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Forecasting Vietnamese tourists' accommodation demand using grey forecasting and ARIMA models

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ABSTRACT

The development of the tourist accommodation sector significantly contributes to the overall growth of tourism. The need for accurate predicting the demand for tourist accommodation of international and domestic tourists is a key goal for future good preparation and appropriate strategy. The objective of this study is to show some Grey forecasting models involving GM (1, 1), Verhulst, DGM (1,1), and ARIMA models consist of ARIMA (0, 1, 1) for the projection of the future number of domestic and international visitors serviced by tourist accommodation establishments in Lam Dong province. The author of this study applies four essential criteria Mean absolute percentage error (MAPE), Mean absolute deviation (MAD), Mean square error (MSE), Root mean square error (RMSE) to compare the various forecasting models outcomes and to examine which suitable forecasting models can improve the capability to project the number of future international and domestic tourists served by tourist accommodations in Lam Dong province. The monthly statistics of number tourists serviced of tourist accommodation and total revenue from tourist accommodation service in Lam Dong province covering in the period from January 2012 to October 2018 are obtained from the official website of general statistics office of Lam Dong province and statistical yearbook of Lam Dong in order to guarantee the accuracy of forecasting procedure. The key findings of this study are that ARIMA (1, 1, 1) (1, 1, 1) model can effectively predict the number of domestic tourists with more accurate outcomes with a minimum predicted errors. Besides that, the number of international visitors serviced by tourist accommodation can be obtained more accurately by using the ARIMA (1, 1, 1) (1, 1, 1) model. In the case of total revenue from tourist accommodation service in Lam Dong province, ARIMA (0, 1, 1) (0, 1, 1), GM (1, 1), DGM (1, 1) models have better performance than the Verhulst model. The forecasting results also showed the number of international and domestic tourists serviced by tourist accommodation in Lam Dong is growth slightly. Therefore, Lam Dong Authority must make good preparation and appropriate strategies to response exactly at any changes and supply for tourist accommodation markets.

1. Introduction

Tourist accommodation is a fundamental element of the tourism product to the tourists. It has close correlation with the development of tourism industry. The classification (for example: luxury, low-budget hotel), scope and nature of accommodation are the key factors to determine the value and volume of tourism that is probable at any tourist attraction places. Industry needs in tourist accommodation sectors have become more short-term concentrated, and aimed to change quickly with continuous changing characteristic of market need. In recent years, the number of both domestic and international tourists visit Lam Dong, especially Da Lat, strongly increased. This has led to the diversity and the dramatic growth in number and improvement of the quality of local hotel-related business and services such as motels, hotels, homestay (Fig. 1). Tourist accommodation sector in Lam Dong province from 2009 – 2017 has developed

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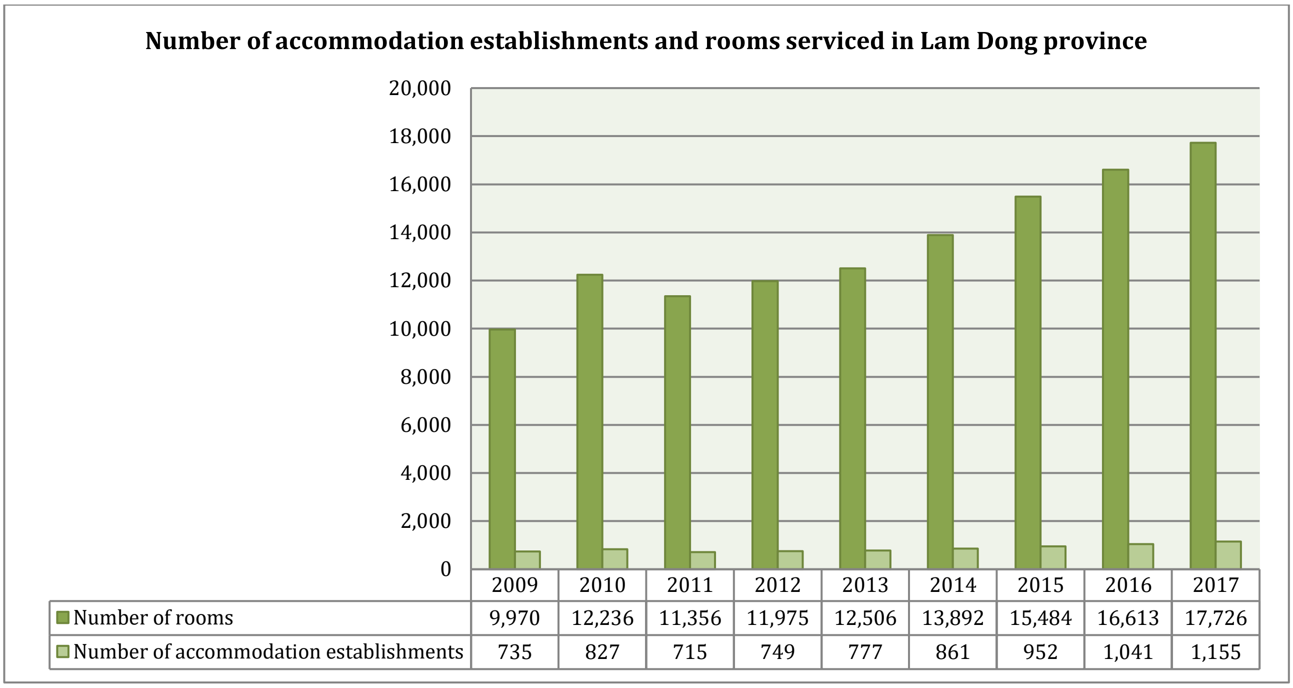
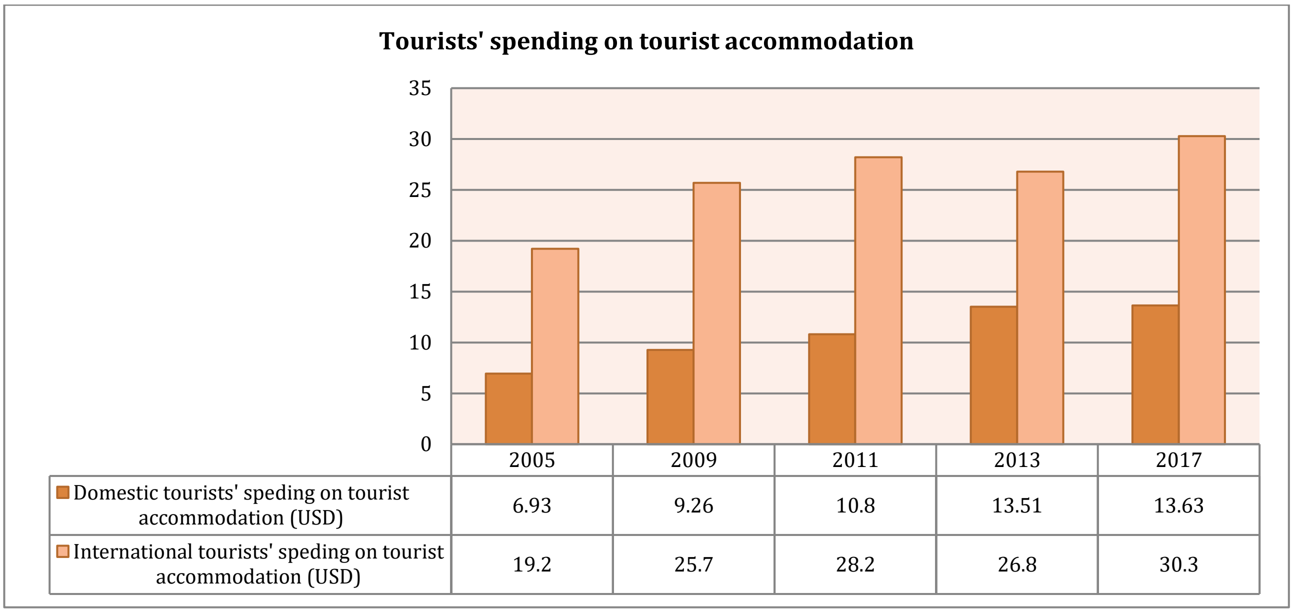
substantially. In 2009, there were 735 accommodation establishments with the capacity of 9,970 rooms. These numbers tend to go up significantly in 2017 in which 1,155 accommodation establishments and 17,726 rooms.



