assesses the FA's existing surroundings in light of the issue we need to solve. Fish behaviors have often been simulated by trial and error, with the most beneficial outcomes being put into practice following assessment. Fish swarms exhibit three biological activities that we observe and examine in this paper, searching, following, and swarming. These behaviors are optimized through iterative learning, allowing the AF to effectively adapt to their environment and improve the accuracy of tourism demand forecasts.

- Bulletin

The optimum condition of the AF and the ideal severity of the problem are recorded in the bulletin. Every AF makes motions, and revisions, and compares its current condition with the bulletin. The value in the bulletin will be changed if the AF condition is improved right now. This process of continuous monitoring and updating enhances the optimization of the algorithm, ensuring that the AF is consistently aligned with the best-known solutions for forecasting tourism demand effectively. The optimization procedure facilitated by using swarm intelligence complements the model's potential to conform to converting situations, making sure extra dependable predictions throughout peak travel intervals.

As a result, the AFSO-DGRU now not simplest improves the accuracy of forecasting traveler arrivals however additionally gives valuable insights for tourism stakeholders, allowing them to make informed decisions in an increasingly aggressive marketplace. The algorithm 1 shows the AFSO-DGRU.

Algorithm 1

$M = number\_of\_fishes$
$D = dimensionality$
$W = initialize\_fish\_positions(M, D$
$eta = initialize\_scale\_variable$
$for\ iteration\ in\ range(max\_iterations)$:
  $for\ each\ fish\ in\ W$:
    $W\_j = select\_random\_neighbor(fish)$
    $if\ evaluate\_objective(W\_j) > evaluate\_objective(fish)$:
      $fish.position = update\_position(fish, W\_j)$
    $if\ is\_near\_companion(fish)$:
      $fish.position = update\_position\_to\_center(fish$
    $W\_max = find\_best\_neighbor(fish)$
    $if\ is\_optimal(W\_max, fish)$:
      $fish.position = move\_towards(W\_max)$
  $best\_fish = find\_best\_fish(W)$
$g\_s = DGRU\_update(fish, eta)$
$predictions = combine\_outputs(W)$
$return\ predictions$

## Results and Discussion

This section details the experimental setup and the contrast segment, focusing at the assessment of the proposed approach the usage of error parameters. By systematically presenting these elements, it facilitates a comprehensive understanding of the method's performance relative to existing approaches.

1. Experimental Setup

The following Table 1 describes the experimental setup for the study.

Table 1. Example of the caption for the table

| Component | Specifications |
|---|---|

| | |
|---|---|
| Processor | Intel Core i7 equivalent |
| RAM | 16 GB DDR4 |
| GPU | NVIDIA GeForce GTX 1060 with CUDA support |
| Storage | SSD with at least 512 GB capacity |
| Programming language | Python |
| Software Requirements | TensorFlow/keras or PyTorch, NumPy, Pandas |
| Data Source | Google Trends data for web search analysis |

2. Comparison Phase

Forecasting error is the term used to describe the discrepancies that might occur between the actual and expected numbers for the arrival of the tour. One essential phase in the forecasting process involves evaluating the prediction error. It can determine the forecasting ability of the model accuracy by computing the prediction error.

The model is better and the predicted result is nearer to the real outcome when the predicts arrival with a higher degree of quality.  Selecting MAE, MSE, MAPE, and RMSPE to analyze to compare the accuracy of the prediction functions of various models. They are determined using the methods in (12) – (15). The following Figure (2-5) illustrates the graphical outcome for the error parameters such as MSE, MAE, MPAE, and RMPSE. Table 2 shows the comparison of the proposed method with RF–DE–LSTM (Peng et al. 2021).

$$MAE = \frac{\sum_{j=1}^{j=n} |z_j - z|}{m} \quad (12)$$

$$MSE = \frac{\sum_{j=1}^{j=n} (z_j - z)^2}{m} \quad (13)$$

$$MAPE = \frac{\sum_{j=1}^{j=n} |z_j - z|/z}{m} \quad (14)$$

$$RMSPE = \frac{\sum_{j=1}^{j=n} \left((z_j - z)/z\right)^2}{m} \quad (15)$$

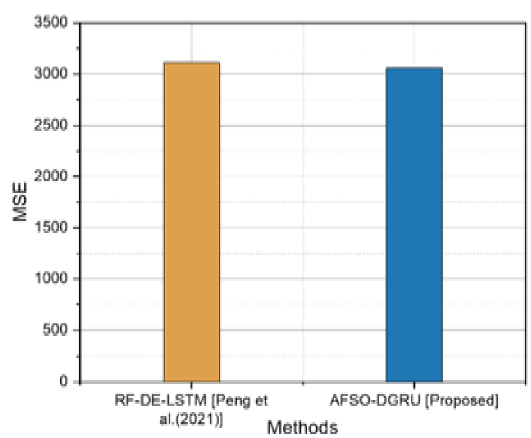


Figure 2. Outcome of MSE

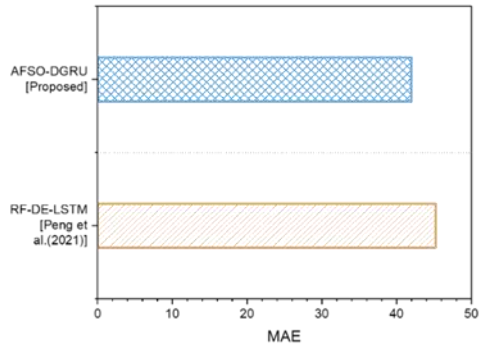


Figure 3. Result of MAE

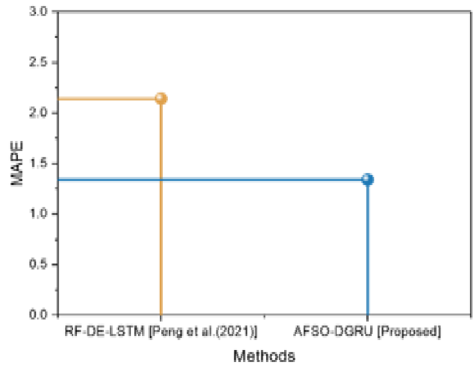


Figure 4. Performance of MAPE

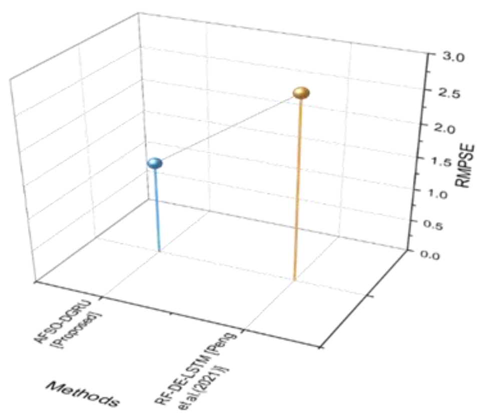


Figure 5. Performance of MAPE

Table 2. Comparison of proposed and existing

| Methods | RMPSE | MSE | MAE | MAPE |
|---|---|---|---|---|
| RF–DE–LSTM [Peng et al.(2021)] | 2.80 | 3108.95 | 45.23 | 2.14 |
| AFSO-DGRU [Proposed] | 1.43 | 3059.85 | 42.01 | 1.34 |

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