BASS DIFFUSION AND GREY MODELS TO FORECAST NEW TOURISM PRODUCT: A CASE STUDY OF TANAH AINA RESORT IN MALAYSIA

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Thesis submitted in fulfillment of the requirements
for the award of the degree of
Master of Science

Centre of Mathematical Sciences
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MARCH 2021

ACKNOWLEDGEMENTS

First and foremost, I am very grateful to Allah The Almighty for granting me strength and eases in finishing this project.

I want to acknowledge both my supervisor and co-supervisor, Dr Noratikah Binti Abu and Dr Noryanti Binti Muhammad for every unending help, supports, encouragements and unending advice.

Besides, I would like to extend my gratitude to my biggest backbone, my dad and mom, Mohd Khaidi Bin Satar and Noriah Binti Mat Noh for believing in me in the first place in finishing this journey. Not forgotten to other family members that help me a lot.

A big thanks for Universiti Malaysia Pahang for the facilities in the university and also for UMP internal grant RDU1703183 and PGRS1903204 which gave financial support for conferences and other events related to this thesis. Special thanks to Tanah Aina Sdn. Bhd. for their willingness to share the data. Without them, this project will still be incompleted.

Last but not least, special thanks to other academicians and fellow researchers who have shared tips and comments in expanding the knowledge. I am also grateful to my friends for always be there through ups and downs.
Thank you all for your support and understanding.

ABSTRAK

Ramalan permintaan pelancongan telah menerima perhatian daripada pihak penyelidik kerana industri pelancongan melibatkan pelaburan yang besar dan memberikan pulangan yang tinggi kepada sebuah organisasi dan kepada negara. Pelbagai kajian ramalan permintaan pelancongan yang telah diterbitkan, namun kurang tumpuan diberikan kepada ramalan permintaan produk pelancongan baru. Kajian ini memfokuskan kepada aplikasi model resapan Bass dan model ramalan grey Bass kepada ramalan permintaan produk pelancongan baru. Model resapan Bass adalah model yang berpengaruh dalam kalangan penyelidik untuk ramalan permintaan produk baru dan model ramalan grey terkenal dengan kebolehan mengendalikan sekurang-kurangnya empat data. Kombinasi kedua-dua model, model ramalan grey Bass digunakan untuk pertama kali dalam aplikasi ramalan permintaan produk pelancongan baru di Malaysia. Produk pelancongan baru yang dikaji adalah dua pusat peranginan ekopelancongan; Tanah Aina Fahad dan Tanah Aina Farrah Soraya. Data bulanan daripada Tanah Aina Fahad dan Tanah Aina Farrah Soraya telah dikumpulkan dari 2014 hingga 2018 dan ditukarkan kepada data tahunan untuk anggaran potensi pasaran. Tiga parameter yang terlibat dalam model-model berkaitan terdiri daripada potensi pasaran, m, koefisien inovasi, p, dan koefisien peneladanan, q. Kaedah anggaran parameter dan nilai potensi pasaran yang berbeza telah digunakan. Kajian ini mendapati model ramalan grey Bass mempunyai prestasi yang lebih baik berbanding model resapan Bass untuk set data Tanah Aina Fahad berdasarkan penilaian ramalan menggunakan purata peratusan ralat mutlak. Selain itu, untuk Tanah Aina Farrah Soraya, model resapan Bass menunjukkan prestasi yang lebih baik berbanding model ramalan grey Bass tetapi nilai parameter potensi pasaran, m memberikan kesan signifikan kepada prestasi ramalan. Kajian akan datang boleh ditambah baik dengan menggunakan kaedah anggaran parameter berlainan serta nilai p dan q untuk mendapatkan ramalan terbaik.

ABSTRACT

Tourism demand forecasting has been acknowledged by researchers as tourism industry involves a large investment and gives a high return to the organisations and to the countries. Among various tourism demand researches that have been published, yet little attention that focus on the new tourism product forecasting. This study focuses on the application of Bass diffusion model (BDM) and grey Bass forecasting model to the new tourism product demand forecasting. Bass diffusion model is an influential model among researchers in forecasting the new product and grey forecasting model is popular because of its ability to handle as low as four data. The combination of these two models, called grey Bass forecasting model is used for the first time in the application of forecasting the new tourism product demand in Malaysia. The new tourism products studied are ecotourism resorts; Tanah Aina Fahad and Tanah Aina Farrah Soraya. Monthly data from Tanah Aina Fahad and Tanah Aina Farrah Soraya are collected from 2014 until 2018 and are converted to yearly data for the estimation of potential market. There are three parameters involved in both models namely; potential market, m, coefficient of innovation, p and coefficient of imitation, q. Parameters estimation method and different value of potential market are employed. The study finds that the grey Bass forecasting model has a better performance compared to the basic BDM for Tanah Aina Fahad dataset based on the evaluation of forecast using mean absolute percentage error. Besides, for Tanah Aina Farrah Soraya, BDM shows a better performance than grey Bass forecasting model but the value of m gives a significant effect in the forecasting performance. Future research can be improved by using other methods in the estimation of parameters and applying the best values of p and q to achieve the best forecast.

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LIST OF SYMBOLS

$f(t)$	Probability distribution function
$F(t)$	Cumulative distribution function
m	Potential market
p	Coefficient of innovation
q	Coefficient of imitation
$S(t)$	Sales at time t
t^*	Time of peak sales
x	Background value of $\frac{dx}{dt}$
$x^{(0)}(k)$	Actual value
$x^{(1)}(k)$	Accumulated generating operator (AGO) value
$\hat{x}^{(0)}(n)$	Predicted value
$Y(t)$	Cumulative number of adopters
$z^{(1)}(k)$	Mean operation on $x^{(1)}(k)$

LIST OF ABBREVIATIONS

AGO	Accumulating generation operator
BDM	Bass diffusion model
GM	Grey model
MAPE	Mean absolute percentage error
OLS	Ordinary least square

CHAPTER 1

INTRODUCTION

1.1 Preface

This chapter covers research background which overviews the whole research. It is followed by problem statements on forecasting the new tourism product demand in Malaysia. This chapter also includes research objectives and scopes which explain the purposes of this study to be conducted and ends with a conclusion of this research.

1.2 Research Background

This thesis studies about the forecast of new tourism product in Malaysia. New product is identified according to six categories; new to the world, new to the firm, product improvements, cost reduction, additions to existing product lines, and repositioning (Crawford & Benedetto, 2010). New to the world product is a product that never exists before meanwhile new to the firm product is a product that is new to the company but has existed before. The changes in term of specifications and functions of the product is identified as product improvements. Cost reduction does not change the specifications of the product but affecting the behaviour of the buyers. Addition to existing product lines from the same type of product with different characteristics for example, different colours which may affect the choice of customers. The last category means the product is being targeted to the different target market.

Tourism industry is considered as one of the main profit contributors to a country. Each destination serves different tourism products according to the destination pull factors, for example; culture of the local people, natural resources and environmental factors. The products served need to follow visitors' changing demands from time to time in order to ensure continuous visitors and providing long-term profits (Jaafar & Maideen, 2012). Smith (1994) suggested that the tourism product was presented by the amalgam of five elements; physical plant (natural resources and environment), service, hospitality, freedom of choice, and involvement. Smith (1994) also stated that tourism product was defined by "facilitation of travel and activity of individuals away from home environment".

Therefore, putting the theory of the diffusion of new products into this tourism context, a new tourism product can be defined as a new facility and service that is designed for the satisfaction of the visitors. However, the difference between solid product and tourism product are there will always be consumers for the former as long as the product meets the demands. For the latter, the challenges arise when there is no new innovation made to the product that would attract the public attention and the visitors are changing, then, results in the falling of the number of visitors to the place.

The existence of the new tourism products which caters the needs of visitors are also important to increase the attendance of visitors into the country. Variety of new tourism products were built, from amusement parks for people who love both indoor and outdoor thrilling games, to shop outlets for shopaholic, and also excursion to art, historical or religious buildings. Apart from that, tourism accommodation, e.g.: hotels, resorts, and homestays are also considered as tourism products because accommodation is important in fulfilling the needs of visitors while travelling.

Malaysia is located in south-east Asia with the tropical climate, making it suitable for visitors to access the country during the entire year. It is famous for its local attractions, from landmarks and parks to islands. In additions, the beauty of Malaysia lies within its people with multi-cultural and multi-religious nations. Taking advantages of Malaysia's diversity, Tourism Malaysia launched attractive and impactful slogans such as "Malaysia Truly Asia" to reflect and promote the country internationally and not leaving behind to encourage its own people to travel to nearby destinations by using a slogan "Dekat Je". In conjunction of the campaign, Malaysia is expected to welcome 25 million visitors every year.

Number of tourist arrivals in Malaysia presented in Table 1.1 shows a steady increasing trend from 2007 until 2014 and there is slight drop in 2015. The decrease of tourist arrivals is affected by the occurrence of natural disasters such as haze and flood. Besides, the major cause is due to the introduction of goods and service tax (GST) in April 2015 which increases the consumer price. In 2016, the attendance increases and the number decreases again in the following year. It is reported that the number of tourist arrivals decrease in 2018 because lack of funding for tourism industry in Malaysia. If this decreasing trend in the number of arrivals continues, this gives a poor impact to the industry as Tourism Malaysia targeted 36 million tourist arrivals approaching the year of 2020. The number of tourist arrivals to Malaysia from 2007 until 2018 is illustrated in Figure 1.1.

Table 1.1 Number of tourist arrivals and receipts to Malaysia

Year	Arrivals (Million)	Receipts (RM/Billion)
2018	25.83	84.1
2017	25.95	82.1
2016	26.76	82.1
2015	25.72	69.1
2014	27.44	72.0
2013	25.72	65.4
2012	25.03	60.6
2011	24.71	58.3
2010	24.58	56.5
2009	23.65	53.4
2008	22.05	49.6
2007	20.97	53.4

Source:www.pahangtourism.org.my

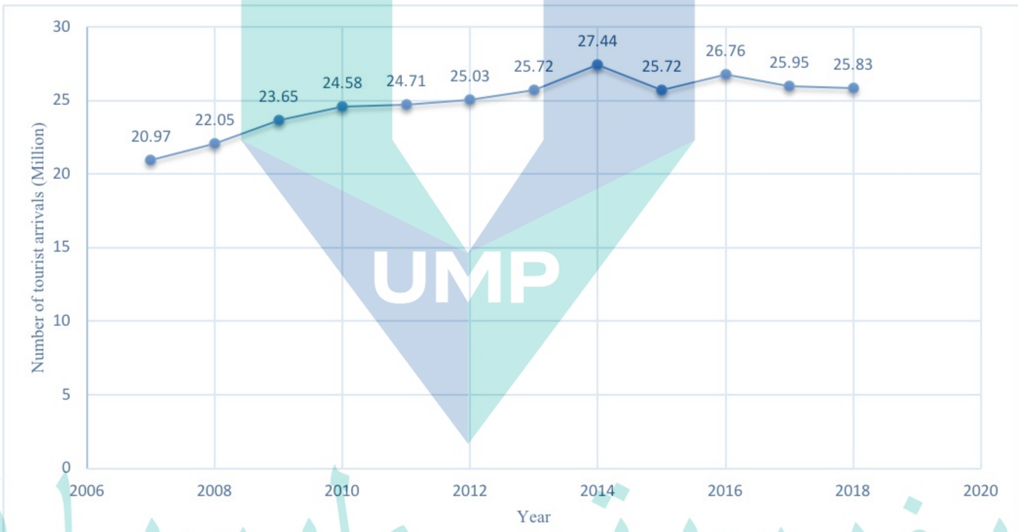

Figure 1.1 Number of tourist arrivals to Malaysia from 2007 until 2018

This study concentrates on the new tourism product demand in Malaysia, specifically, in Pahang, a state located on the east coast of Peninsular Malaysia. It is the largest state in Peninsular Malaysia and is rich of its nature from islands, beaches to highlands and have plenty of tourism products to be offered to the visitors. As Pahang is rich for its natural environment, tourism practitioners benefitted from this asset and turns it into tourist attraction. For example, Cameron Highlands, Fraser's Hill, and Tioman Island. The question is: if the government or tourism practitioners keep building tourism places or products to attract more visitors, how long could the place maintained before the number of visitors drop? The answer to this question can be helped through forecast. Therefore, when a new tourism product is built, the number of possible visitors can be forecasted in order for the management to analyse the performance and expecting any consequences in the future.

The new tourism product that becomes the focal point in this study is Tanah Aina, which are owned by Tanah Aina Sdn. Bhd. It has 10 locations across Malaysia from Johor, Pahang to Selangor which consists of ecotourism resort, beachfront resort, cafe, and orchard resort. Among all ten branches, our focus is only for Pahang branches; ecotourism resort with the theme of modern settings while in nature, namely Tanah Aina Fahad and Tanah Aina Farrah Soraya. Tanah Aina Fahad and Tanah Aina Farrah Soraya are both located in Raub, Pahang. They are opened to public in 2014, hence, the author will consider these resorts as the new tourism products.

Tanah Aina Fahad is located approximately 175 km from Kuala Lumpur with 2 hours 14 minutes journey by car. Meanwhile, Tanah Aina Farrah Soraya is located about 70 km, which is more than one hour drive from Kuala Lumpur. The locations of Tanah Aina Fahad and Tanah Aina Farrah Soraya from Kuala Lumpur are shown in Figures 1.2 and 1.3, respectively. Tanah Aina Fahad is accessible by cars, meanwhile Tanah Aina Farrah Soraya is accessible only by 4x4 vehicle. Visitors who have arrived at Tanah Aina Farrah Soraya's will be taken by their staffs to be commuted to the accommodations. These resorts have been the choice for couples, families and large group of visitors for meetings and team building trainings. Both of these locations serve ranges of facilities for example, hotel's coffee shop, training and meeting rooms. Besides, these accommodations are special because they are surrounded by natural landscapes of rainforests and river.