	2009	2010	2011	2012	2013	2014	2015	2016	2017
Number of rooms	9,970	12,236	11,356	11,975	12,506	13,892	15,484	16,613	17,726
Number of accommodation establishments	735	827	715	749	777	861	952	1,041	1,155

Fig. 1: Number of accommodation establishments and rooms serviced in Lam Dong Province from 2009 to 2017

According to the Vietnam National General Statistics Office, the amount of spending of on tourist accommodation service has been increased slightly in group of domestic visitors starting from 6.93 USD in 2005 to 13.63 USD in 2017 (Fig. 2). The international visitors tend to go up more significantly in the period of 12 years beginning from 19.2 USD to 30.3 USD. In general, the tendency of tourists' consumption on lodging is higher over time which creates a potential environment for the growth of overall tourism.



	2005	2009	2011	2013	2017
Domestic tourists' speding on tourist accommodation (USD)	6.93	9.26	10.8	13.51	13.63
International tourists' speding on tourist accommodation (USD)	19.2	25.7	28.2	26.8	30.3

Fig. 2: Tourists' spending on tourist accommodation

However, this sector is facing some challenges: lack of timely management concentration, limited number of professional human resources in hospitality industry, ineffective control in price which causes the conflict of interest between hotel-related business owners and visitors. According to the Ministry of Culture, Sports and Tourism of Vietnam, the quality inspection procedure of tourist accommodation sector mostly focuses on the inspection of three to five-star rating hotels. Besides that, in the period 2010 - 2015, the three to five-star hotels after the inspection or ratings procedure have been negligent in sanitation and quality management.

2. Research objectives

Tourism depends on many different sectors and industries, one of which is the hotel and tourist accommodation. There have been fluctuations in the number of international and domestic visitors as well as purpose of visit, length of stay and type of tourist accommodation. The uncertain number of tourists affects the hotel industry, a key player in tourism. There is a lack of strategic and control planning for hotel development in each particular region by the Vietnamese governments and there are no accurate figures for developers' reference. Therefore, many hotel projects have carried out based on developers' assumptions about the future demand of rooms or in other words, the number of tourists accommodated by lodging services in the cities. The hotel or tourist accommodation industry in some specific areas has not been able to reliably forecast the number of tourists requiring accommodation. For the objective of competition with other regions and attracting more potential visitors, it is obvious that visitor accommodation in Lam Dong province needs an accuracy vision for future tourists' demand of hotel. In order to response to the uncertainty of accommodation needs for the tourists arriving in a specific area, there is needed a model that can project the future accommodation demands by the tourists. These projections will make it possible for the players in the hotel industry to react in appropriate time to the anticipated changes in tourist accommodation demand over time and also to maximize returns on investments.

The need for accurate tourist accommodation projection is a vital component in hotel or visitor accommodation industry planning and management strategies. Thus, this study presents the model of ARIMA, GM (1, 1), Verhulst, DGM (1, 1) to test which models can handle the forecast accuracy of this situation.

3. Literature review

3.1. Tourist accommodation

Holiday accommodation or lodging is a basic foundation of tourism industry since it is an essential and fundamental component which tourism supplies to satisfy customers' requirements of location where they can relax and revive during their trip. As a result of fast development of tourism industry, commercial accommodations currently become well-known in most areas, especially tourist destinations. There is close relation between size and categories of accommodation and location with the services supplied. Depend on the targeted consumers groups, the diverse services and amenities of accommodation facilities vary (Poudel, 2013). Tourist accommodation types can be classified by the following categories: hotels, resorts, motels, motor inns, rented apartments, guesthouses, bed and breakfast, backpackers, hostels, and caravan parks/camping grounds.

3.2. Future tourist accommodation demand forecasting

Establishment of modeling and forecasting is an important area in tourism and hospitality industry for their adequate future preparation. In recent period of time, researchers have paid even more attention to this potential sector. There has been a rise in the interest in forecasting the hotels demand based on hotel-specific data (Wu et al., 2017). The forecasts for future visitors' hotel demand will bring many advantages to hotel practitioners with the improvement in implementation of operational policy such as late cancelations, early departures, price discrimination, reservations by higher-value customers, overbooking policy (Wu et al., 2017). It is said that the hotel demand forecasting has also been used for future hotel business planning, hotel business operation management, planning for purchasing facilities to support hotel business operation and inventory management (Wu et al., 2017). The hotel accommodation demand could be determined by a variety of elements varying from different perspectives. The prediction of hotel demand for tourism industry is usually related to hotel revenue management (Wu et al., 2017). The profit of each available room as an aspect of financial performance, for instance, revenue earned per available room (RevPAR) and total sales revenue could be used to measure hotel demand. Many scholars stated that there are some elements related to the scale of hotel demand, such as the number of rooms served, guest arrivals, the number of nights guests stay, and occupancy rates of hotel (Wu, 2010). According Weatherford and Kimes (2003), the vital aspects of hotel revenue management is forecasting future occupancy rates and hotel guest arrivals and they stated that it is crucial to make the accurate forecasting which enable hoteliers to make the right decision to appropriately allocate hotel resources and modify pricing strategies.

3.3. Previous hotel or tourist accommodation modeling and forecasting studies

Yüksel (2007) applied a plenty of versions of exponential smoothing, as well as ARIMA and some Delphi methods aimed to forecast monthly hotel arrivals in a five star hotel in Ankara using 149 monthly series of data and made the comparison by using error measures the results with those from MA, Simple, Holt's, Winter's Exponential Smoothing and ARIMA. Another study is forecasting uncertain tourists accommodation demand in long term by applying and evaluating the Holt-Winters process, an extension of the exponentially weighted moving average (EWMA) (Rajopadhye et al., 2001). This aimed to forecast the uncertain demand for rooms at a hotel for each arrival day served by tourist accommodation by collecting data from past observation.

Other scholars applied nonlinear time series models in the attempt to forecast tourism and hotel demand, such as the Markov-switching model and the self-exciting threshold autoregressive model. Rajopadhye et al. (2001) indicated that some scholars have applied the Holt-Winters method (a special version of the exponential smoothing technique) to predict hotel room demand each day in a specific property. They applied time series models to predict tourist accommodation demand in Kenya. The authors focused on the Box and Jenkins (1976) models to generate a forecasting model using quarterly data on bed occupancy rate by tourists coming to Kenya in the period of time from 1974 to 2011. Van Lohuizen and Smith (2017) used two different components – international visitor nights and domestic visitor nights. Forecasting hotel demand uncertainty (Ampountolas, 2018) was conducted by analyzing the average historical hotel data of nine hotels located in the city center of London with the usage of time series Bayesian VAR models - an econometrics instrument used for multivariate time series analyses. Other study is the application of the Box and Jenkins (1976) models and the twelve differenced SARMA (2, 2)(0, 2) which are considered as the optimal model to forecast tourist accommodation demand in New Zealand (Lim and Chan, 2009).

3.4. Grey system forecasting

The concept of the Grey system theory was founded by Julong D (1989) as a technique for conducting quantitative forecasting. Grey theory is well-known in academic environment for simple calculation and satisfactory outcomes.

3.4.1. GM (1, 1)

Definition 1: Let
$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)), x^{(0)}(k) \geq 0$
$X^{(1)}$ is the 1-AGOsequence of $X^{(0)}$, that is
$x^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)\right);$

where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \qquad k = 1,2,\cdots n.$$

then

$$x^{(0)}(k) + ax^{(1)}(k) = b \tag{1}$$

is referred to as the original form of model GM (1,1), and actually it is a difference equation.

The parameter vector of Eq. 1 can be estimated using the least square method, which satisfies

$$\hat{a} = (B^T B)^{-1} B^T Y \tag{2}$$

where

$$Y = \begin{bmatrix} x^{(0)} & (2) \\ x^{(0)} & (3) \\ \cdots & \\ x^{(0)} & (n) \end{bmatrix}, B = \begin{bmatrix} -x^{(1)} & (2) & 1 \\ -x^{(1)} & (3) & 1 \\ \cdots & & \\ -x^{(1)} & (n) & 1 \end{bmatrix} \tag{3}$$

Definition 2: Let $x^{(0)}, x^{(1)}$ just like definition 1, let

$$Z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \cdots, z^{(1)}(n));$$

where

$$z^{(1)}(k) = \frac{1}{2}(x^{(1)}(k) + x^{(1)}(k-1)),$$

then

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{4}$$

is referred as the even form of the model GM (1, 1).