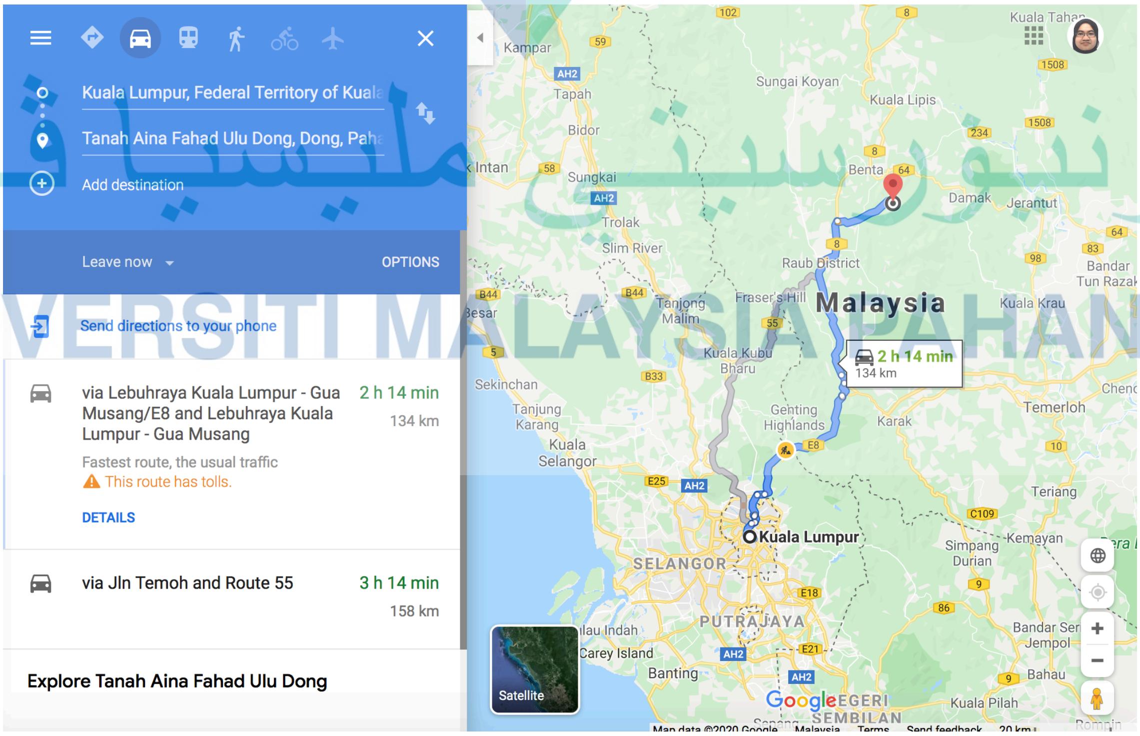

Figure 1.2 Location of Tanah Aina Fahad from Kuala Lumpur

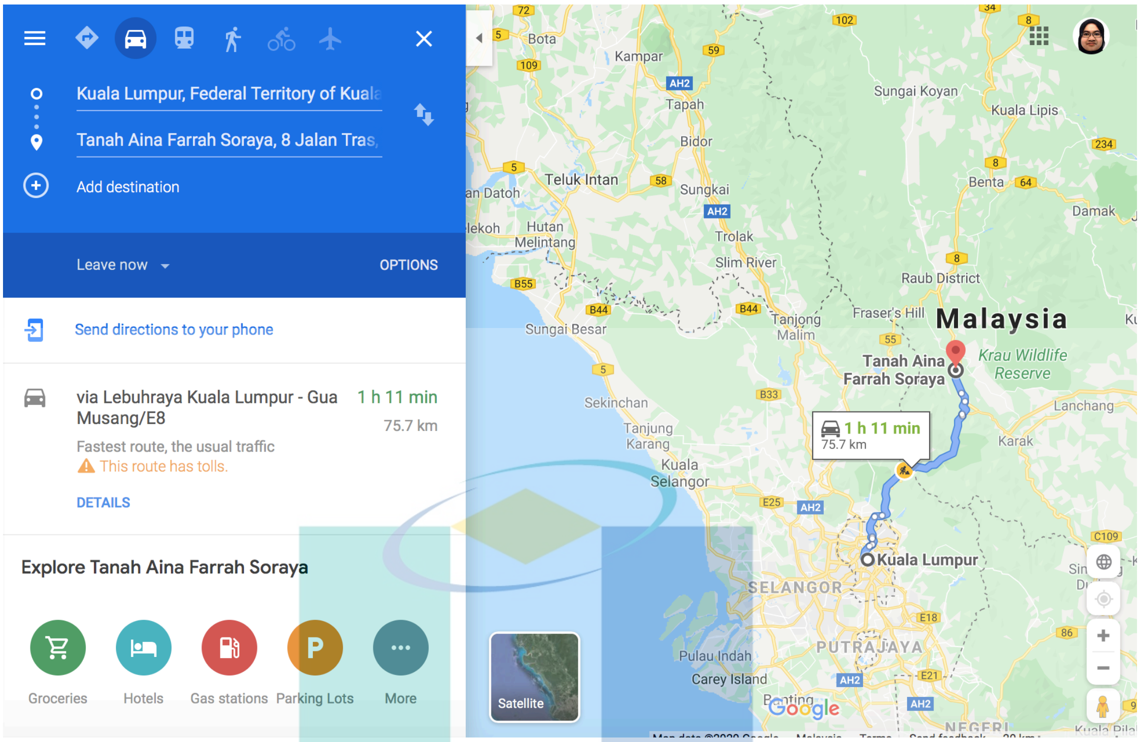

Figure 1.3 Location of Tanah Aina Farrah Soraya from Kuala Lumpur

Tanah Aina Fahad has different types of lodgings; terrace rooms and luxurious tents. Meanwhile, Tanah Aina Farrah Soraya offers 20 different chalets with different amazing scenery where they can choose river or forest views. The price of both accommodations starts at RM300 per room, which can accommodate two adults and two kids. For a large business groups, the dorms are available at RM 5000 per night. Figure 1.4 shows the signboard in front of Tanah Aina Fahad, meanwhile Figures 1.5, 1.6, and 1.7 are among the accommodations in Tanah Aina Fahad and Tanah Aina Farrah Soraya.

Other than that, there are several outdoor activities offered for the visitors. The visitors can enjoy night walking in the forest, jungle and river trekking, and flying fox activities. The jungle and river trekking is guided by a professional tour guide which makes it safe for first time visitors joining this activity. The activities can be done in small and large groups. Figure 1.8 shows the river trekking activity joined by a large group of visitors. Besides, Figure 1.9 is the night walk trail facility in the resort. Both Tanah Aina Fahad and Tanah Aina Farrah Soraya are perfect and comfortable places for visitors who seek for adventure and but at the same time, need for relaxation in nature.

Figure 1.4 Tanah Aina Fahad's signboard

Figure 1.5 Tanah Aina Fahad's accommodation (chalet)

Figure 1.6 Tanah Aina Fahad's accommodation (tent)

Figure 1.7 Tanah Aina Farrah Soraya's accommodation

Figure 1.8 A group of visitors during river trekking activity.

Figure 1.9 Night walk trail.

1.3 Problem Statement

Tourism Malaysia and tourism practitioners have been partnering in building new tourism product to encourage more local and international visitors. Due to an increase in the number of the new tourism product in Malaysia, less attention has been paid on the performance of the product.

Moreover, the number of study that covers this area is also scarce. In the case of Tanah Aina Fahad and Tanah Aina Farrah Soraya, the collection of data on the number of visitors since they are opened are not tracked. Therefore, to prevent the negative possible outcomes in the future such as decreasing in the number of visitors which affect the sales and profit of the mentioned products, researchers need to study on the forecast of the new tourism products.

Hence, because of this arising problems, this study will employ the model to help the management to acknowledge their current and future number of visitors to the places so that suitable actions can be taken to prevent the decreasing of the number of visitors in the future.

1.4 Research Questions

The research questions of this study are:

(a) What are the trend of the number of visitors of the new tourism product in Pahang?

(b) What are the methodologies applied to forecast the new tourism product demand in Pahang?

(c) How does the best forecasting model to forecast the new tourism product demand in Pahang being selected?

1.5 Research Objectives

The objectives of this study are to:

(a) Analyse the trend of the number of visitors to the new tourism product in Pahang;

(b) Apply the developed methodologies of Bass diffusion model and its combination with Grey forecasting model in forecasting new tourism product demand in Pahang;

(c) Propose the best forecasting model to forecast the new tourism product demand in Pahang and interpret its findings.

1.6 Research Scope

1.6.1 Scope of the Data

The data used in this study is a secondary data which is collected from Tanah Aina Sdn. Bhd. The author focuses on the two locations which are; Tanah Aina Fahad and Tanah Aina Farrah Soraya from the year October 2014 until 2018. Monthly data of the visitors to each places are collected. The annual number of visitors to Pahang are also obtained from Tourism Pahang.

1.6.2 Scope of the Model

The forecasting models used are Bass diffusion model (BDM) and the combination of BDM with grey theory. The combination model of BDM with grey theory is called grey Bass forecasting model. Both models are used to forecast the new tourism product demand in Malaysia.

1.7 Research Significance

There are several research significances which could improve the research gap from the previous studies.

As the data were collected from the tourism product, the number of visitors to the places are observed. Therefore, the trend of visitors to the tourism products can be seen. Consequently, this trend will be used to forecast the number of future visitors. The result from the forecast will aid the tourism management in generating new ideas to satisfy the visitors' changing demands and ensuring long-term profits for the company and industry.

Besides, the study will also contribute as a reference for future research in tourism related topics especially in Malaysia. On the other hand, this result will add as the reference of application of the employed models; BDM and Grey forecasting model.

1.8 Organisation of the Thesis

This thesis covers six chapters. In the last section of this thesis, the reference and appendices are included. Chapter 1 overviews the whole thesis which includes; preface, research background, problem statement, research objectives, research scope, research significance and also this section, organisation of the thesis.

Chapter 2 describes the literature review of this research. Past studies of demand forecasting, tourism demand and tourism product forecasting are presented in this section. Besides, this chapter discusses in details on the application of the models applied in this study. Literature review on parameter estimation method and forecast evaluation method are also discussed in this chapter.

Next, research methodology is detailed in Chapter 3. The theory and derivations of BDM, grey forecasting model and grey Bass forecasting model are explained. At the end of the chapter, the details on forecast evaluation procedure and data specification are discussed.

The results obtained in this study are discussed in Chapter 4. The estimation of parameters using ordinary least square (OLS) of Tanah Aina Fahad is explained in the first part, followed by the forecast of Tanah Aina Fahad using BDM. The succeeding part in the chapter explains for the case of Tanah Aina Farrah Soraya. Besides, the employment of grey Bass forecasting model for the new tourism products are presented in this chapter. Then, the results of forecast in both models are compared by evaluating their mean absolute percentage error (MAPE).

Chapter 5 discusses the implementation on different market potential used for the grey Bass forecasting model. The decision on which value of potential market, m give the best performance in forecasting is explained. Then, the performance of the BDM and grey Bass diffusion model are investigated and compared.

The study is summarised and concluded in Chapter 6. The best forecasting model between BDM and grey Bass forecasting model is suggested in this chapter. Then, the suggestions including the improvement for future research is presented in the chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The literature background is summarised in this chapter. It begins with review on forecasting, including demand forecasting, followed by tourism demand forecasting and tourism product forecasting. Next, the literature of the models used which are, Bass diffusion model (BDM), Grey forecasting model and the combination of grey Bass forecasting model are discussed. At the end of the chapter, literature on parameter estimation and forecast evaluation methods, are detailed further.

2.2 Forecasting

Forecasting has been an important part in many sectors; not only to predict the future but also for the practitioners to have a better planning and attention for upcoming challenges. Inaccurate forecast are considerable but accurate ones give an important advantages (Athiyaman & Robertson, 1992). Forecasting can be defined as the technique of predicting future by analysing the trends using current and previous data (Hyndman & Athanasopoulos, 2018).

The methods of forecasting are either qualitative, quantitative or the combination of both methods. Qualitative forecasting is mainly about judgements and opinions of the researcher to make wise decisions for the future good while quantitative forecasting is a prediction using mathematical models. Quantitative methods are practiced in forecasting sales and profits in a business, expected visitors to an event and also to predict the number of accidents on a highway.The reviews on demand forecasting, tourism demand forecasting and tourism product forecasting are detailed in Sections 2.2.1, 2.2.2 and 2.2.3, respectively.

2.2.1 Demand Forecasting

Demand forecasting is the scientific estimation of a product's or service's future demand. Demand forecasting provides a crucial role in businesses development and growth of the companies or industries. Researchers have applied various methods to demand forecasting in wide key areas which will be discussed further in this section.

Y. Wang, Wang, Zhao, and Dong (2012) modified the residual errors in seasonal autoregressive integrated moving average (SARIMA) to predict accuracy in forecasting electricity demand using China electricity industry as the subject study. The study reported that even though there were rapid growth of power generators, it still cannot fulfill the electricity demand in China. The data from China Electricity Council was collected. Results showed that China's electricity demand grows in the next consecutive years provided that it is influenced by the seasonal changes.

Ren, Suganthan, Srikanth, and Amaratunga (2016) extended the study on short-term electricity demand in Australia and applied Artificial Neural Network (ANN) method, named single hidden layer neural network with fixed random weights (RWSLFN). The results show that RWSLFN with direct input-output connections performed better than RWSLFN without direct input-output connections.

Venkatesh, Ravi, Prinzie, and Van Den Poel (2014) proposed forecasting of ATM's cash demand using clustering methods and four neural network models. The available data was collected from Neural Forecasting Competition website called NN5 which consist of cash withdrawal in two years from different ATMs across England. The data was collected on each day-of-the-week. The findings from this study could reduce operational costs for ATMs and could be used by other centers in other similar geographical region.

Ke, Zheng, Yang, and Chen (2017) studied on short-term passenger demand forecast of online mobility service. The researchers proposed fusion convolutional long short-term memory network (FCL-Net) and compared the model with classical time series prediction models and state-of-art machine learning algorithms. Didi Chuxing, which is an application of ride service platform in China provided the data for this study. The researchers concluded that the proposed model gave a robust performance compared to the other mentioned models.

Brentan, Luvizotto, Herrera, Izquierdo, and Pérez-García (2017) applied adaptive Fourier time series process with support vector regression (AFS-SVR) to forecast short-term water demand. This study used hourly data of water demand from residential area in

Brazil. Then, the study was carried out by using 400 days of the data for in-sample dataset and the following 140 days to prove the accuracy of the model. The result indicated that the hybrid model of AFS-SVR gave high predictive accuracy in the forecast. In addition, the proposed model supported the water operators to program an efficient system in saving energy and water.

González Perea, Camacho Poyato, Montesinos, and Rodríguez Díaz (2019) studied about water demand in Southern Spain used in agriculture. Daily data was collected and analysed using ANN model called Multilayer Perceptron Network (MLP). This study also emphasised that even though large information are available recently due to big data era, the data in irrigated agriculture is still limited. The result showed that the developed model, MLP, increased the forecasting accuracy and make it a robust model to forecast daily water demand in agriculture. The studies for demand forecasting are summarised according to the cases and methods in Table 2.1.

Table 2.1 Summary of study for demand forecasting

Authors	**Case**	**Method**
Wang et al. (2012)	Electricity	Modified residual approach in seasonal ARIMA
Ren et al. (2016)	Electricity	ANN
Venkatesh et al. (2014)	ATM's cash demand	Clustering and neural networks
Ke et al. (2017)	Passenger demand on online mobility service	Deep learning approach
Brentan et al. (2017)	Water supply	AFS-SVR
Perea et al. (2019)	Water demand	ANN

2.2.2 Tourism Demand Forecasting

Tourism industry has become an important industry for every country. Tourism forecasting have existed about more than half a century of history and have contributed the largest in tourism economics industry (Jaafar & Maideen, 2012). Studies on tourism demand forecast have used various methodologies and have been applied across the globe.

In Malaysia, Tang and Tan (2015) predicted the country's inbound tourism by focusing on two variables, namely, environmental pollution and crime rate. The researchers used non-stationary panel data approach to analyse the data on tourist arrivals to Malaysia from 1989 to 2010. It was found that the terrorist attack occurred in September 2001 and pollution influenced the number of inbound tourism to Malaysia negatively as the number of tourist arrivals into the country indicated reduction during the period. Gunter and Önder (2015) forecasted the foreign tourists to Paris from different countries; Germany, Italy, Japan, United Kingdom (UK) and United States (US). The models involved in this study were univariate and multivariate models. The findings showed that univariate model performed better for UK and US source markets while multivariate model performed better for German and Italian source markets.

Yang, Pan, Evans, and Lv (2015) investigated Chinese tourist arrival with search engine data. Auto-regressive moving average (ARMA) model was used and the result showed that Baidu data performed better than Google due to Baidu's higher market share in China. The data were provided by Google query data and Baidu query data from January 2004 and from June 2006 respectively. X. Li, Pan, Law, and Huang (2017) extended the study using composite search index by forecasting tourism demand to Beijing. The quantitative data were assembled from both Baidu's search engine using tourism related keywords from January 2011 to August 2015 and from Beijing Tourism Association (BTA) to forecast weekly tourist arrival. Generalised Dynamic Factor Model (GDFM) was used as the model has the ability to process high-dimensional data. In conclusion, the econometric model with the new index has the best forecasting accuracy in one-week and four-week forecasts.

Apart from that, Law, Li, Fong, and Han (2019) concluded that deep learning approach forecast better than support vector regression (SVR) and ANN model. The study forecasted tourist arrivals to Macau and measured the 92 monthly data ranging from January 2011 until August 2018, collected from Macau government. The study had included the search keywords from Baidu and Google in the forecast. Therefore, the findings also mentioned that other influencing factors, such as data from blogs, social media or search keywords play a big role in tourism demand forecast. Silva, Hassani, Heravi, and Huang (2019) applied monthly data to forecast international tourism demand to ten European countries. The datasets were obtained from Eurostat database. Silva et al. (2019) proposed Denoised Neural Networks Autoregressive (DNNAR) model and compare it to basic NNAR, ARIMA and exponential smoothing (ETS). The study found that the proposed model, DNNAR outperformed the other three models in all countries. This is because the use of Singular Spectrum Analysis (SSA) improved the accuracy in forecasting. The studies used for tourism demand forecasting are summarised in Table 2.2.

Table 2.2 Summary of study for tourism demand forecasting

Authors	Hypothesis	Model	Remarks
Tang and Tan (2015)	Tourism demand forecast to Malaysia	Non-stationary panel data approach	Environmental pollution and crime rate gave negative effect to the number of tourist arrivals.
Gunter and Onder (2015)	Forecasting international city tourism demand for Paris	Uni and multivariate models	Univariate for UK and US source markets while multivariate for German and Italians source markets.
Yang et al. (2015)	Forecasting Chinese tourist volume with search engine data	Auto-regression moving average (ARMA)	Baidu index performs better than Google Index due to Baidu's higher market share in China.
Li et al. (2017)	Forecasting tourism model with composite search index	Generalised Dynamic Factor Model (GDFM)	The econometric model with the new index has the best forecasting accuracy in one-week and four-week forecasts.
Law et al. (2019)	Forecast tourism demand to Macau	Deep learning approach	Deep learning approach outperformed SVR and ANN models.
Silva et al. (2019)	Forecasting tourism demand in 10 countries	DNNAR	DNNAR outperformed NNAR, ARIMA and ETS.

2.2.3 Tourism Product Forecasting

Aforementioned in Section 1.2, a tourism product is a facility or service that is designed to attract visitors or tourists away from home. Meanwhile, new tourism product is defined as facility or services that is recently opened to attract visitors and to satisfy their demands. There are emerging number of studies in the past decade which focused on tourist arrivals (Moro & Rita, 2016). On the contrary, only small number of studies concentrated on the tourism product as well as the new tourism product. Moreover, this situation is on the opposite direction with the increasing in the number of tourism product planned by the government and tourism practitioners.

Hsiao, Jaw, and Huan (2009) conducted a study to tourism facility management of the theme parks in Taiwan. The theme parks managements were facing with declining visitors. Then, the managements of theme parks held a Coffee Festival to boost the visitors' attendances. Bass diffusion model (BDM) was used to analyse the effect of Coffee Festival by observing long-term attendance to the theme park. The result stated that the Coffee Festival strengthened the visitors' attendances to the hosts.

Kunc (2009) forecasted the development of wine tourism in Chile. Kunc stated that a lot of effort and investments in infrastructure had been done for wine tourism but still, not affecting the increment of number of wine tourists in Chile. Kunc obtained the data from the survey method sourced from Chilean National Statistics Institute. The model used is BDM. The finding showed that the number of domestic wine visitors to Chile may reach 200 000 people per year.

Although there is no mentioned on the tourism product forecasting in the study, campground is considered as a tourism product based on the definition of tourism product in Section 1.2. Rice, Park, Pan, and Newman (2019) forecasted five popular campgrounds in America. Monthly data were collected from Recreation Information Database (RIDB) from 2007 until 2017. Six methods were employed; moving average (MA), seasonal autoregressive integrated moving average (SARIMA), exponential smoothing (ETS), K-nearest neighbor (KNN), neural network autoregression (NNAR), and the combination of ETS, KNN, and NNAR. Among the six models, the combination of ETS, KNN and NNAR models have the best accuracy.

Besides, Volchek, Liu, Song, and Buhalis (2019) employed Google Trends index in forecasting of five London museums. Higher frequency of data which is weekly data was collected in the study. Time series models and ANN method were used and the researchers concluded that every models have equal performances. In addition, the researchers suggested that more online-based researches need to be carried out in the future because of its feasibility and convenience in obtaining large data.

Based on the studies mentioned in this section, lack of discussion that emphasised on the new tourism product definition and its forecast in one study. Therefore, researchers need to focus on this specific area which is the forecast of the new tourism product, so better strategies and plans can be contributed to the tourism industry development.

2.3 Forecasting Model

This study considered two forecasting models; BDM and its combination with grey forecasting model, called grey Bass forecasting model. This section will discuss the application of BDM, grey forecasting model and grey Bass forecasting model, which are explained in Section 2.3.1, Section 2.3.2 and Section 2.3.3, respectively.

2.3.1 Bass Diffusion Model

New product launching is a critical phase for managements because the products' sales in the future have been a guessing game for them (Bass, 1969; Thomas, 1985). Besides, the problems when dealing with new products are lack of historical data available and time consuming because manual attention in terms of specifying the products' potential markets are required (Abu & Ismail, 2013). Therefore, realising the limitations, Bass diffusion model (BDM) had become the standard for new product's forecasting (Bass, 1969; Jha, Gupta, & Kapur, 2008).

Bass (1969) classified the theory of diffusion of new products into two; innovators and imitators. Innovators, solely depend on their independent decisions while imitators are influenced by other people in the society. Bass addressed innovators as risk-takers and fearless. Unlike imitators, the innovators do not feel the pressure in purchasing the products over time. Besides, Bass mentioned that the innovation factor reflects the product meanwhile imitation factor reflects both products and customer characteristics. This shows that high magnitude of the coefficients of innovation and imitation means there is high influence of diffusion of the new product in the market. The growth of the number of new adopters can be represented in Figure 2.1.

Based on Figure 2.1, both imitators and innovators fall under the umbrella of adopters (Ismail & Abu, 2013). Once the new product is newly introduced to the market, the number of innovators decrease as the time passes. However, due to strong exter-

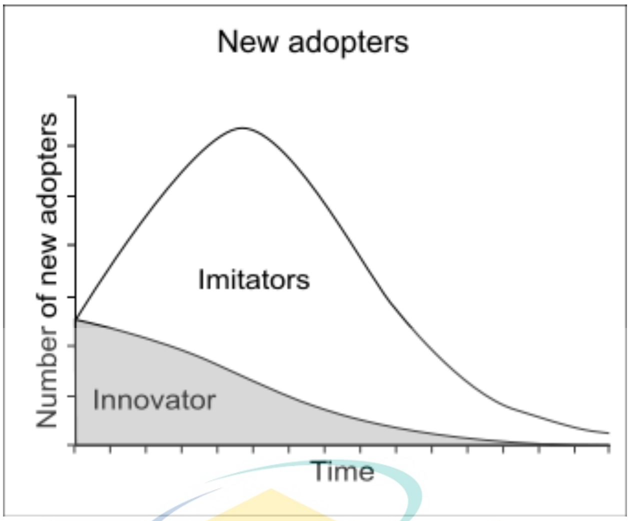

Figure 2.1 Growth of the number of new adopters. (Ismail & Abu, 2013)

nal influence, the number of imitator increases (Bass, 1969). Mahajan and Muller (1979) supported this diffusion theory by stating 'the model represent the level of spread of innovation among a given set of adopters'. The researchers also mentioned that the estimation of parameters depend on the presence of historical data.

The data is considered limited data when there is less than 30 data sample, which can be said about four to 30 data sample, then, forecasting can be done. No data is defined when there is below than three data (Mahajan, Muller, & Bass, 1990). Essentially, lack of focus on tourism products and their number of visitors' data might be the reason why less groundwork is available in this topic. The application of BDM for the new product had been widely used in various areas by researchers and Bass admitted that Bass model has been influential to the application with the real data and also for theoretical research (Bass, 2004).

Dunn et al. (2012) applied BDM in medical areas to determine the adoption of new medicines by the doctors in Australia. Between 1992 and 2010, monthly prescriptions volumes for drugs were collected. The results showed that Australian prescribers took eight years before new medicine is introduced.

Lim et al. (2012) estimated 3G mobile subscription of 31 provinces in China using classical BDM. Previously, they examined the performance of 2G subscriptions using stochastic frontier analysis (SFA) in terms of technical issues, so the users could make an upgrade to 3G if the issues are being removed. Then, re-estimation of 3G subscriptions are made using modified BDM. Comparing both original and modified model, they later found that the potential users for 3G are up to nearly 300 million subscribers.

According to Seol, Park, Lee, and Yoon (2012), BDM are used to forecast the new media services between the year 2010-2015, using the questionnaires of the theory of the niche. This study was based on Korean provider, which consists of digital cable TV (DCATV), satellite TV and new-emerging competitors, internet protocol TV (IPTV). As a result, the researchers predicted that the satellite TV are facing downside of demands in 2012. In moderate-competition case, IPTV took over DCATV with slightly higher demand. However, for strong-competition scenario, DCATV has a better demand than IPTV.

Islam (2014) has applied BDM to forecast the adoption of photo-voltaic (PV) solar panels in households. The study was conducted in Ontario, Canada. The data collected was not based on historical data because the adoption of PV solar panels are still in early stage. Therefore, the theory in BDM are applied to predict the diffusion of the panels. Hence, the study suggested that younger people with awareness in renewable source are more prone to adopt PV solar panels. In addition to this study, the result of word-of-mouth effect has a significant impact in the adoption rates.

S. Li, Chen, and Zhang (2017) used Generalised BDM to forecast electric vehicles in China. The objective of the study was to relate the number of charging stations with the diffusion sales of electric vehicles. The results show that in the earlier stage and developing stage of electric vehicles' sales, faster growth of sales can be achieved by having developed charging stations. According to the forecast result, the cumulative sales of electric vehicles are expected to achieve five millions approaching the end of 2020.

Y. Li, Ma, and Li (2017) conducted similar research by forecasting Chinese electric vehicles using Generalised BDM. The researchers forecasted the product with low presence of data which is only seven data of electric vehicles. Despite the use of low number of data, the forecasting results followed cumulative sales volume of Chinese electric vehicle closely. This means that Generalised BDM can be used to forecast the product with low presence of data and can be used as a reference to this study.