The even form of the model GM (1, 1) is also essentially a difference equation. The parameter vector of Eq. 4 can also be estimated with Eq. 2, but it should be paid attention to that the elements of matrix B are different from that in the Eq. 3, which is

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{5}$$

Definition 3: The following differential equation

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{6}$$

is called a whitenization (or image) equation of the even form

$$x^{(0)}(k) + az^{(1)}(k) = b$$

of the model GM (1, 1).

3.4.2. Discrete grey model – DGM (1, 1)

Definition 4: The difference equation as follows

$$x^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2 \tag{7}$$

is called as a discrete form of model GM (1, 1) or a basic of discrete grey model (DGM). For the general process to acquire all details about Discrete Grey models, a full book about Grey Systems Theory written by Nguyen and Tran (2019) can be referred.

The parameter vector

$$\hat{\beta} = [\beta_1, \beta_2]^T$$

in the Eq. 7 is similar to the Eq. 2, where

$$Y = \begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \vdots \\ x^{(1)}(n) \end{bmatrix} B = \begin{bmatrix} x^{(1)}(1) & 1 \\ x^{(1)}(2) & 1 \\ \vdots & \vdots \\ x^{(1)}(n-1) & 1 \end{bmatrix}.$$

Then the least squares estimate sequence of the grey differential equation:

$$x^{(1)}(k+1) = \beta_1 x^{(1)}(k) + \beta_2$$

Satisfies

$$\hat{\beta} = (B^T B)^{-1} B^T Y.$$

3.4.3. Verhulst model

The Verhulst model was introduced by Pierre Franois Verhulst - a German biologist (Wang et al. 2009). The Verhulst model's main objective is to limit the entire growth for a system and it is efficient in the description of some increasing processes, for instance, an S-curve with a saturation region.

$$Verhulst\ 1: x^{(0)}(k) + az^{(1)}(k) = b(z^{(1)}(k))^{\alpha}$$

is established as the GM(1,1) power model.

$$Verhulst\ 2: \frac{dx^{(1)}}{dt} + ax^{(1)} = b(x^{(1)})^{\alpha} \text{ (Ver. 2)}$$

is known as the whitenization equation of GM (1, 1) power model when: $X^{(0)}$ is assumed to be a sequence of raw data; $X^{(1)}$: a sequence of accumulation of generation of $X^{(0)}$; $Z^{(1)}$: adjacent neighbor mean of $X^{(1)}$.

Theorem 1:

$$x^{(1)}(t) = \left\{e^{-(1-\alpha)at}\left[(1-\alpha)\int be^{(1-\alpha)at}dt + c\right]\right\}^{\frac{1}{1-\alpha}}$$

(Verhulst 3) is the solution of equation (Verhulst 2).

Theorem 2: With $X^{(0)}$; $X^{(1)}$ and $Z^{(1)}$ (as above), let

$$B = \begin{bmatrix} -z^{(1)}(2) & \left(z^{(1)}(2)\right)^{\alpha} \\ -z^{(1)}(3) & \left(z^{(1)}(3)\right)^{\alpha} \\ \vdots & \vdots \\ -z^{(1)}(n) & \left(z^{(1)}(n)\right)^{\alpha} \end{bmatrix}, Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}$$

then the least squares estimate of the parametric sequence $\hat{\boldsymbol{a}} = [a, b]^T$ of the equation (Verhulst 1) is

$$\hat{a} = (B^T B)^{-1} B^T Y.$$

When the power of the equation (Verhulst 1) $\alpha = 2$, the resultant model is

$$x^{(0)}(k) + az^{(1)}(k) = b(z^{(1)}(k))^2 \text{(Verhulst 4)}.$$

This is the Grey Verhulst model, and

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b(x^{(1)})^2 \text{(Verhulst 5)}.$$

This is known as the whitenization equation of Grey Verhulst.

Theorem 3: The solution of equation (Verhulst 5) is

$$x^{(1)}(t) = \frac{1}{e^{at}\left[\frac{1}{x^{(1)}(0)} - \frac{b}{a}(1-e^{-at})\right]} = \frac{ax^{(1)}(0)}{e^{at}[a - bx^{(1)}(0)(1-e^{-at})]} = \frac{ax^{(1)}(0)}{bx^{(1)}(0) + \left(a - bx^{(1)}(0)\right)e^{at}} \text{ (Ver. 6)}.$$

The time response sequence of the grey Verhulst model is:

$$\hat{x}(k+1) = \frac{ax^{(1)}(0)}{bx^{(1)}(0) + \left(a - bx^{(1)}(0)\right)e^{ak}} \text{ (Ver. 7)}$$

3.5. ARIMA model

This model is based on the Box–Jenkins methodology (Box and Jenkins, 1976) as an appropriate technique for short term estimation based on hourly, daily, weekly, quarterly, annual data. The Box and Jenkins (1976) models are really well-known success in academic research and contribute significantly and successfully in forecasting (Chu, 2014).

ARIMA (autoregressive integrated moving average) is one of the most commonly used time series analysis model to predict the future values of a data sequence. Its primary application is utilized in the short term prediction area requiring at least 40 historical data points. The general model ARIMA (p, d, q) (P, D, Q) model can involve seasonal element of time series data analysis, it includes these primary parameters:

p: the number of autoregressive terms
q: the number of moving average terms
d: the number of times a series
P: the number of seasonal autoregressive components
Q: the number of seasonal moving average terms
D: the number of seasonal differences

Here is a review of some of the types of non-seasonal ARIMA models that are commonly encountered is given below:

- **ARIMA (1, 0, 0)= first-order autoregressive model:** This is an "ARIMA (1, 0, 0) + constant" model in which time series could be projected as a multiple of its own previous value plus a constant if it is stationary and auto-correlated. The forecasting equation in this case is $\hat{Y}_t = \mu + \phi_1 * Y_{t-1}$ which is Y regressed on itself lagged by one period. If the mean of Y equals zero, then the constant term would not be added.
- **ARIMA (0, 1, 0) = random walk:** This is the simplest possible model if the series Y is not stationary in which the autoregressive coefficient is equal to 1. It could be classified as an "ARIMA (0, 1, 0) model with constant" because it consists of (only) a non-seasonal difference and a constant term. The prediction equation for this model can be

written as $\hat{Y}_t=\mu + Y_{t-1}$ where the constant term: the medium change from period to period in Y.

- **ARIMA (1, 1, 0) = differenced first-order autoregressive model:** This is a first-order autoregressive model with one order of non-seasonal difference and a constant term. If the random walk model has auto-correlated errors, the problem might be fixed by the addition of one lag of the dependent variable to the prediction equation. This would be the following prediction equation: $\hat{Y}_t=\mu+ Y_{t-1}+\phi_1 (Y_{t-1}-Y_{t-2})$.
- **ARIMA (0, 1, 1) without constant = simple exponential smoothing:** For some non-stationary time series, the random walk model does not perform well. In other words, this model uses an exponentially weighted moving average of past values to estimate more accurately the mean. The prediction equation for the simple exponential smoothing model can be written as $\hat{Y}_t=Y_{t-1}-(1-\alpha)*e_{t-1}=Y_{t-1}-\theta_1 e_{t-1}$ with $\theta_1= 1-\alpha$.
- **ARIMA (0, 1, 1) with constant = simple exponential smoothing with growth:** It would cause some complications to apply the SES model as an ARIMA model. Firstly, the estimated coefficient of MA (1) is allowed to be lower than zero and as a result, a smoothing factor is higher than 1 in the SES model. This is usually not permitted by the SES model process. Secondly, there is an option of involving a constant term in the ARIMA model in order to assess an average non-zero trend. The prediction equation of ARIMA (0, 1, 1) model with constant is $\hat{Y}_t=\mu+ Y_{t-1}-\theta_1 e_{t-1}$.
- **ARIMA (0, 2, 1) or (0, 2, 2) without constant = linear exponential smoothing:** They are ARIMA models which use two non-seasonal differences in combination with MA terms. The second difference of a series Y at period t of the ARIMA (0, 2, 2) model without constant forecasts is equivalent to a linear function of the previous two forecast errors: $\hat{Y}_t=2 Y_{t-1}-Y_{t-2}-\theta_1 e_{t-1}-\theta_2 e_{t-2}$ in which θ_1 and θ_2 are the MA (1) and MA (2) coefficients respectively.
- **ARIMA (1, 1, 2) without constant = damped-trend linear exponential smoothing**: The forecasting equation of ARIMA (1, 1, 2) is $\hat{Y}_t=Y_{t-1}+\phi_1 (Y_{t-1}-Y_{t-2})-\theta_1 e_{t-1}-\theta_1 e_{t-1}$. It is commonly advised to apply this model in which at least one of two parameters p or q is no larger than 1.