Recently, Grasman and Kornelis (2019) applied stochastic BDM to forecast product sales for stocks management. The model accuracy was estimated using 95% confidence interval which contains about 95% of the data. The results showed that the model was acceptable in estimating future sales. Consequently, reducing the risk of overestimation of stocks.

Generally, BDM had been used in various areas, from medical areas to telecommunication and vehicles. Even though BDM are introduced in 1960s, its applications are still relevant to be used to forecast new product after five decades. The applications of the

BDM model used in tourism studies were found in Hsiao et al. (2009) and Kunc (2009) as mentioned in Section 2.2.3. However, the study did not focus on the new product but on the new event held in the theme parks and wine tourism. These studies supported that BDM is also applicable in tourism industry which will be applied to forecast the new tourism product in Malaysia in this research.

2.3.2 Grey Forecasting Model

Grey System theory was firstly proposed by Deng Julong in 1982 (Ju-Long, 1982). This theory able to work with the system with information scarcity and uncertainty (Sun X, Sun W, Wang, Zhang, & Gao, 2016). Julong (1989) mentioned that grey theory consists of the following scopes; grey relational space, grey generating space and grey forecasting. This thesis will focus on grey forecasting which uses grey model to forecast the new product.

This section will discuss on the previous application of the grey model. G. D. Li, Wang, Masuda, and Nagai (2011) supported that grey model requires only small number of data (four data). Besides, the researchers mentioned that the model has simple calculation and can use random sample data set. This study forecasted short term load forecasting for electrical power using first order grey model with one variable, GM (1,1), and second order grey model with one variable, GM (2,1). In addition, this study used only four data to forecast the next day daily electricity load. The result showed that GM (2,1) performed better than GM (1,1) and emphasised that accurate forecast can be made using limited number of data available.

Ou (2012) studied on improved grey forecasting model based on genetic algorithm (GAIGM) to forecast agricultural output. The data provided by the Annual Report of the Council of Agriculture Executive Yuan, were divided into two parts; 1998 – 2008 which is the in-sample data set and 2009 to 2010 for the out-of-sample data set. The former data was used to forecast agricultural output and the latter was used to compare the performance of the model with its new data sets. Ou (2012) concluded that the GAIGM (1,1) is better model compared to GM (1,1) and IGM (1,1) and also suitable model to forecast the agricultural output in Taiwan.

Xia and Wong (2014) studied grey forecasting model in fashion retailing. Point-of-sales (POS) data were taken from three retailers selling high-ended, medium and basic fashion items. Then, the researchers proposed seasonal discrete grey model (SDGM) to suit the seasonality of fashion industry. As a conclusion of this study, the proposed model of SDGM (1,1) has the best performance. The model also has the solution of seasonality and solve the problem with inadequate data.

Intharathirat, Abdul Salam, Kumar, and Untong (2015) forecasted municipal solid waste (MSW) quantity in Thailand using multivariate grey models. As a result, grey model with convolution integral, GMC (1,5) is the most accurate which gives the mean absolute percentage error (MAPE) of 1.16%. In this study, the researchers predicted the MSW collection increase 1.40% per year which is about 40 000 tonnes per day in 2013 to about 50 000 tonnes per day in 2030. The most important factor that affecting the MSW increment is the population density, followed by urbanisation, employment, and household size.

Other than that, grey-Markov model was used by Sun X et al. (2016) to predict the annual foreign tourist arrival in China. The data were collected from China National Tourism Administration starting from 1997 until 2003. Cuckoo-Markov Chain-Segment grey Model, CMCSGM (1,1) model was considerably more efficient and reliable than the conventional Markov Chain-grey Model, MCGM (1,1).

Ene and Öztürk (2017) used grey model to forecast return flow of end-of-life vehicles. This study was based on the data from twelve regions in Turkey and the data were collected from Turkish Statistical Institute (TURKSTAT). The study found that the number of registered vehicles are higher than the number of discarded vehicles. This showed that there is an increment in the number of vehicles. Moreover, the vehicles are being sold in secondary market. Considering the data used was a real data, the model gave a good result with the accuracy of 90.8%, which means that the proposed model have a high accuracy to the forecast of return flow end-of-life vehicles in Turkey.

Dang H, Nguyen, Wang, Day, and Dang T (2020) applied grey theory in the study of medical tourism. Data from six major medical tourism destinations in Asia are used. The study found that there is increasing in the number of visitors due to medical tourism purposes in the future. Besides, the researchers highlighted that Thailand will be the main destination of medical travelers compared to Malaysia, India, Singapore, South Korea and Taiwan. The results also mentioned that medical facilities and tourism sources play a bigger role while cost and marketing does not give significant role in promoting medical tourism industry.

2.3.3 Grey Bass Forecasting Model

Z. X. Wang (2013) introduced grey Bass model to improve the accuracy of forecasting of new product. In this study, Z. X. Wang (2013) compared grey Bass power model with traditional grey Bass model. Wang conducted the study on blog's diffusion in China from the year 2002 until 2007 and founded that the grey Bass power model has higher accuracy than the traditional grey Bass model. Wang also suggested that further variety of study can be conducted in the future using the proposed model.

Besides, Ismail, Abu, and Sufahani (2016) introduced the combination of Bass diffusion model with grey theory in forecasting the automobile industry in Malaysia. The researchers discussed about the latest car model in 2010 from Perusahaan Otomobil Nasional Berhad (PROTON), named Proton Inspira. However, Proton Inspira was categorised as no historical data, so, comparative study of Proton Wira aeroback were used. As a result, Proton Wira aeroback can be used to represent Proton Inspira and the researchers forecasted that the number of sales of Proton Inspira increased after the launching and decreased after the peak demand. Even though automobile and tourism industry are relatively different, this study can be reflected as a reference due to the study about the new product. Moreover, both forecasting model, Bass diffusion model and grey forecasting model will be applied to the study of the new tourism product so that the applicability of the model in the tourism industry could be evaluated.

2.4 Parameter Estimation Method

The three parameters involve in Bass diffusion model and grey Bass forecasting model are potential market, m, coefficient of innovation, p, and coefficient of imitation, q. Generally, there are four estimation procedures to estimate parameters in Bass model. The estimation procedures consist of ordinary least square (OLS), non-linear ordinary square (NLS), maximum likelihood (MLE), and algebraic estimation (AE) (Leifer, Mahajan, & Wind, 1987). When Bass model was first introduced, Bass (1969) applied OLS procedure and OLS is the simplest estimation for the model compared to NLS, MLE and AE. According to Satoh (2000), NLS procedure is suggested to be the best fit to the data. However, Leifer et al. (1987) mentioned that the parameters estimated from MLE and NLS requires further judgments and another AE procedure. Therefore, OLS estimation is chosen to be used in this study because it is easy to be implemented and is explained in Section 3.4.

2.5 Forecast Evaluation Method

In real life application, accuracy of forecast is important because inaccurate forecasts are costly (Klimberg, Sillup, Boyle, & Tavva, 2010). Forecast evaluation is a method used to measure the accuracy of forecast. There are many forecast evaluation methods have been used in the past, such as mean absolute percentage error (MAPE), root mean square error (RMSE), and relative absolute error (RAE). However, there is no exact answers on which methods provide the best forecasting evaluation because the measures of forecast accuracy are not fully applicable and can give misleading results (Hyndman & Koehler, 2006). The author stated that mean absolute deviation (MAD), MAPE, and RMSE are applicable to be used in the same set of data and they are simple methods that are widely applied. Klimberg et al. (2010) mentioned that MSE and RMSE is affected by the magnitude of data when evaluating the forecast. Lower number of data will affect the forecast error when the value of data is high.

Ou (2012) and Ding, Hipel, and Dang (2018) applied MAPE and RMSE to evaluate the forecast on agricultural output in Taiwan and on China's electricity usage, respectively. Xia and Wong (2014) applied mean squared error (NMSE) and MAPE. Accuracy of forecast in G. D. Li et al. (2011) was measured using MAPE, RMSE, and Theil's U statistic. For Theil's U statistic, if the value is 0, the error is lower. Meanwhile, if the value is 1, the forecasting ability is bad. In the application of grey Bass forecasting model by Z. X. Wang (2013) to forecast blog scale in China, the author used average precision for forecast evaluation. It can be concluded that various methods have been used to measure the forecast. In this study, the data collected from Tanah Aina Sdn. Bhd. is positive and the data consists of large values. Therefore, MAPE will be applied because of its simplicity.

2.6 Summary

This chapter reviews upon the studies done by previous researchers relating to the new tourism product demand forecasting. It starts with the review of demand forecasting, tourism demand forecasting and followed by the tourism product forecasting. Then, the review on application of Bass diffusion model and grey forecasting model are presented.

Based on the discussion in this chapter, the author found the gap of this study with previous literature. There are limited number of previous studies related to tourism product, especially on the new tourism product forecasting. Therefore, this research will be conducted further. The derivation of Bass diffusion model, grey forecasting model and the grey Bass forecasting model will also be discussed in details in Chapter 3.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

In this chapter, the methodology of the Bass diffusion and grey forecasting model are explained thoroughly with the equations and procedures. Grey forecasting model is not being used in this study for forecast but will be introduced in this chapter. Then, grey Bass forecasting model is discussed. This chapter ends with forecasting evaluation and the conclusion.

3.1.1 Operational Framework

The operational framework of this study starts with first phase; data collection where the author has the discussion with the management of Tanah Aina and Tourism Pahang. In second phase, after the collection of data, the data is analysed using Bass diffusion model and grey Bass forecasting model. The parameters m, p, and q are estimated accordingly. Each of the procedures of these models are detailed further in Section 3.2 and Section 3.8. Then, the forecasts using the models are done. If the data is satisfied, mean absolute percentage error (MAPE) is applied for forecast evaluation in the third phase. Otherwise, the procedure of the data analysis needs to be repeated. In the final phase, the models will be compared and the results are discussed so the conclusion can be made. The operational framework of the research is summarised in Figure 3.1.

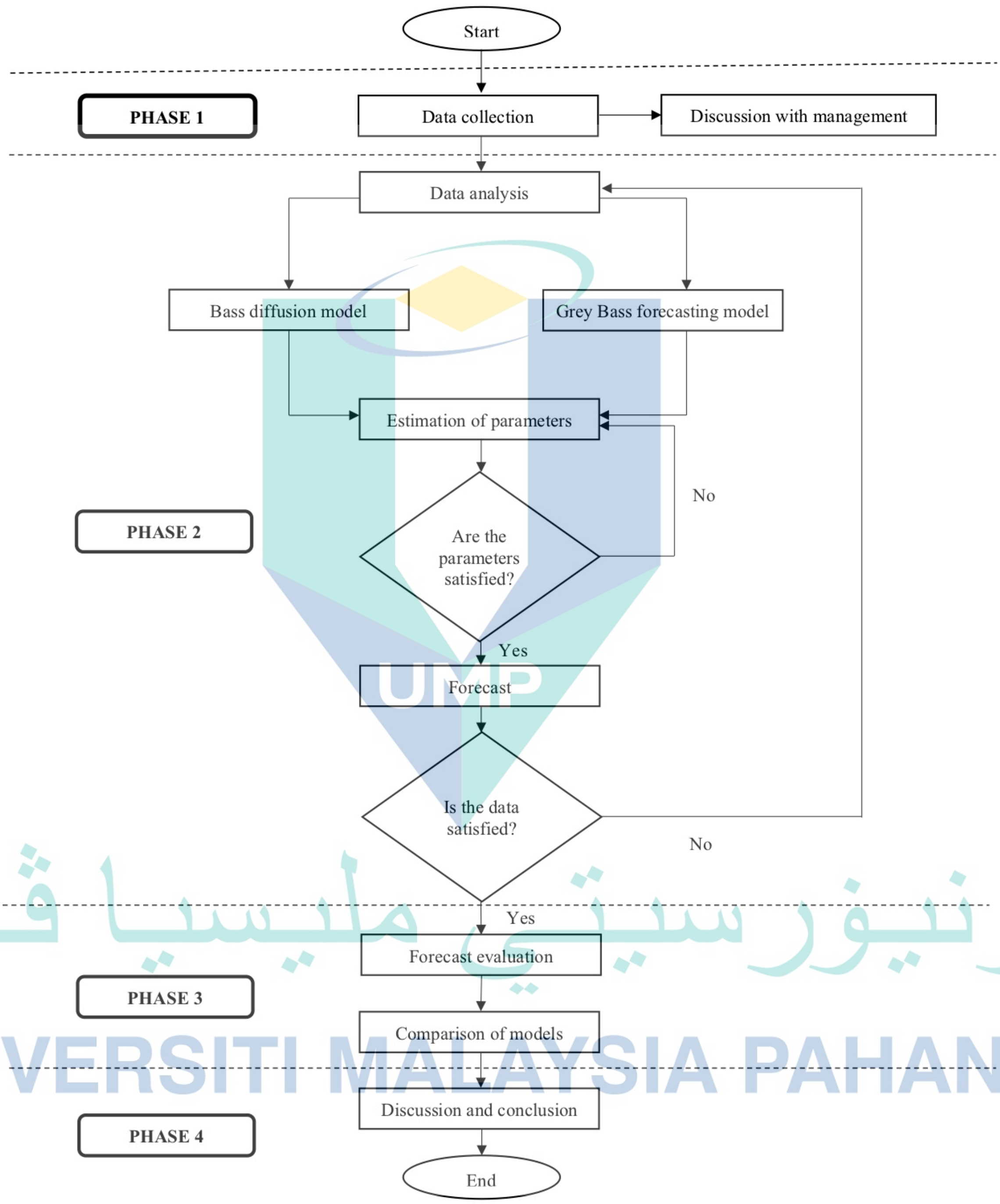

Figure 3.1 Flowchart of operational framework

3.2 Bass Diffusion Model (BDM)

Bass (1969) constructed a model, named Bass diffusion model (BDM), in order to forecast the early purchase of new products. Bass model pointed two types of users; innovators and imitators. Innovators, solely depend on their independent decisions while imitators are influenced by other people in the society as explained in Chapter 1. Besides, Bass classified the imitators into four, namely, early adopters, early majority, late majority, and laggards. BDM is widely applied because of its ability to work with small number of data, which is the main concern when working with the new product. Therefore, BDM is proposed in this study to forecast the new tourism product demand based on the number of visitors to the place.

3.2.1 Derivation of Bass Diffusion Model

BDM is firstly proposed as

$$\frac{f(t)}{1-F(t)} = p + \left(\frac{q}{m}\right) Y(t) \qquad 3.1$$

where

$f(t)$ = the portion of the potential market that adopts at time t

$F(t)$ = the portion of the potential market that has adopted up to and including time t (cumulative)

t = time from product launch and assumed to be non-negative

m = potential market (ultimate number of purchases of product)

p = coefficient of innovation

q = coefficient of imitation

$Y(t)$ = number of previous buyers at time t

Equation (3.1) is proposed based on the theory of 'the probability that an initial purchase will be made at time given that no purchase has yet been made is a linear function of the number of previous buyer' (Bass, 1969).

Given that $f(t)$ is the time derivation of $F(t)$;

$$f(t) = \frac{d[F(t)]}{dt} \tag{3.2}$$

where $f(t)$ is probability density function (pdf) and $F(t)$ is cumulative distribution function (cdf).

$$F(t) = \int_0^t f(t)dt, F(0) = 0$$

Then, $Y(t)$ which is the total number of purchasing in interval $(0, t)$ is written as

$$Y(t) = \int_0^t S(t)dt = m\int_0^t f(t)dt = mF(t) \tag{3.3}$$

where the number of adopters is equal to the number of sales at time t,

$$S(t) = mf(t) \tag{3.4}$$

Using equations (3.3) and (3.4), equation (3.1) can be rewritten as

$$f(t) = \big[p + qF(t)\big]\big[1 - F(t)\big] \tag{3.5}$$

$f(t)$ can be found by solving non-linear differential equation in equation 3.5.

Substituting equation (3.5) into equation (3.2),

$$\frac{d[F(t)]}{dt} = p + (q - p)F(t) - q\big[F(t)\big]^2$$

$$\int dt = \int \frac{1}{p + (q - p)F(t) - q\big[F(t)\big]^2} dF(t)$$

$$t + c = \int \frac{1}{(p + qF(t))(1 - F(t))} dF(t) \tag{3.6}$$

Using partial fractions, we solve the right hand side (RHS) of equation (3.6) as

$$t + c = \int \left[\frac{q}{p + q}\right]\left[\frac{1}{p + qF(t)}\right] + \left[\frac{1}{p + q}\right]\left[\frac{1}{1 - F(t)}\right] dF(t)$$

$$-(t + c)(p + q) = \ln\left(\frac{q - qF(t)}{p + qF(t)}\right)$$

$$\big(p + qF(t)\big)e^{-(t+c)(p+q)} = q - qF(t) \tag{3.7}$$

Let $e^{-(t+c)(p+q)} = \mu$, substitute into equation (3.7),

$$p\mu + qF(t)\mu = q - qF(t)$$

$$F(t) = \frac{q - p\mu}{q\mu + q}$$

$$\therefore F(t) = \frac{q - pe^{-(t+c)(p+q)}}{q\big(e^{-(t+c)(p+q)} + 1\big)}. \tag{3.8}$$

$F(t = 0) = 0$, equation (3.8) can be written as

$$0 = \frac{q - pe^{-c(p+q)}}{q + qe^{-c(p+q)}}$$

$$c = -\left[\frac{1}{p+q}\right] \ln \frac{q}{p}. \tag{3.9}$$

Substituting equation (3.9) into equation (3.8), we have

$$F(t) = \frac{q - pe^{-\left[t + \left(\frac{-1}{p+q}\right)\left(ln\frac{q}{p}\right)\right](p+q)}}{q + qe^{-\left[t + \left(\frac{-1}{p+q}\right)\left(ln\frac{q}{p}\right)\right](p+q)}} \tag{3.10}$$

Letting $\alpha = e^{-\left[t + \left(\frac{-1}{p+q}\right)\left(ln\frac{q}{p}\right)\right](p+q)}$. Then, simplifying α, we have

$$\alpha = \frac{q}{p}e^{-t(p+q)}$$

Equation (3.10) can be written as

$$F(t) = \frac{q - p\alpha}{q + q\alpha} \tag{3.11}$$

Then, substituting α, equation (3.11) becomes

$$F(t) = \frac{1 - e^{-t(p+q)}}{1 + \frac{q}{p}e^{-t(p+q)}} \tag{3.12}$$

Substituting equations (3.12) into (3.5) and let $u = e^{-t(p+q)}$,

$$f(t) = p + (q - p)\left[\frac{1 - u}{1 + \frac{q}{p}u}\right] - q\left[\frac{1 - u}{1 + \frac{q}{p}u}\right]^2 \tag{3.13}$$

Substituting $u = e^{-t(p+q)}$, equation (3.13) becomes,

$$f(t) = \left[\frac{(p+q)^2}{p}\right]\left[\frac{e^{-t(p+q)}}{1 + \frac{q}{p}e^{-t(p+q)}}\right] \tag{3.14}$$

Substituting equation (3.14) into equation (3.4), sales at t becomes,

$$S(t) = m\left[\frac{(p+q)^2}{p}\right]\left[\frac{e^{-t(p+q)}}{1 + \frac{q}{p}e^{-t(p+q)}}\right] \tag{3.15}$$

We have $S(t) = mf(t)$ is the number of adopters at time t and $Y(t) = mF(t)$ is the cumulative number of adopters at time t, which is the cdf. The pdf is given as

$$f(t) = \begin{cases} F(t), & t = 1 \\ F(t) - F(t-1), & t > 1. \end{cases} \tag{3.16}$$

Equation (3.16) is used to forecast the demand of new products since Bass introduced the equation in 1969.

Another formulation of BDM shown as equation (3.15) can be derived from equation (3.4). The number of adopters or sales at t can be written as

$$S(t) = m\left[P(t) - P(t)F(t)\right], \qquad 3.17$$

where $P(t)$ is the probability of purchase at time t.

Given equation (3.3), $Y(t) = mF(t)$, then sales at becomes,

$$S(t) = P(t)\left[m - Y(t)\right], \qquad 3.18$$

Substituting equations 3.1 into 3.18, then it can be written as

$$S(t) = \left[p + \left(\frac{q}{m}\right)Y(t)\right](m - Y(t)), \qquad 3.19$$

The sales at t becomes,

$$S(t) = pm + (q-p)Y(t) - \frac{q}{m}\left[Y(t)\right]^2 \qquad 3.20$$

which is also called basic Bass diffusion equation.

Equation 3.20 also can be presented as

$$S(t) = \underbrace{[p \times \text{remaining potential}]}_{\text{innovation effect}} + \underbrace{[q \times \text{adopters} \times \text{remaining potential}]}_{\text{imitation effect}}$$

where $S(t)$ is the sales or number of adopters at time t, $p\left[m - Y(t)\right]$ is the innovation effect and $q\left(\frac{Y(t)}{m}\right)\left[m - Y(t)\right]$ is the imitation effect. At $t = 0$, $S(t) = pm$ where pm is the total number of buyers begin by innovators.

Equation 3.20 was used for forecasting demand of new products. In addition, Bass (1969) used theory of diffusion in order to formulate time of peak sales and magnitude of peak sales for new product. The time and magnitude of peak sales are derived as follow:

Differentiating equation 3.15,

$$S'(t) = \frac{\frac{m}{p}(p+q)^3 e^{-t(p+q)}\left(\frac{q}{p}e^{-t(p+q)} - 1\right)}{\left(\frac{q}{p}e^{-t(p+q)} + 1\right)^3} \qquad 3.21$$

$S'(t) = 0$, is when the sales rate reaches its peak, so we have

$$\frac{\frac{m}{p}(p+q)^3 e^{-t(p+q)}\left(\frac{q}{p}e^{-t(p+q)}-1\right)}{\left(\frac{q}{p}e^{-t(p+q)}+1\right)^3} = 0$$

Simplifying,

$$t^* = \ln\frac{q}{p}\left(\frac{1}{p+q}\right) \qquad 3.22$$

Substituting time of peak sales from 3.22 into 3.15 to get the magnitude of peak sales,

$$S(t)^* = m\left[\frac{(p+q)^2}{p}\right]\left[\frac{e^{-\left(\ln\frac{q}{p}\left(\frac{1}{p+q}\right)\right)(p+q)}}{\left(1+\frac{q}{p}e^{-\left(\ln\frac{q}{p}\left(\frac{1}{p+q}\right)\right)(p+q)}\right)^2}\right] \qquad 3.23$$

Simplifying equation 3.23,

$$S(t)^* = m\left[\frac{(p+q)^2}{p}\right]\left[\frac{\left(\frac{p}{q}\right)}{\left(1+\left(\frac{q}{p}\right)\left(\frac{p}{q}\right)\right)^2}\right]$$

$$S(t)^* = \left[\frac{m(p+q)^2}{4q}\right] \qquad 3.24$$

From equation 3.20, Bass concluded that the number of purchase at time t was

$$S(t) = pm + (q-p)Y(t) - \frac{q}{m}[Y(t)]^2$$

where $S(t)$ is a function of cumulative adopters, $Y(t)$.
Optimal time at peak sales is $t^* = \ln\frac{q}{p}\left(\frac{1}{q+p}\right)$ and the size of peak sales is $S(t)$=$\frac{m(p+q)^2}{4q}$.

3.3 Parameter Estimation

In BDM equation, the parameters which required to be estimated are the coefficient of innovation p, coefficient of imitation q and potential market m. The diffusion of product is successful when $p \leq q$ because the adoption curve reaches its peak points. However, in the opposite case of $p \geq q$, the adoption curve will not reach its peak points and remains to grow. Then, resulting in the diffusion of product to be unsuccessful (Bass, 1969; Mahajan & Muller, 1979).

Mahajan et al. (1990) stated that the diffusion of analogous product needs to be analysed before using the parameters for new product forecasting. The procedure in choosing the best parameters are as follows:

1. The reasonability of the parameter. For a successful diffusion, both p and q need to be positive and $p \leq q$. The value for both also must be in the interval of [0,1].
2. The potential market m should be equal or exceed first purchase in time series.
3. Comparison of mean absolute percentage error (MAPE) between actual and forecast data.

The estimation methods that will be used in this study is ordinary least square (OLS) and is explained in Section 3.4.

3.4 Ordinary Least Square Estimation

The ordinary least square (OLS) is commonly used for estimation parameters in linear relations. Bass (1969) stated that this estimation is achieved from the discrete or regression of the differential equation of

$$\frac{dY(t)}{dt} = \left[p + \left(\frac{q}{m}\right) Y(t)\right] (m - Y(t)), \qquad 3.25$$

Equation 3.25 is discretised by forward differences as:

$$Y(t_i) - Y(t_{i-1}) = pm + (q-p) Y(t_{i-1}) - \frac{q}{m} Y^2(t_{i-1}), t = 2, 3, ... \qquad 3.26$$

Then,

$$S(i) = a + bY(t_{i-1}) + cY^2(t_{i-1}),$$

where $Y(t_i)$ is the sales at time t, $Y^2(t_{i-1})$ is the cumulative sales through period t_{i-1} and $a = pm$, $b = q - p$ and $c = -\frac{q}{m}$. Hence, $-mc = q$, $\frac{a}{m} = p$, and $b = q - p = -mc - \left(\frac{a}{m}\right)$. We have that $cm^2 + bm + a$ where m can be estimated using the quadratic formula of $\frac{-b \pm \sqrt{b^2 - 4ac}}{2c}$. Then, the parameters of p, q and m can be estimated.

3.5 Procedure of Bass Diffusion Model

The procedure of Bass diffusion model (BDM) starts with the identification of the new product. The next step is data exploration where historical data of the new product is collected. After data exploration, the step on model fitting is performed and the parameters can be calculated directly. Three parameters in BDM are p (innovators), q (imitators) and m (potential market). The estimation of parameters is as described in Section 3.3. The final step is the forecast of the number of sales by substituting the value of parameters estimated in equation 3.20. The procedure of BDM is shown in Figure 3.2.

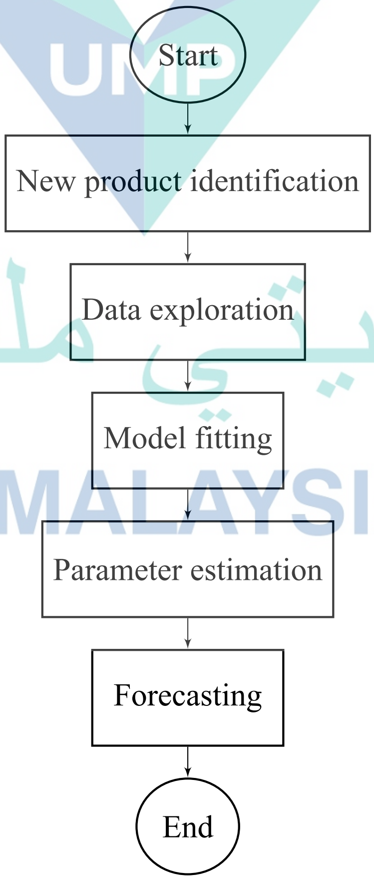

Figure 3.2 Bass diffusion model procedure

3.6 Grey Forecasting Model

Among grey forecasting models, Grey Model (GM) First Order One Variable, GM (1,1), is widely used by researchers (Ou, 2012). Besides, the model requires only small amount of data, as low as four data for forecasting (Ene & Öztürk, 2017). GM (1,1) is a time series forecasting model and its differential equation have a time-varying coefficient. This means that the model is renewed as new data become available to the prediction model (Abu & Ismail, 2015).