4. Data collection and description

In this study, the researcher concentrates on predicting the demand of international and domestic tourist serviced by lodging sector in Lam Dong province, as well as total revenue generating from Lam Dong lodging activities in period of next 6 months.

In order to guarantee the proposed approach, the research collect and analyze monthly statistics which cover a period from January, 2012 to October, 2018 from official website of General Statistics Office of Lam Dong province and statistical yearbook of Lam Dong. The data were obtained from the website consist of Monthly Total Revenue from lodging services, International Tourists Serviced by tourism accommodations, Domestic Visitors serviced by holiday accommodation.

The group of domestic customers: for the general trend over time, the highest number of tourists served by holiday accommodations was the month during Lunar New Year (varying between January and February) and the summer time (from June to August) since people have holiday time during these time and the lowest months were March, April, September, October. In January 2012, the number of domestic equaled to 232,855 people which was much higher than the remaining months due to Lunar Tet Holiday. This number went down to 187,807 and 167,412 in February and March respectively. This number tended to improve from June to August which was all over 200,000 customers. During this time, students usually have summer time so this contributed significantly to the growth in number of domestic visitors. In the following year, domestic tourists in Tet Holiday in 2013, 2014, 2015, 2016, 2017, 2018 were respectively 273,812; 192,456; 208,800; 273,500; 295,300; 296,600.

These statistics tended to be much lower in March every year. There were dramatic changes when it turned into summer time in which the number of visitors increased significantly from June to August. The most impressive change in this period of time is the increased approximately 97,000 from 208,845 visitors in May, 2013 to 304,673 in June, 2013 and went up more than 40,000 in July, 2013 (Fig. 3).

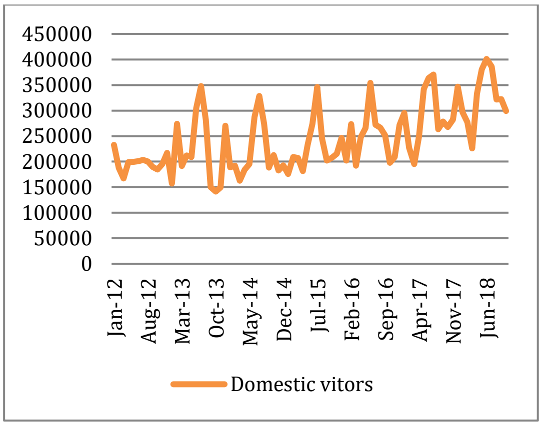


Fig. 3: Monthly number of domestic tourists serviced by holiday accommodation in Lam Dong

The group of international visitors: the number of tourists increased over time. However, the number of visitors has fluctuated every month. There is a different pattern in group of international tourists comparing to domestic group. They have been much higher at the end of each year starting from November to February of next year since during this time, the weather in many foreign countries become much colder than other months so that the foreigners usually found some places warmer to relax after a hard-working year. Seeing from the graph, the statistics varied from under 10,000 to around 25,000 in the period of 49 months (January, 2012 to January, 2016). There was an impressive change in data of the remaining months when they tended to increase mostly over 25,000. The most dramatic number increased to the peak of 43,000 in February, 2018 and then went down with the high slope in the next following months (Fig. 4).

Fig. 4: Monthly number of international tourists serviced by holiday accommodation in Lam Dong

Total revenue generating from lodging activities: as we can see on the graph, total revenue from holiday accommodation sector in Lam Dong varied every month which were depended on the number of tourists serviced by lodging sector. The earning each month in 2012 was not over 2.5 million USD. From 2013 to 2017, the returns varied between 2.5 million USD to 3.5 million USD and at the end of 2017, it increased to the peak of 4.84 million USD. Then the income from lodging activities went down to 3.33 million USD in January, 2018 and went up over 4 million USD for the rest of 2018 (Fig. 5).

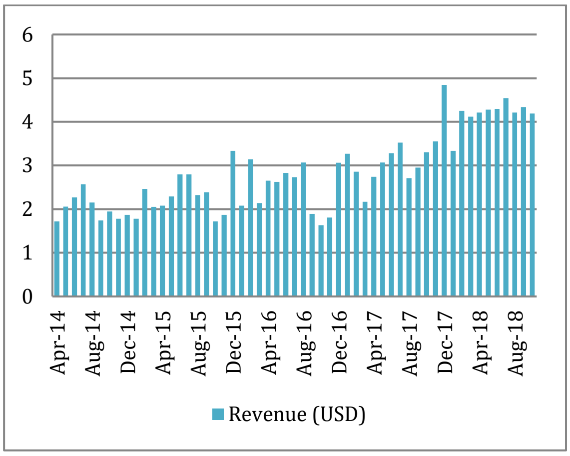


Fig. 5: Total revenue gaining from lodging activities in Lam Dong province

Table 1 shows the description of statistics on the numbers of international and domestic tourists visiting to Lam Dong and total revenue gaining from tourist accommodations activities in Lam Dong. The mean of lodging earning, and the number of domestic and international visitors are 2.83; 245,514.1; 17,953.16 respectively. The highest value of domestic tourists is 401,000 and the lowest number is 141,515 while the maximum of international visitors equals to 43,000 and minimum is 5,270.

Table 1: Descriptive statistics

Statistic	Minimum	Maximum	Mean	Variance (n)	Standard deviation (n)
Domestic visitors served by accommodation establishments	141,515	401,000	245,514.1	3,961,586,748	62,941.13717
International visitors served by accommodation establishments	5,270	43,000	17,953.16	90,618,031.16	9,519.350354
Revenue	1.63	4.84	2.83	0.766	0.875

5. Data description and analysis

The accuracy of outcomes from the forecasting process is directly affected by the quality of the information and data collected. In the description part, the data were collected from January, 2012 to October, 2018 from the official website of General Statistics Office of Lam Dong. The number of international and domestic tourists serviced by tourist accommodation in Lam Dong fluctuates every month during this period of time. In general, the total number of tourists each year has increased significantly. In this part, we consider these following models to predict the tourist accommodation demand in Lam Dong based on the data collected from January, 2012 to October, 2018:

✓ **GM (1, 1)**

- International Visitors serviced by tourist accommodation establishment: a= − 0.0191; b= 7415.7775 so the equation $(1-e^{a})\left(x^{(0)}(1)-\frac{b}{a}\right)=7501.4044$.
- Domestic Visitors serviced by tourist accommodation establishment: a= − 0.0070; b= 180344.7027 so the equation $(1-e^{a})\left(x^{(0)}(1)-\frac{b}{a}\right)=181345.4135$.
- Total revenue earned by tourist accommodation establishment: a= −0.0169; b= 1.7058 so the equation $(1-e^{a})\left(x^{(0)}(1)-\frac{b}{a}\right)=1.7203$.

✓ **DGM (1, 1)**

- International Visitors serviced by tourist accommodation establishment: $\beta_1=1.0192$; $\beta_2=7533.6968$, so the equation $x^{(0)}(1)(\beta_1-1)+\beta_2=7691.8393$.
- Domestic Visitors serviced by tourist accommodation establishment: $\beta_1=1.0070$; $\beta_2=$

7533.6968, so the equation $x^{(0)}(1)(\beta_1 - 1) + \beta_2 =$ 181338.0389.