Accumulating Generation Operator (AGO) is the key theory of grey theory which helps to smooth the randomness of raw data to become a monotonic increasing function. AGO performs a linear transformation to the original data vector and partially eliminates the fluctuation of the original data series given that the data is strictly positive.

The differential equation used in GM (1,1) is,

$$\frac{dx}{dt} + ax = b \tag{3.27}$$

where x is the background value, $\frac{dx}{dt}$ is the derivative of the unknown function x, and a and b are the parameters. The grey differential equation is

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{3.28}$$

where

$$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1) \tag{3.29}$$

The whitenisation equation (image) of the grey differential equation is given as

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{3.30}$$

The solution of the whitenisation equation is then, which is called the time response function

$$x^{(1)}(t) = \left[x^{(1)}(0) - \frac{b}{a}\right] e^{at} + \frac{b}{a} \tag{3.31}$$

The solution of grey differential equation called time response sequence is given by

$$\hat{x}^{(1)}(k+1) = \left[x^{(1)}(0) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a}, k = 1, 2, ..., n \qquad 3.32$$

where $x^{(1)}(0) = x^{(0)}(0)$ is the initial value.

3.7 Procedure of Grey Forecasting Model

Step 1: Non-negative time series data sequence is generated by

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n))$$

Step 2: Performing an Accumulated Generating Operator (AGO)

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

where $x^{(1)}(k)$ is written as $x^{(1)} = (x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n))$.

Step 3: The background value, $z^{(1)}(k)$, that is the mean of operation on $x^{(1)}$ is given as

$$z^{(1)}(k) = \text{MEAN}(x^{(1)}(k)) = 0.5(x^{(1)}(k) + x^{(1)}(k-1))$$

where $z^{(1)}(k)$ is written as $z^{(1)} = (z^{(1)}(1), z^{(1)}(2), ..., z^{(1)}(n))$.

Step 4: Construct 1st ordinary differential equation (ODE) of GM(1,1) Given that 1st ODE

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

where a is developing coefficient, b is the grey input and the whitening equation of 1st ODE is $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$.

Step 5: Estimate development coefficient a, and grey input b.

Rearrange 1st ODE, let k = 2, 3, …, n, we have

$$x^{(0)}(2) = -az^{(1)}(2) + b$$

$$x^{(0)}(3) = -az^{(1)}(3) + b$$

$$\vdots$$

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

Therefore,

$$y_n = BP_{IB}$$

where

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}, \qquad y_n = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, \qquad P_{IB} = \begin{pmatrix} a \\ b \end{pmatrix}$$

By applying the rules of Ordinary Least Square (OLS),

$$P_{IB} = \left(B^T B\right)^{-1} B^T Y_n$$

Step 6: Solve the whitening equation using Laplace transformation,

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

$$L\left\{\frac{dx^{(1)}}{dt}\right\} + L\{ax^{(1)}\} = L\{b\}$$

$$sx^{(1)}(s) - u(0) + ax^{(1)}(s) = \frac{b}{s}$$

By replacing $u(0)$ where $u(0)$ is an initial value, $x^{(1)}(1) = x^{(0)}(1)$, then,

$$sx^{(1)}(s) - x^{(0)}(1) + ax^{(1)}(s) = \frac{b}{s}$$

$$sx^{(1)}(s) - x^{(0)}(1) + ax^{(1)}(s) - \frac{b}{a} = \frac{b}{s} - \frac{b}{a}$$

$$x^{(1)}(s) = \frac{x^{(0)}(1) - \frac{b}{a}}{s+a} + \frac{\frac{b}{a}}{s}$$

Apply inverse Laplace transformation

$$L^{-1}\left\{x^{(1)}(s)\right\} = L^{-1}\left\{\frac{x^{(0)}(1) - \frac{b}{a}}{s+a}\right\} + L^{-1}\left\{\frac{\frac{b}{a}}{s}\right\}$$

Solution of whitenisation equation is

$$\hat{x}^{(1)}(k) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-a(k-1)} + \frac{b}{a},$$

where $x^{(1)}(1) = x^{(0)}(1)$.

Step 7: Recover data by using inverse AGO

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), k = 1, 2, 3, ...$$

Predicted value is then, written as

$$\hat{x}^{(0)} = \left(\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), ..., \hat{x}^{(0)}(n)\right).$$

The procedure of grey forecasting model is viewed as follows in Figure 3.3.

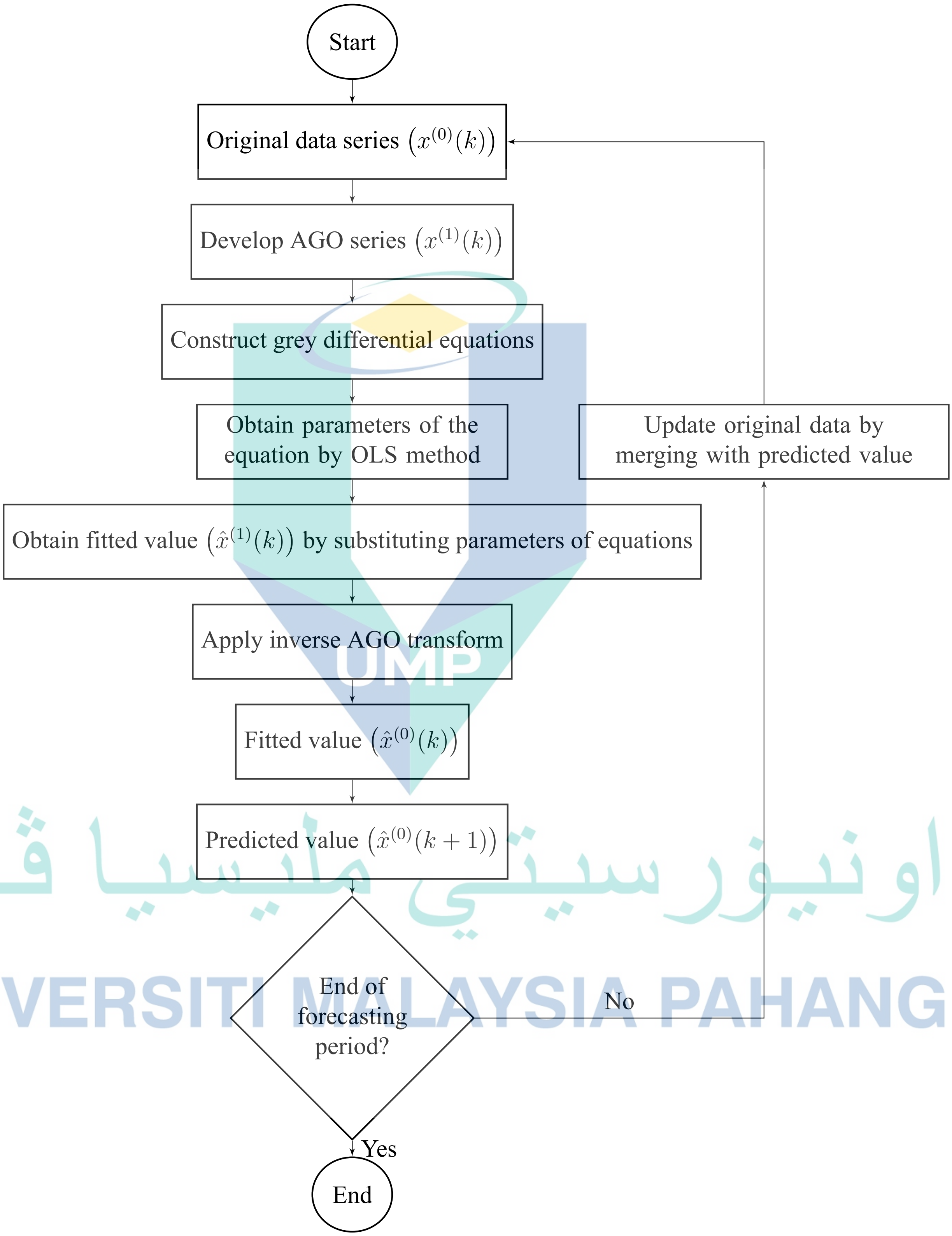

Figure 3.3 Grey forecasting model procedure

3.8 Bass Diffusion Model with Grey Theory

This section will introduce the equation of the combination of Bass diffusion model with grey theory. Bass diffusion model with grey theory is called grey Bass forecasting model in this study. From equations 3.3 and 3.19 of basic Bass diffusion model, the equation can also be written in differential equation form as follows

$$\frac{dY(t)}{dt} = p\left[m - Y(t)\right] + q\left(\frac{Y(t)}{m}\right)\left[m - Y(t)\right] \qquad 3.33$$

where $Y(t)$ is the cumulative sales, m is the potential market, p is the coefficient of innovation and q is the coefficient of imitation. Let $Y(t) = x$, then, equation 3.33 can be written as (Abu & Ismail, 2015)

$$\frac{dx}{dt} = p(m - x) + qx\left(1 - \frac{x}{m}\right) \qquad 3.34$$

where $\frac{dx}{dt}$ is the derivative of the unknown function x, x is the background value of $\frac{dx}{dt}$ and p, q and m are the parameters. Z. X. Wang (2013) introduced the grey Bass forecasting model as

$$x^{(0)}(k) = p(m - z^{(1)}(k)) + qz^{(1)}(k)\left(1 - \frac{z^{(1)}(k)}{m}\right) \qquad 3.35$$

where $z^{(1)}(k) = 0.5(x^{(1)}(k) + x^{(1)}(k-1))$.

The whitenisation equation known as the image of the grey Bass differential equation is given as

$$\frac{dx^{(1)}}{dt} = p(m - x^{(1)}) + qx^{(1)}\left(1 - \frac{x^{(1)}}{m}\right) \qquad 3.36$$

where $\frac{dx^{(1)}}{dt}$ is the white derivative and $x^{(0)}(k)$ is the grey derivative in both equations 3.35 and 3.36. $x^{(1)}$ is the white background value and $z^{(1)}(k)$ is the grey background value. The solution of Bass whitenisation called the time response function is

$$x^{(1)}(t) = \frac{m\left[\left(p + \frac{q}{m}x^{(1)}(0)\right)\left(me^{t(p+q)}\right) - p\left(m - x^{(1)}(0)\right)\right]}{\left(p + \frac{q}{m}x^{(1)}(0)\right)\left(me^{t(p+q)}\right) + q\left(m - x^{(1)}(0)\right)} \qquad 3.37$$

The time response sequence of grey Bass differential equation is

$$\hat{x}^{(1)}(k+1) = \frac{m\left[\left(p + \frac{q}{m}x^{(1)}(0)\right)\left(me^{k(p+q)}\right) - p\left(m - x^{(1)}(0)\right)\right]}{\left(p + \frac{q}{m}x^{(1)}(0)\right)\left(me^{k(p+q)}\right) + q\left(m - x^{(1)}(0)\right)}, k = 1, 2, \ldots, n \qquad 3.38$$

where $x^{(1)}(0) = x^{(0)}(0) =$ initial value.

The procedures for the grey Bass forecasting model are the same as the procedures of grey forecasting model discussed in Section 3.7. The only difference is at Step 4 is Section 3.9 where the parameters p (innovators) and q (imitators) are estimated using least square method because of the parameters present in the equation of Bass diffusion model. The complete procedures will be discussed further in Section 3.9.

3.9 Procedure of Grey Bass Forecasting Model

Step 1: The list of data is given by

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n))$$

Step 2: Performing Accumulated Generation Operation (AGO) to obtain monotonically increasing series such as

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

Step 3: Average creating of blog accumulative number by using

$$z^{(1)}(k) = \text{MEAN}(x^{(1)}(k)) = 0.5(x^{(1)}(k) + x^{(1)}(k-1))$$

Step 4: Parameters p and q are defined using ordinary least square (OLS) method as follows:

If $\hat{a}$=[p, q]^T, is a sequence of parameters, then

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

The least square estimates sequence of the grey Bass differential equation

$$x^{(0)}(k) = p(m - z^{(1)}k) + qz^{(1)}(k)\left(1 - \frac{z^{(1)}(k)}{m}\right)$$

satisfies $\hat{a} = [B^T B]^{-1} B^T Y = [p,q]^T$.

Step 5: Solution of the Bass whitenisation equation.
Integrating the exact solution of equation

$$\frac{dx^{(1)}}{dt} = p(m - x^{(1)}) + qx^{(1)}\left(1 - \frac{x^{(1)}}{m}\right),$$

we have

$$\int_{x(0)}^{x(t)} \frac{1}{pm + (q-p)x - \frac{q}{m}x^2} dx = \int_0^t dt$$

$$t = \left[\frac{1}{p+q} \ln \frac{p + \frac{q}{m}x}{m - x}\right]_{x(0)}^{x(t)}$$

$$t(p+q) = \ln\left(\frac{p + \frac{q}{m}x(t)}{m - x(t)}\right) - ln\left(\frac{p + \frac{q}{m}x(0)}{m - x(0)}\right)$$

The solution for $x(t)$ is

$$\left(e^{t(p+q)}\right)\left(\frac{p+\frac{q}{m}x(0)}{m-x(0)}\right)=\left(\frac{p+\frac{q}{m}x(t)}{m-x(t)}\right)$$

$$x(t)=\frac{\left[\frac{\left(p+\frac{q}{m}x(0)\right)\left(me^{t(p+q)}\right)-p(m-x(0))}{m-x(0)}\right]}{\left[\frac{q\left(m-x(0)\right)}{m\left(m-x(0)\right)}+\frac{\left(p+\frac{q}{m}x(0)\right)e^{t(p+q)}m}{m\left(m-x(0)\right)}\right]}.$$

The time response function of Bass whitenisation is

$$x^{(1)}(t)=\frac{m\left[\left(p+\frac{q}{m}x^{(1)}(0)\right)\left(me^{t(p+q)}\right)-p\left(m-x^{(1)}(0)\right)\right]}{\left(p+\frac{q}{m}x^{(1)}(0)\right)\left(me^{t(p+q)}\right)+q\left(m-x^{(1)}(0)\right)}$$

and the time response sequence of grey Bass differential equation is

$$\hat{x}^{(k+1)}=\frac{m\left[\left(p+\frac{q}{m}x^{(1)}(0)\right)\left(me^{k(p+q)}\right)-p\left(m-x^{(1)}(0)\right)\right]}{\left(p+\frac{q}{m}x^{(1)}(0)\right)\left(me^{k(p+q)}\right)+q\left(m-x^{(1)}(0)\right)}$$

where $k=1,2,...,n$ and $x^{(1)}(0)=x^{(0)}(0)=$ initial value.

Step 6: Recover $\hat{x}^{(0)}(k)$ by using inverse AGO

$$\hat{x}^{(0)}(k)=\hat{x}^{(1)}(k)-\hat{x}^{(1)}(k-1), k=1,2,3,...$$

Then, the predicted value can be written as

$$\hat{x}^{(0)}=\left(\hat{x}^{(0)}(1),\hat{x}^{(0)}(2),...,\hat{x}^{(0)}(n)\right).$$

The procedures of grey Bass forecasting model are presented as follow in Figure 3.4.

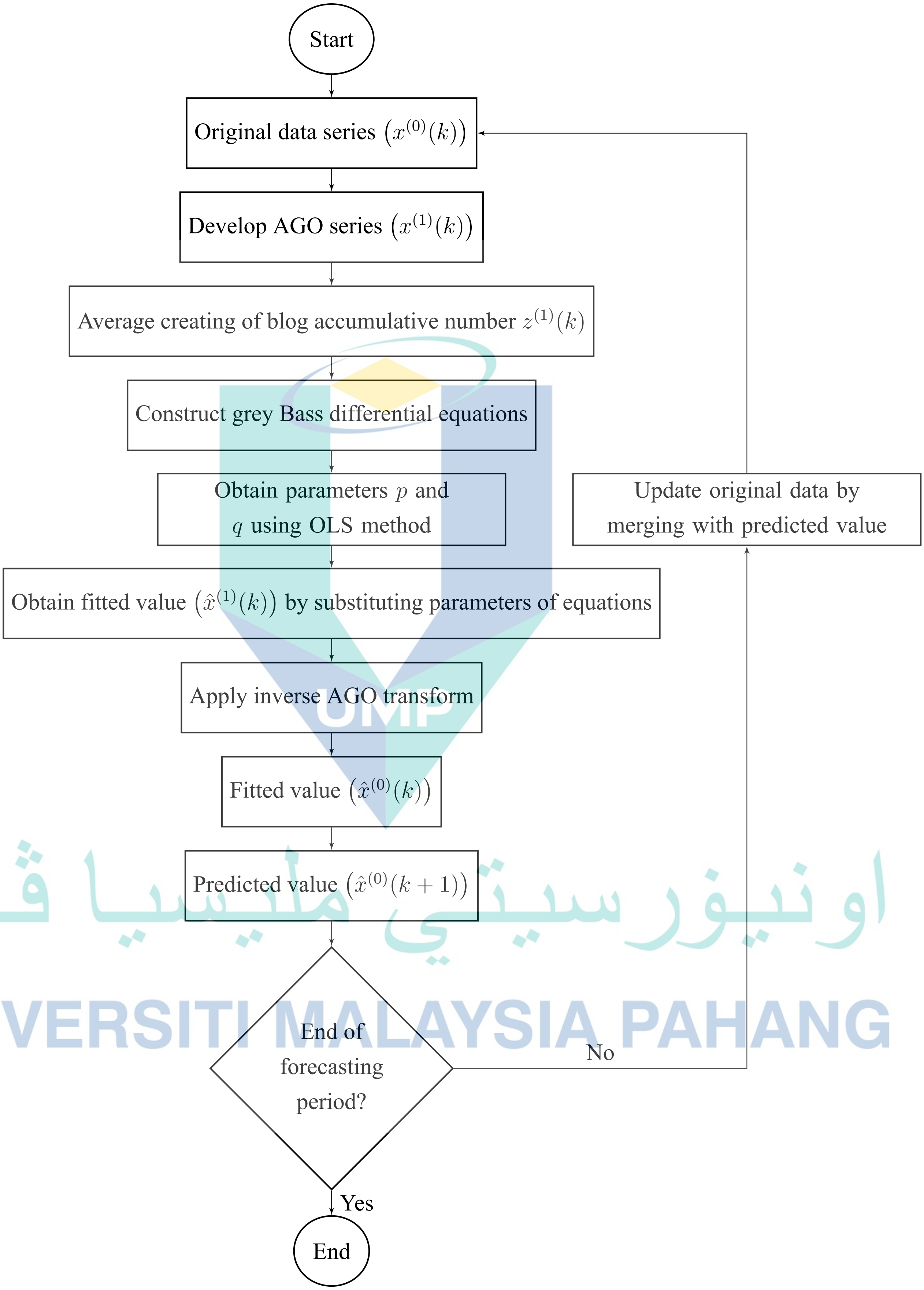

Figure 3.4 Grey Bass forecasting model procedure

3.10 Forecast Evaluation

Forecast evaluation is used to compare the accuracy of two or more different techniques. This measure also helps to find the optimal technique. A forecast error is $e = A - F$, where

$$e = \text{forecast error},$$
$$A = \text{actual value},$$
$$F = \text{forecast value}.$$

In this study, mean absolute percentage error (MAPE) is applied to evaluate the forecast. Cao, Leggio, and Schniederjans (2005) stated that MAPE standardise the error terms to optimise comparisons across variables. MAPE is commonly used in most of forecasting studies because MAPE shows the error in percentage value. Hence, it is easier for researchers to make comparison between the methods. Besides, MAPE is useful when the unit of measurement of actual value is large compared to the other methods (G. D. Li et al., 2011). The model with the lowest value on this estimation is considered as the best forecasting model. The equation of MAPE is

$$MAPE = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{A - F}{A} \right| \tag{3.39}$$

According to Lewis's judgment scale (Lewis, 1982), MAPE value of less than 10% is considered excellent and the values of 10% until 20% are considered good. The values between 20% to 50% are reasonably accepted. Then, MAPE values of greater than 50% gives incorrect results. The Lewis's judgment scale of MAPE is summarised in Table 3.1.

Table 3.1 Scale of Judgment of Forecast Accuracy (Lewis, 1982)

MAPE(%)	Forecasting power
$<$10	Excellent
10-20	Good
20-50	Reasonable
$>$50	Incorrect

3.11 Data Specification

This study uses time series data of ecotourism resorts which are; Tanah Aina Fahad and Tanah Aina Farrah Soraya. The data is from 2014 until 2018. Tanah Aina Fahad and Tanah Aina Farrah Soraya are considered as new tourism products because they are introduced to the public in 2014 and still in their early years of opening. Both of the resorts are located in Raub district, Pahang.

Data collected from Tanah Aina Sdn. Bhd is monthly data of number of visitors from November 2014 until December 2018. The data is then being converted to yearly data to be compared with the number of visitors to Pahang which is annual data. This process is important in the estimation of potential market to Tanah Aina which will be used in Chapter 5. Besides, yearly data is used because this study will forecast the number of visitors to the new tourism products without considering other seasonality factors.

In forecasting, the data need to be split into in-sample and out-sample dataset. In-sample data is used to estimate parameter and model selection meanwhile out-sample data to test the forecasting accuracy (Ou, 2012). In this study, in-sample data is used to estimate the parameters m, p, and q. There is no clear guidance for data splitting. Since this study handles limited number of data with five historical data, the data is split into 2014 until 2017 (four data) as in-sample dataset, meanwhile 2018 (one data) as out-sample dataset. Four data as in-sample dataset agrees with the fact that the minimum number of sample data is four for grey forecasting model (G. D. Li et al., 2011).

3.12 Summary

This chapter discusses briefly about the models used in this research, Bass diffusion model and grey forecasting model. Then, it follows by grey Bass forecasting model and the procedures used in this study. Then, to evaluate the forecast, mean absolute percentage error is applied and the splitting of dataset is explained. As a conclusion, the model with lower value in the method of forecast evaluation will be considered as the best forecasting model.

CHAPTER 4

FORECASTING USING BASS DIFFUSION MODEL AND GREY BASS FORECASTING MODEL

4.1 Introduction

The methodology and procedure of Bass diffusion model (BDM) and grey Bass forecasting model have been discussed in Chapter 3. In this chapter, BDM and grey Bass forecasting model are applied to forecast the new tourism products which are Tanah Aina Fahad and Tanah Aina Farrah Soraya. The three parameters need to be estimated in both models are the coefficient of innovation p, the coefficient of imitation q, and the potential market m. In BDM, these parameters are estimated using ordinary least square (OLS) method, meanwhile in grey Bass forecasting model, m is predicted manually or using analogy (Z. X. Wang, 2013). In this chapter, the same value of m is used for a better comparison of the forecast results between both models. This chapter starts with the descriptions on the data collected from Tanah Aina Fahad and Tanah Aina Farrah Soraya. Then, the parameters are estimated in BDM using OLS and followed by the forecast of the new tourism products in Tanah Aina Fahad and Tanah Aina Farrah Soraya. The procedure is repeated for both products using grey Bass forecasting model. The analysis of results of forecast for both tourism products using BDM and grey Bass forecasting model are compared at the end of this chapter.

4.2 Trends of Visitors to Tanah Aina Fahad and Tanah Aina Farrah Soraya

The data of both eco-tourism products in Raub, Pahang; Tanah Aina Fahad and Tanah Aina Farrah Soraya, are collected from the management of Tanah Aina Sdn. Bhd. As explained in Section 1.2, these two products are suitable for visitors who seek for a short trip away from the city. Besides, nature themes and their accommodations which can serve both small and large groups of visitors are the reasons these resorts have been the visitors' choices.

The author collects monthly number of visitors to Tanah Aina Fahad and Tanah Aina Farrah Soraya which are presented as in Figure 4.1 and Figure 4.1. Both locations are introduced to public in October 2014. Even though they are introduced in the same month and year, Tanah Aina Farrah Soraya has been receiving more overall visitors compared to Tanah Aina Fahad. This is probably due to Tanah Aina Farrah Soraya's location, approximately one hour from Kuala Lumpur.

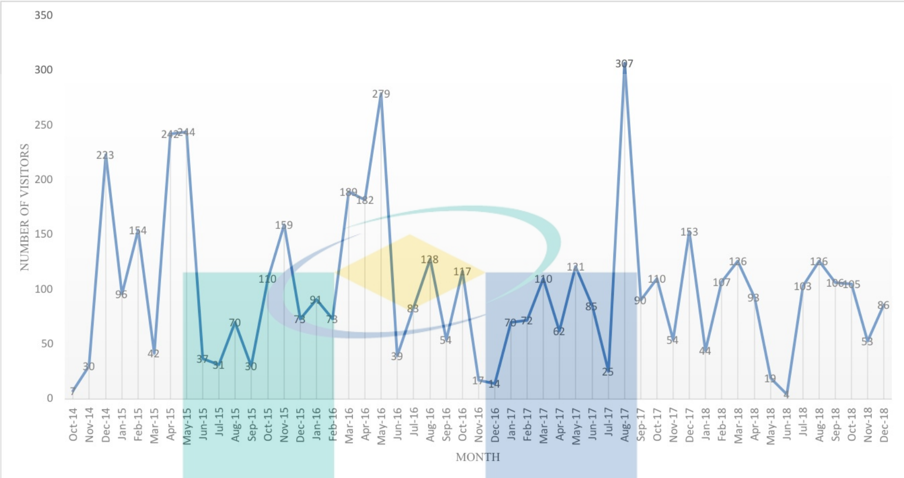

Figure 4.1 Monthly number of visitors to Tanah Aina Fahad from October 2014 until December 2018

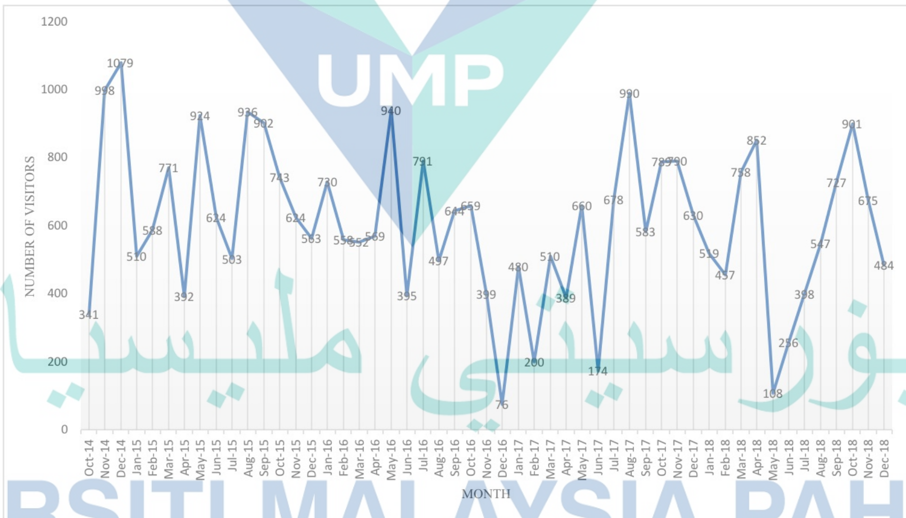

Figure 4.2 Monthly number of visitors to Tanah Aina Farrah Soraya from October 2014 until December 2018

Generally, the number of visitors to tourism places in Malaysia are higher during mid year and at the end of the year due to school holiday's season. In both locations, the number of visitors is higher in the second and third quarter of the year compared to the first and fourth quarter of the year. However, the trend is different in the year 2017. Based on Figure 4.1 and Figure 4.2, the number of visitors to Tanah Aina Fahad and Tanah Aina Farrah Soraya are at peak in August 2017, with 307 and 990 visitors, respectively.