- Total revenue earned by tourist accommodation establishment: $\beta_1 = 1.0170$; $\beta_2 = 1.7246$, so the equation $x^{(0)}(1)(\beta_1 - 1) + \beta_2 = 1.7538$.

✓ **Verhulst**

- International Visitors serviced by tourist accommodation establishment: a= − 0.0319; b= 0.0000 and $\hat{x}^{(1)}(k+1) = \frac{ax^{(1)}(0)}{bx^{(1)}(0)+\left(a-bx^{(1)}(0)\right)e^{ak}}$ (Ver. 7 – mentioned in section 2) in which: $ax^{(1)}(0) = -263.6809$; $a - bx^{(1)}(0) = -0.0245$; and $bx^{(1)}(0) = -0.0074$.
- Domestic Visitors serviced by tourist accommodation establishment: a= − 0.0054; b= 0.0000 and $\hat{x}^{(1)}(k+1) = \frac{ax^{(1)}(0)}{bx^{(1)}(0)+\left(a-bx^{(1)}(0)\right)e^{ak}}$ (Ver. 7 – mentioned in section 2) in which: $ax^{(1)}(0) = -1250.3827$; $a - bx^{(1)}(0) = -0.0037$; and $bx^{(1)}(0) = -0.0016$
- Total revenue earned by tourist accommodation establishment: a= −0.0284; b= −0.0039and $\hat{x}^{(1)}(k+1) = \frac{ax^{(1)}(0)}{bx^{(1)}(0)+\left(a-bx^{(1)}(0)\right)e^{ak}}$ (Ver. 7 – mentioned in section 2) in which: $ax^{(1)}(0) = -0.0489$; $a - bx^{(1)}(0) = -0.0217$; and $bx^{(1)}(0) = -0.0067$.

✓ **ARIMA**

- International Visitors serviced by tourist accommodation establishment: Model parameters: p = 0 / d = 1 / q = 1 / P = 0 / D = 1 / Q = 1 / s = 12; Confidence intervals (%): 95.
- Domestic Visitors serviced by tourist accommodation establishment: Model parameters: p = 1 / d = 1 / q = 1 / P = 1 / D = 1 / Q = 1 / s = 12; Confidence intervals (%): 95.
- Total revenue earned by tourist accommodation establishment: Model parameters: p = 0 / d = 1 / q = 1 / P = 0 / D = 1 / Q = 1 / s = 12; Confidence intervals (%): 95.

6. Actual and forecasting data results

Table 2 and Table 3 are the outcome of analyzing results by applying ARIMA (0, 1, 1) (0, 1, 1), GM (1, 1), DGM (1, 1).

Table 2: The true values and forecasting result for total revenue gaining from tourist accommodation in Lam Dong

	Total Revenue ($)				
	Actual	ARIMA (0, 1, 1) (0, 1, 1)	GM (1, 1)	DGM (1, 1)	Verhulst
Apr-14	1.72	1.720	1.720	1.720	1.720
May-14	2.06	2.060	1.750	1.754	1.758
Jun-14	2.27	2.270	1.779	1.784	1.796
Jul-14	2.57	2.570	1.810	1.814	1.835
Aug-14	2.15	2.150	1.841	1.845	1.874
Sep-14	1.74	1.740	1.872	1.876	1.914
Oct-14	1.95	1.950	1.904	1.908	1.955
Nov-14	1.78	1.780	1.936	1.940	1.996
Dec-14	1.87	1.870	1.969	1.973	2.037
Jan-15	1.78	1.780	2.003	2.007	2.079
Feb-15	2.46	2.460	2.037	2.041	2.122
Mar-15	2.05	2.050	2.072	2.075	2.165
Apr-15	2.08	2.080	2.107	2.111	2.208
May-15	2.29	2.387	2.143	2.146	2.252
Jun-15	2.8	2.674	2.179	2.183	2.297
Jul-15	2.8	2.955	2.217	2.220	2.342
Aug-15	2.32	2.484	2.254	2.258	2.388
Sep-15	2.39	2.182	2.293	2.296	2.434
Oct-15	1.72	2.231	2.332	2.335	2.480
Nov-15	1.87	2.001	2.372	2.375	2.527
Dec-15	3.33	2.472	2.412	2.415	2.574
Jan-16	2.08	2.364	2.453	2.456	2.622
Feb-16	3.14	3.081	2.495	2.498	2.670
Mar-16	2.14	2.543	2.537	2.540	2.718
Apr-16	2.65	2.563	2.581	2.583	2.767
May-16	2.62	2.851	2.625	2.627	2.816
Jun-16	2.83	3.137	2.669	2.671	2.865
Jul-16	2.73	3.172	2.715	2.717	2.915
Aug-16	3.07	2.755	2.761	2.763	2.965
Sep-16	1.89	2.551	2.808	2.810	3.015
Oct-16	1.63	2.128	2.856	2.858	3.066
Nov-16	1.81	2.023	2.905	2.906	3.117
Dec-16	3.06	2.854	2.954	2.955	3.168
Jan-17	3.27	2.459	3.004	3.006	3.219
Feb-17	2.854	3.417	3.056	3.057	3.270
Mar-17	2.17	2.563	3.108	3.108	3.322
Apr-17	2.74	2.724	3.161	3.161	3.373
May-17	3.07	2.985	3.214	3.215	3.425
Jun-17	3.28	3.372	3.269	3.269	3.477
Jul-17	3.52	3.490	3.325	3.325	3.529
Aug-17	2.71	3.289	3.382	3.381	3.581
Sep-17	2.95	2.742	3.439	3.439	3.633
Oct-17	3.3	2.713	3.498	3.497	3.685
Nov-17	3.55	3.056	3.557	3.557	3.737
Dec-17	4.84	4.269	3.618	3.617	3.789
Jan-18	3.33	4.226	3.680	3.678	3.841
Feb-18	4.25	4.538	3.742	3.741	3.893

Mar-18	4.12	3.871	3.806	3.804	3.944
Apr-18	4.21	4.260	3.871	3.869	3.996
May-18	4.28	4.534	3.937	3.935	4.048
Jun-18	4.29	4.853	4.004	4.001	4.099
Jul-18	4.54	5.026	4.072	4.069	4.150
Aug-18	4.21	4.665	4.142	4.138	4.201
Sep-18	4.34	4.466	4.212	4.209	4.252
Oct-18	4.19	4.478	4.284	4.280	4.302
Nov-18		4.645	4.357	4.353	4.403
Dec-18		5.748	4.431	4.427	4.453
Jan-19		5.414	4.507	4.502	4.502
Feb-19		5.727	4.584	4.578	4.551
Mar-19		5.060	4.662	4.656	4.600
Apr-19		5.449	4.741	4.735	4.648

Table 3: The true values and forecasting result for domestic visitors and international visitors serviced by holiday accommodations

	International visitors served by tourist accommodation establishments					Domestic visitors served by accommodation establishments				
	Actual	ARIMA (0, 1, 1) (0, 1, 1)	GM (1, 1)	DGM (1, 1)	Verhulst	Actual	ARIMA (1, 1, 1) (1, 1, 1)	GM (1, 1)	DGM (1, 1)	Verhulst
Jan-12	8256	8256.000	8256	8256	8256	232855	232855.000	232855	232855	232855
Feb-12	5421	5421.000	7645.72	7691.84	8460.2653	187807	187807.000	182627	182974.89	233722.687
Mar-12	7225	7225.000	7792.82	7839.18	8667.9825	167412	167412.000	183918	184261.11	234592.167
Apr-12	8678	8678.000	7942.74	7989.33	8879.1311	199275	199275.000	185218	185556.37	235463.431
May-12	8029	8029.000	8095.55	8142.37	9093.6867	199881	199881.000	186527	186860.74	236336.472
Jun-12	7380	7380.000	8251.3	8298.33	9311.6202	201114	201114.000	187846	188174.28	237211.284
Jul-12	5615	5615.000	8410.05	8457.29	9532.8983	203163	203163.000	189173	189497.05	238087.859
Aug-12	14458	14458.000	8571.85	8619.29	9757.4831	200064	200064.000	190511	190829.12	238966.19
Sep-12	5543	5543.000	8736.76	8784.39	9985.3323	189460	189460.000	191857	192170.55	239846.269
Oct-12	7822	7822.000	8904.85	8952.65	10216.3988	184471	184471.000	193213	193521.41	240728.089
Nov-12	12678	12678.000	9076.17	9124.14	10450.6309	195449	195449.000	194579	194881.77	241611.643
Dec-12	13630	13630.000	9250.79	9298.91	10687.9722	217234	217234.000	195954	196251.69	242496.922
Jan-13	12089	12089.000	9428.76	9477.03	10928.3617	157268	157268.000	197339	197631.24	243383.919
Feb-13	23821	14681.938	9610.16	9658.56	11171.7333	273812	168601.310	198734	199020.49	244272.626
Mar-13	10597	16539.180	9795.05	9843.57	11418.0167	191695	211843.128	200139	200419.5	245163.036
Apr-13	15468	16638.315	9983.5	10032.1	11667.1366	212203	241079.306	201554	201828.35	246055.139
May-13	9724	14356.133	10175.6	10224.3	11919.0129	208845	203289.256	202978	203247.1	246948.929
Jun-13	8339	12017.513	10371.3	10420.1	12173.5613	304673	246815.260	204413	204675.82	247844.397
Jul-13	8984	9668.440	10570.9	10619.7	12430.6924	347854	307938.771	205858	206114.59	248741.535
Aug-13	9489	16328.624	10774.2	10823.1	12690.3128	281847	326889.508	207313	207563.47	249640.334
Sep-13	12914	8197.212	10981.5	11030.5	12952.3246	150362	242144.000	208778	209022.54	250540.786
Oct-13	10237	10863.207	11192.8	11241.7	13216.6253	141515	152380.202	210254	210491.86	251442.883
Nov-13	12098	14843.753	11408.1	11457.1	13483.1088	149489	152487.928	211740	211971.51	252346.616
Dec-13	12710	14870.009	11627.6	11676.5	13751.6644	270502	200189.300	213237	213461.56	253251.977
Jan-14	11794	13989.156	11851.3	11900.2	14022.1781	188974	201880.027	214744	214962.09	254158.957
Feb-14	13901	17351.155	12079.3	12128.1	14294.5319	192456	227164.436	216262	216473.17	255067.546
Mar-14	16019	11492.351	12311.7	12360.5	14568.6043	162766	146855.875	217791	217994.86	255977.737
Apr-14	12632	15421.032	12548.6	12597.2	14844.2706	183830	189102.151	219330	219527.26	256889.521
May-14	12901	11797.272	12790	12838.5	15121.403	195307	189089.834	220880	221070.42	257802.887
Jun-14	11020	11105.136	13036.1	13084.4	15399.8708	287392	248098.285	222442	222624.43	258717.828
Jul-14	8966	10419.790	13286.9	13335.1	15679.5407	328343	309871.816	224014	224189.37	259634.334
Aug-14	10265	14230.479	13542.5	13590.5	15960.2769	274159	293269.302	225597	225765.31	260552.396
Sep-14	9086	10541.030	13803	13850.8	16241.9417	188237	210965.240	227192	227352.32	261472.004
Oct-14	8601	9885.703	14068.6	14116.1	16524.3954	213083	188866.942	228798	228950.5	262393.15
Nov-14	10800	12744.097	14339.3	14386.5	16807.4966	182500	214606.457	230415	230559.9	263315.823
Dec-14	13599	13225.432	14615.1	14662.1	17091.1027	192818	245952.199	232044	232180.62	264240.015
Jan-15	14200	12998.901	14896.3	14943	17375.0703	176000	143320.379	233684	233812.73	265165.715
Feb-15	15600	17022.122	15182.9	15229.2	17659.2548	208800	201635.170	235336	235456.32	266092.914
Mar-15	5270	13000.537	15475	15520.9	17943.5115	207240	175590.518	236999	237111.46	267021.603
Apr-15	11700	11897.539	15772.7	15818.2	18227.6955	181500	218816.241	238674	238778.23	267951.77
May-15	11700	10082.276	16076.2	16121.2	18511.662	232600	206546.570	240361	240456.72	268883.407
Jun-15	9000	9291.212	16385.5	16430	18795.2666	273900	279355.254	242060	242147.01	269816.504
Jul-15	12800	8608.449	16700.7	16744.7	19078.3656	346100	323263.322	243771	243849.18	270751.05
Aug-15	10100	13074.931	17022	17065.4	19360.8166	245400	286215.968	245494	245563.32	271687.035
Sep-15	15100	10612.309	17349.5	17392.3	19642.4782	202000	193909.090	247230	247289.5	272624.449
Oct-15	11600	11614.028	17683.3	17725.5	19923.2108	207500	191534.890	248977	249027.82	273563.282
Nov-15	14900	14689.343	18023.5	18065	20202.8765	215200	219695.749	250737	250778.36	274503.524
Dec-15	19600	16591.485	18370.2	18411	20481.3396	246300	263488.694	252509	252541.21	275445.163
Jan-16	15300	17032.474	18723.7	18763.7	20758.4668	202200	204341.148	254294	254316.45	276388.19
Feb-16	27500	20167.753	19083.9	19123.1	21034.1274	273500	234003.940	256092	256104.16	277332.594
Mar-16	16300	17379.741	19451	19489.4	21308.1937	192100	231582.494	257902	257904.44	278278.365
Apr-16	27300	20003.590	19825.3	19862.7	21580.5409	247600	225215.296	259725	259717.38	279225.491
May-16	25000	21004.566	20206.7	20243.2	21851.0476	265900	252433.721	261560	261543.06	280173.962
Jun-16	20900	20625.474	20595.4	20631	22119.5958	354300	338759.666	263409	263381.58	281123.767
Jul-16	19600	21026.554	20991.7	21026.1	22386.0714	272100	375242.671	265271	265233.02	282074.896
Aug-16	16500	22257.094	21395.5	21428.9	22650.3639	266500	251371.096	267146	267097.47	283027.336
Sep-16	22300	20614.399	21807.1	21839.4	22912.3669	251400	185331.398	269034	268975.03	283981.078
Oct-16	17500	19938.556	22226.7	22257.7	23171.9783	198000	254997.298	270936	270865.79	284936.11
Nov-16	19300	22266.021	22654.3	22684	23429.1001	209300	210424.374	272851	272769.84	285892.42
Dec-16	24400	23932.312	23090.2	23118.6	23683.6387	271700	254645.273	274780	274687.27	286849.999
Jan-17	35200	23510.278	23534.4	23561.4	23935.505	295300	236809.384	276722	276618.19	287808.833
Feb-17	28300	32273.066	23987.2	24012.7	24184.6145	227500	313224.716	278678	278562.67	288768.913
Mar-17	27100	24883.147	24448.6	24472.7	24430.8873	195300	216728.077	280648	280520.83	289730.226
Apr-17	36500	30309.115	24919	24941.4	24674.2481	250000	206256.216	282631	282492.75	290692.761
May-17	34200	30804.716	25398.4	25419.2	24914.6264	342100	279620.365	284629	284478.53	291656.506
Jun-17	30800	29789.012	25887.1	25906.1	25151.9563	363400	392075.848	286641	286478.27	292621.45
Jul-17	28200	30095.452	26385.1	26402.3	25386.1768	370300	406536.105	288667	288492.06	293587.581

Aug-17	30200	30370.134	26892.7	26908	25617.2315	263700	314091.825	290708	290520.02	294554.888
Sep-17	19200	31234.081	27410.1	27423.5	25845.0687	278600	225823.253	292762	292562.23	295523.358
Oct-17	26200	25796.221	27937.5	27948.8	26069.6414	267700	260058.982	294832	294618.79	296492.98
Nov-17	33000	28743.355	28474.9	28484.1	26290.9072	282300	287475.608	296916	296689.81	297463.741
Dec-17	35200	31935.098	29022.8	29029.7	26508.8283	346600	326740.387	299014	298775.39	298435.63
Jan-18	42200	33829.046	29581.1	29585.8	26723.3713	296600	319523.753	301128	300875.63	299408.634
Feb-18	43000	36288.082	30150.2	30152.5	26934.5074	277400	341339.442	303256	302990.63	300382.742
Mar-18	37000	31194.074	30730.3	30730.1	27142.2118	226100	305046.847	305400	305120.5	301357.941
Apr-18	33700	36846.020	31321.5	31318.7	27346.4643	332900	333878.676	307559	307265.35	302334.22
May-18	29000	35171.029	31924.1	31918.6	27547.2487	380700	367076.477	309733	309425.27	303311.564
Jun-18	27200	32794.590	32538.3	32530	27744.5526	401000	427885.846	311922	311600.37	304289.964
Jul-18	24100	32252.067	33164.3	33153.1	27938.368	386200	445866.351	314127	313790.76	305269.405
Aug-18	27600	33365.448	33802.4	33788.1	28128.6901	321600	392906.554	316347	315996.55	306249.875
Sep-18	25900	31875.043	34452.7	34435.3	28315.5183	322300	351733.106	318583	318217.85	307231.363
Oct-18	24100	32061.139	35115.5	35094.9	28498.8551	299300	346342.623	320835	320454.76	308213.855
Nov-18		38851.209	35791.09	35767.18	28855.0822		354877.081	323102.7	322707.395	310181.8
Dec-18		41766.797	36479.67	36452.3	29027.9944		409529.914	325386.5	324975.864	311167.229
Jan-19		43529.578	37181.5	37150.54	29197.4584		384451.047	327686.5	327260.28	312153.611
Feb-19		45963.633	37896.83	37862.15	29363.4927		400505.882	330002.7	329560.754	313140.934
Mar-19		41090.437	38625.93	38587.39	29526.1182		363339.413	332335.3	331877.399	314129.184
Apr-19		46599.750	39369.05	39326.53	29685.3584		395206.051	334684.3	334210.33	315118.349

Fig. 6 illustrates the results from prediction of international visitors serviced by tourist accommodations from January, 2012 to October, 2018. They have fluctuating shape. Fig. 7 shows the outcomes from projection of domestic visitors serviced by tourist accommodations from January, 2012 to October, 2018. They are fluctuating lines over the time. Fig. 8 is fluctuating which shows the forecasted revenue from tourist accommodations activities from April, 2014 to October, 2018.

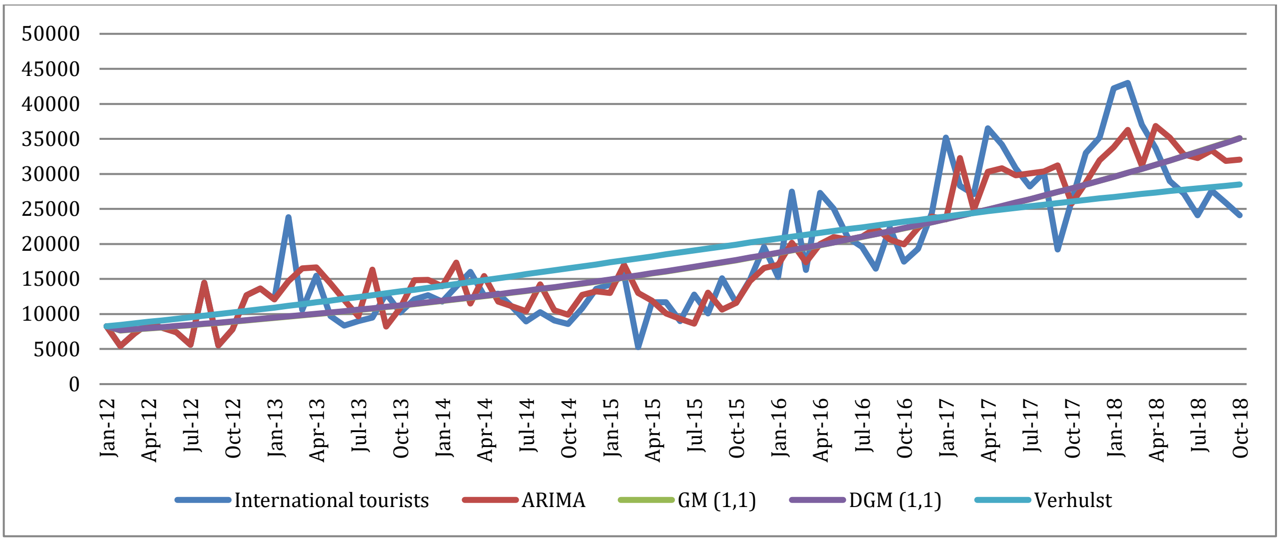


Fig. 6: Forecasting result for international visitors serviced by tourist accommodations

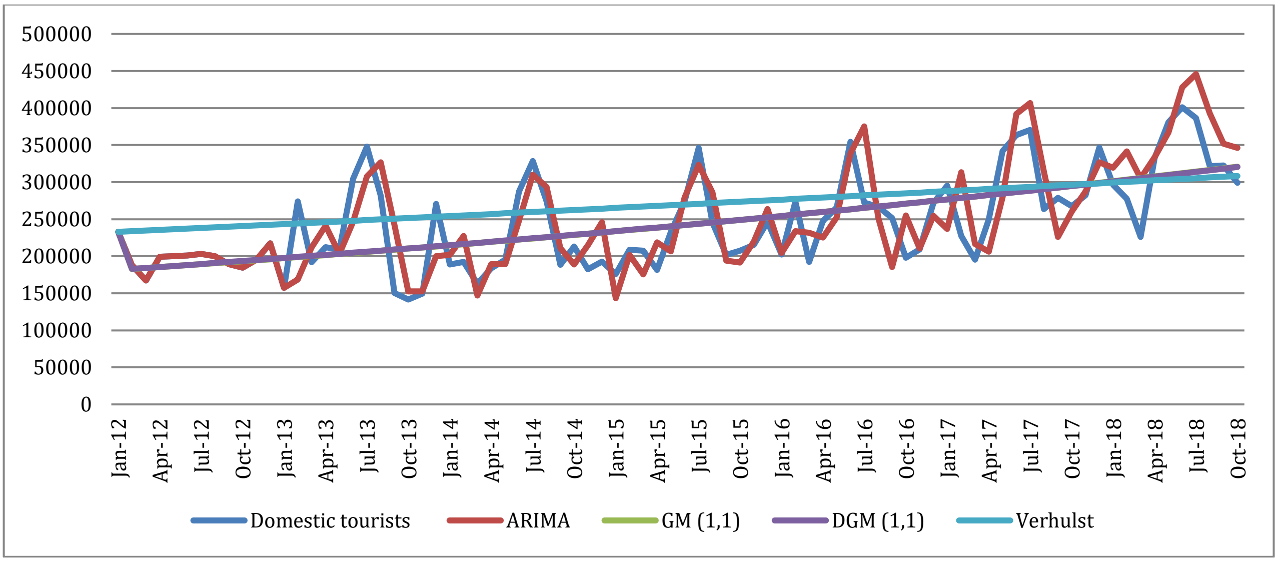


Fig. 7: Forecasting result for domestic visitors serviced by tourist accommodations

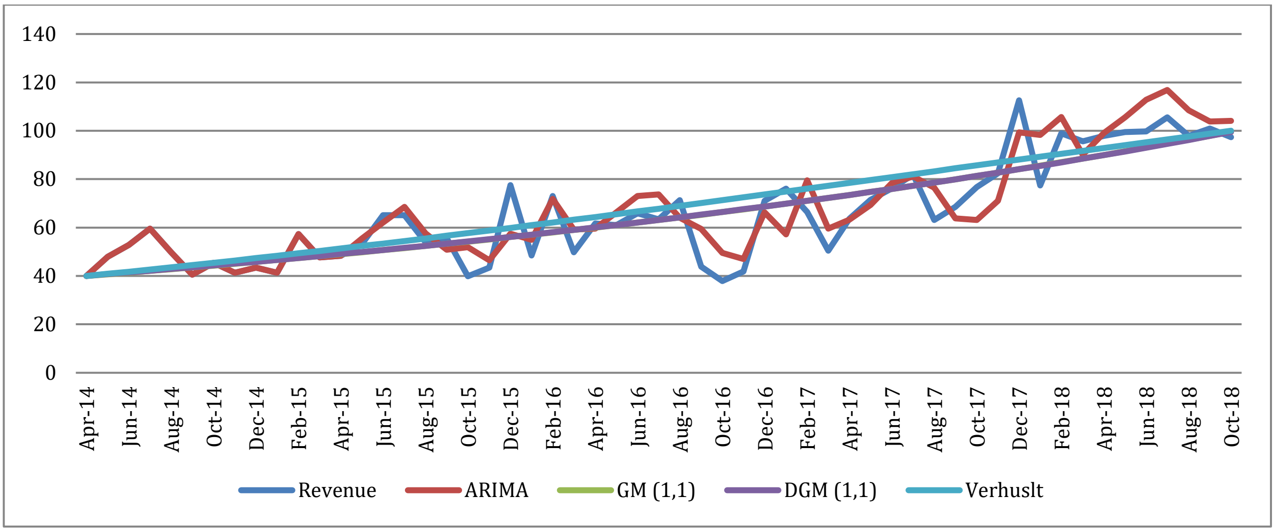


Fig. 8: Forecasting result for total revenue gaining from tourist accommodation

7. Accurate inspection analysis of forecasting ability

It is common to examine the forecasting accuracy by testing the difference between forecasts and the real value of demand among different models. There are a number of measurements for this assessment as follows. In the literature review, many scholars have concentrated on different ways to evaluate the accuracy of forecasting models' ability (Table 4).

Table 4: Previous studies which used accuracy criteria

Author	Accuracy evaluation components
Song and Li (2008)	The MAPE and root mean square percentage error (RMSE) to test the tourism demands forecasting ability
Yüksel (2007)	The MAPE, mean absolute deviation (MAD), and mean squared deviation (MSD)
Rajopadhye et al. (2001)	The MAD and the MAPE to measure the performance of the forecast ability
Schwartz (1999)	The MAD, MAPE, mean squared error (MSE), and standard deviation error (SDE) to monitor the accuracy of hotels' occupancy forecasts

- **The mean absolute percentage error (MAPE):** One of the most common means is used to measure error which is popularly applied in forecasting. It is the average of the absolute percentage errors of forecasts. Error is expressed by actual value minus the forecasted value. Percentage errors are summed without regard to sign to compute MAPE. MAPE perform well to evaluate forecast error when the actual data has significant seasonality and demand fluctuates considerably from one period to the following period. The smaller the MAPE is, the more accurate the forecast is. MAPE is defined as follows:

$$\text{MAPE} = \frac{\sum_{t=1}^{n}\left|\frac{At-Ft}{At}\right|}{n} * 100,$$

where A_t is the actual value and F_t is the forecast value.

When MAPE is close to 0, the forecasting model is highly accurate and has provided good performance, and vice versa. Besides this, in accordance with the value of MAPE, the precision rate of forecasting model can be classified into four levels: excellent, good, qualified and unqualified (Table 5).

- **Mean squared error (MSE):** To measure the average squared difference between the estimated values and actual values. The higher MSE is, the higher the variance of forecast error is.

$$\text{MSE} = \frac{\sum_{t=1}^{n}(At-Ft)^2}{n}$$

- **Root Mean Square Error (RMSE):** RMSE is a part of the criteria for forecasting accuracy evaluation that shows the sample standard deviation of the differences between predicted values and actual values. It can be utilized as comparative method to compare forecasting accuracy for the same series of data across different used models. According to the RMSE criterion, the smaller the error is, the more accurate the forecasting ability of this model performs. "Although they are in a loose sense estimates of the averages of the variances across time". RMSE is calculated using the following equation:

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(At-Ft)^2}{n}}$$

- **Mean absolute deviation (MAD):** To measure the average distance between each data point and the mean of a dataset. It gives us an idea about the variability in a dataset. MAD has ability to compare the accuracy of many different forecasting techniques.

$$MAD = \frac{\sum_{t=1}^{n}|At-Ft|}{n}$$

Table 6 shows in details the criteria to evaluate the ability to forecast future demand. In this case, ARIMA (1, 1, 1) (1, 1, 1), is the only model shows a reliable way when their parameters of MAPE, MSE, RMSE and MAD are in the acceptable range. GM (1, 1), Verhulst and DGM (1, 1) are not chosen in this area because it perform poorly forecasting ability.

Table 7 summarizes in details the parameter of MAPE, MSE, RMSE and MAD to evaluate the ability to forecast. The outcome shows that ARIMA (0, 1, 1) (0, 1, 1), is reliable model for forecasting demand of international customers. GM (1, 1), Verhulst and DGM (1, 1) are not ideal models in this field.

Table 8 shows a comparison of four models to each other with four criteria, it is clear to see the "excellent" and "good" of evaluation of ARIMA (0, 1, 1) (0, 1, 1), GM (1, 1), DGM (1, 1) models to be chosen in forecasting tourist accommodation demand for total revenue generating from lodging activities. Verhulst are rated to be "reasonable".

Table 5: Rankings of MAPE

MAPE	Forecasting power
<10	Highly accurate forecasting
10 – 20	Good forecasting
20 – 50	Reasonable forecasting
>50	Inaccurate forecasting

Table 6: Criteria to evaluate the forecasting models of Domestic Visitors

Domestic visitors	ARIMA (1, 1, 1) (1, 1, 1)	GM (1, 1)	DGM(1, 1)	Verhulst
MAD	27948.15987	38156.2136	50293.56299	50293.56299
MAPE	0.113177661	0.158813025	0.23124677	0.23124677
MSE	1463833052	2406538908	3343387724	3343387724
RMSE	38260.07125	49056.48691	57822.03493	57822.03493
Evaluation	Good	Reasonable	Poor	Poor

Table 7: Criteria to evaluate the forecasting models of international visitors

International visitors	ARIMA (0, 1, 1) (0, 1, 1)	GM (1, 1)	DGM(1, 1)	Verhulst
MAD	2986.797779	4024.645551	4028.782685	4545.874116
MAPE	0.173078379	0.249804375	0.250905804	0.314128693
MSE	17357709.65	27683101.79	27682248.17	33164433.17
RMSE	4166.258471	5261.473348	5261.392227	5758.856933
Evaluation	Reasonable	Poor	Poor	Poor

Table 8: Criteria to evaluate the forecasting models of total revenue

Revenue	ARIMA (0, 1, 1) (0, 1, 1)	GM (1, 1)	DGM (1, 1)	Verhulst
MAD	0.255320124	0.354982	0.355	0.381536364
MAPE	0.089682898	0.140718	0.140767	0.157914554
MSE	0.125766434	0.225618	0.225621	0.265900574
RMSE	0.354635636	3.522638	0.474996	0.51565548
Evaluation	Excellent	Good	Good	Reasonable

8. Conclusion and discussion

Thus the objective of this study is to use the models of ARIMA, GM (1, 1), Verhulst, DGM (1, 1) to develop an easy and accurate way to forecast the demand for tourist accommodations. This study applies the parameter MAPE, MAD, MSE, RMSE to test which models can have better forecasting performance with the minimum projected errors. The forecasting outcomes show that some ARIMA models are good enough to the number of international tourists or domestic tourists of Lam Dong holiday accommodation industry since their MAPE, MAD, MSE, RMSE are reliable for the evaluation. In the case of revenue, ARIMA, GM (1, 1), DGM (1, 1) are appropriate methods with higher accuracy.

There are several practical implications from this study. Firstly, this study gives an overview about current situation in Lam Dong hotel industry. Secondly, it suggests an effective method for forecasting the domestic and international tourists accommodated by Lam Dong lodging sector and total return from the lodging sector investment.

Thirdly, in the case of the lodging revenue tend to continuously increase in the next half year, using the ARIMA, GM (1, 1), DGM (1, 1) models perform better than Verhulst. Besides that, for both international and domestic tourists, the application of ARIMA model works more effectively than the others. The research can conclude that ARIMA is applicable in forecasting these data sets.

Finally, the result provides an overall trend of the growth in number of tourists in the next 6 months which is grow slightly. Therefore, the governments must have some appropriate planning to balance the demand and supply and to guarantee the sanitation and quality of hotel industry satisfying tourists' requirements; enhance relative fundamental construction for hotel-related business markets; timely and synchronous adjustment in price system to increase the competition.

Compliance with ethical standards

Conflict of interest

The authors declare that they have no conflict of interest.

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