The seasonal number of visitors are usually affected by holiday season and the weather. Heavy rainfall from November to February in the east coast of Malaysia and the locations of these two Tanah Aina resorts in Pahang, are one of the factors of lower visitors during the period. Besides, heavy rainfall which can cause flood affecting people's decision in visiting the tourism places in the east coast region.

Based on the explanation in Section 3.11, these monthly data is converted to yearly data because the author will forecast the number of visitors to the new tourism product without considering other seasonality factors. Yearly data of Tanah Aina Fahad and Tanah Aina Farrah Soraya from 2014 until 2018 are presented in Figures 4.3 and 4.4, respectively.

Figure 4.3 Yearly number of visitors to Tanah Aina Fahad from 2014 until 2018

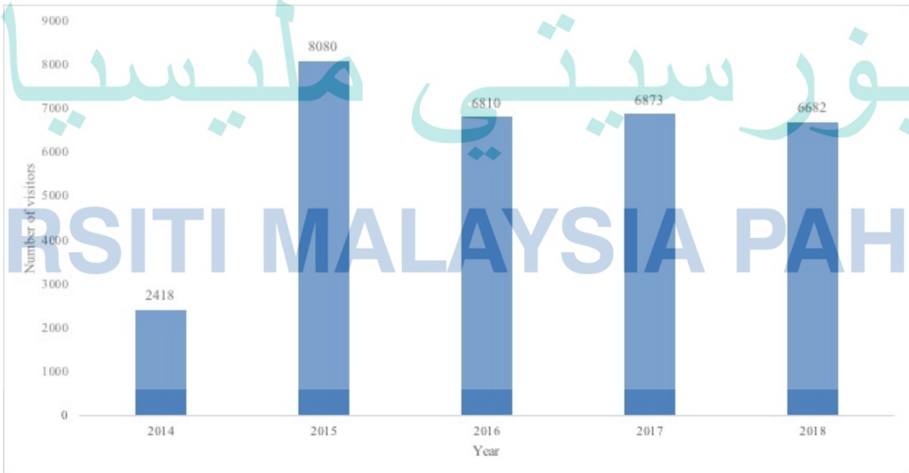

Figure 4.4 Yearly number of visitors to Tanah Aina Farrah Soraya from 2014 until 2018

During the first year of opening to the public in 2014, 260 visitors visited Tanah Aina Fahad and the number increased rapidly for the following year. However, the number of visitors decrease slightly for the consecutive years and it continued to show a downfall in 2018 as shown in Figure 4.3. As there are five data available, this study will consider Tanah Aina Fahad as limited data case.

Based on Figure 4.4, nearly 2500 visitors accommodated Tanah Aina Farrah Soraya in 2014. It showed that the product received a great support from the people compared to Tanah Aina Fahad with only 260 visitors in the first year. The number fluctuated to 8080 in 2015. Then, the visitors decreased in 2016 and facing a slight increment of visitors in 2017. However, the number of visit dropped again in 2018. This situation is probably affected by the lack of funding by the government for tourism industry. Since the data available is only five data, the data of Tanah Aina Farrah Soraya is also considered as limited data.

4.3 Ordinary Least Square Estimation for Tanah Aina Fahad

In BDM, the parameters that need to be estimated before proceeding with the forecasting process are the coefficient of innovation p, coefficient of imitation q, and potential market m as explained in Chapter 3. OLS method is used to estimate the parameters and the analysis is done using MATLAB software. MATLAB code on the estimation of parameters and forecast using BDM is detailed in Appendix B. The results of parameters estimation are shown in Table 4.1.

Table 4.1 Results of parameters estimations for Tanah Aina Fahad in BDM

Parameter	**Value**
m	5891
p	0.0138
q	0.9397

The value of m is 5891 and the values for p and q are 0.0138 and 0.9397, respectively. Based on Section 3.3, p needs to be less than q to indicate that the new product diffusion is successful and the visitors (sales) will continue to grow and reaches its maximum number of visitors. Based on Table 4.1, the value of p is less than q. Hence, these parameters values from the OLS estimation are used to forecast the number visitors to Tanah Aina Fahad.

4.4 Bass Diffusion Model for Tanah Aina Fahad

After the estimation of parameters, the parameters are used to forecast the number of visitors using BDM. This forecast is performed using MATLAB software. Table 4.2 presents the result of 10 years forecast of current and cumulative visitors to Tanah Aina Fahad using BDM.

Table 4.2 Actual and forecasted number of visitors to Tanah Aina Fahad using BDM

Year	Actual current visitors	Forecast current visitors	Actual cumulative visitors	Forecast cumulative visitors
2014	260	133	260	133
2015	1288	318	1548	451
2016	1266	683	2814	1134
2017	1259	1169	4073	2303
2018	972	1397	5045	3700
2019		1101		4801
2020		617		5418
2021		282		5700
2022		116		5816
2023		46		5862
2024		18		5880

Based on Table 4.2, there is an increasing number of visitors from 2014 until it reaches its peak in 2018. After that, the number keep decreasing which follows the growth of the number of new adopters as explained in Section 2.3.1. Actual and forecasted current visitors are shown in Figure 4.5.

From Figure 4.5, direct comparison between actual data and forecasted data can be seen clearly. Actual data reaches its maximum visitors in 2015 and the numbers faced the downfall in the following year. As compared to actual data, forecasted data of BDM takes four years after opening year to reach the maximum number which is 1397 visitors in 2018. Figure 4.6 shows the cumulative visitors to Tanah Aina Fahad.

Figure 4.6 displays the actual and cumulative forecast of visitors to Tanah Aina Fahad. The number of visitors increase since the first year until it reaches the peak number called the saturation level. After 2019, the number of visitors keep decreasing and if the forecast happens at a longer range, there are no visitors visiting the place. At this point, the management need to take action to create new innovation and development to attract more visitors to Tanah Aina Fahad. If the number of visitors to the tourism products and

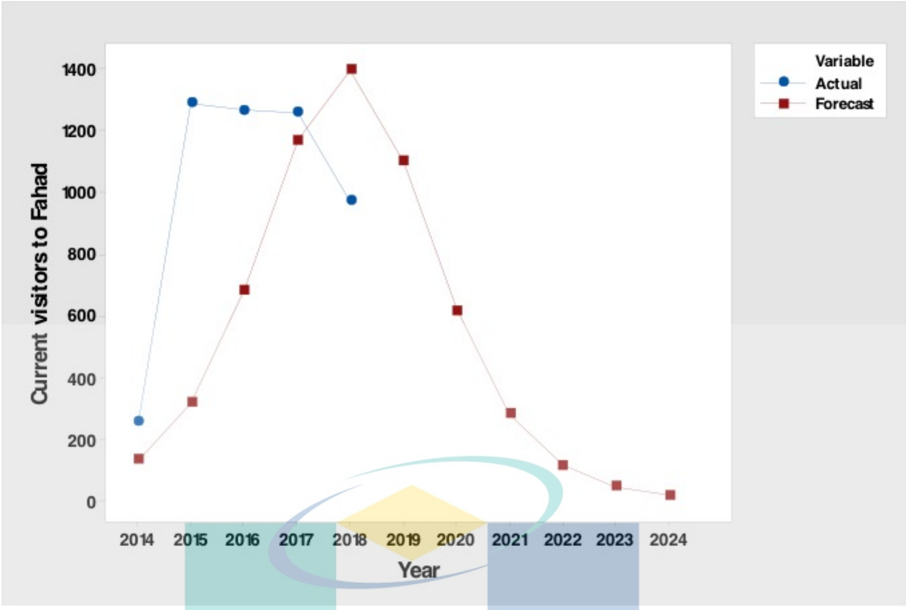

Figure 4.5 Actual and forecasted current number of visitors to Tanah Aina Fahad using BDM

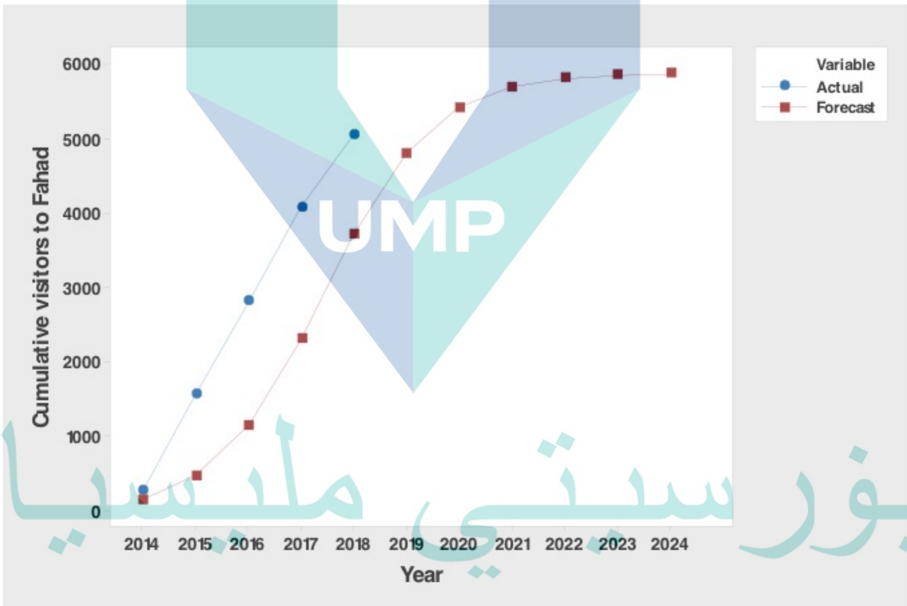

Figure 4.6 Actual and forecasted cumulative number of visitors to Tanah Aina Fahad using BDM

to Malaysia as a whole are affected by the fundings, the government should maintain the allocated budget for the tourism industry. The forecast reveals that the year saturation level is happening in 2018 with 1397 visitors. Therefore, BDM can be applied in forecasting visitors to Tanah Aina Fahad.

4.5 Ordinary Least Square Estimation for Tanah Aina Farrah Soraya

OLS is used in estimating the parameters for Tanah Aina Farrah Soraya data. This data is also analysed using the same code to estimate parameters in Appendix B. The analysis of data yields the results shown in Table 4.3.

Table 4.3 Results of parameters estimation for Tanah Aina Farrah Soraya in BDM

Parameter	Value
m	34076
p	0.0229
q	0.8860

Based on Table 4.3, the values of p and q also show that they satisfy the condition of the new product diffusion to be successful which is $p \leq q$. Therefore, these parameters values are used in BDM to forecast Tanah Aina Farrah Soraya.

4.6 Bass Diffusion Model for Tanah Aina Farrah Soraya

The values of parameters estimated in Section 4.5 using OLS are then used to forecast the number of visitors to Tanah Aina Farrah Soraya using BDM. The forecast is done in MATLAB software and the results of forecast are displayed in Table 4.4.

Table 4.4 Actual and forecasted number of visitors to Tanah Aina Farrah Soraya using BDM

Year	Actual current visitors	Forecast current visitors	Actual cumulative visitors	Forecast cumulative visitors
2014	2418	1226	2418	1226
2015	8080	2693	10498	3919
2016	6810	5098	17308	9017
2017	6873	7406	24181	16423
2018	6682	7469	30863	23892
2019		5216		29108
2020		2780		31888
2021		1272		33160
2022		541		33701
2023		223		33924
2024		91		34015

Table 4.4 presents actual and forecasted visitors to Tanah Aina Farrah Soraya using BDM. The forecast results show there is increasing number of visitors. The forecast reaches maximum in 2018 with 7469 number of visitors before it keeps decreasing after 2018, the peak values because it also follows the concept of BDM where the number of new adopters decrease. The graph of actual and forecasted current visitors as well as cumulative actual and forecasted visitors are shown in Figures 4.7 and 4.8 respectively.

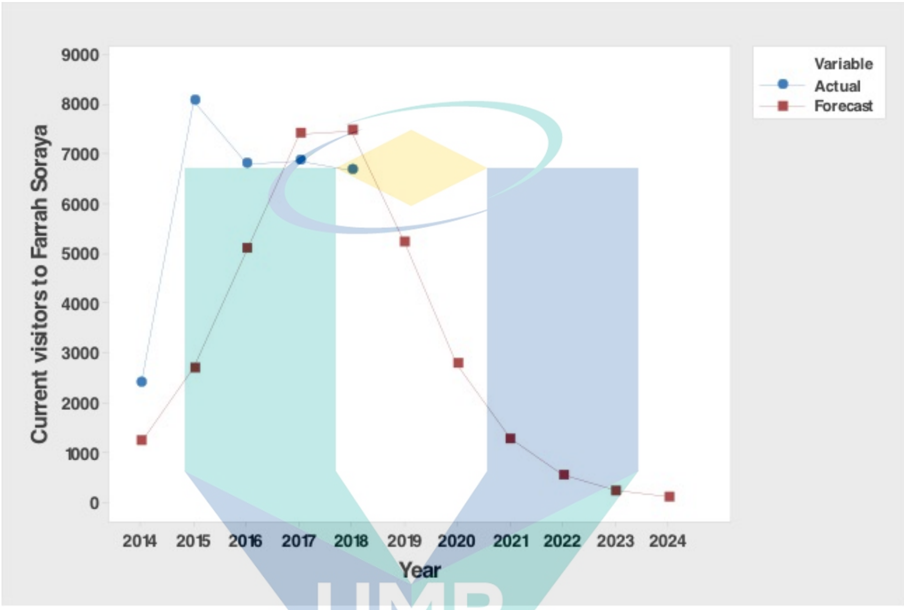

Figure 4.7 Actual and forecasted current number of visitors to Tanah Aina Farrah Soraya using BDM

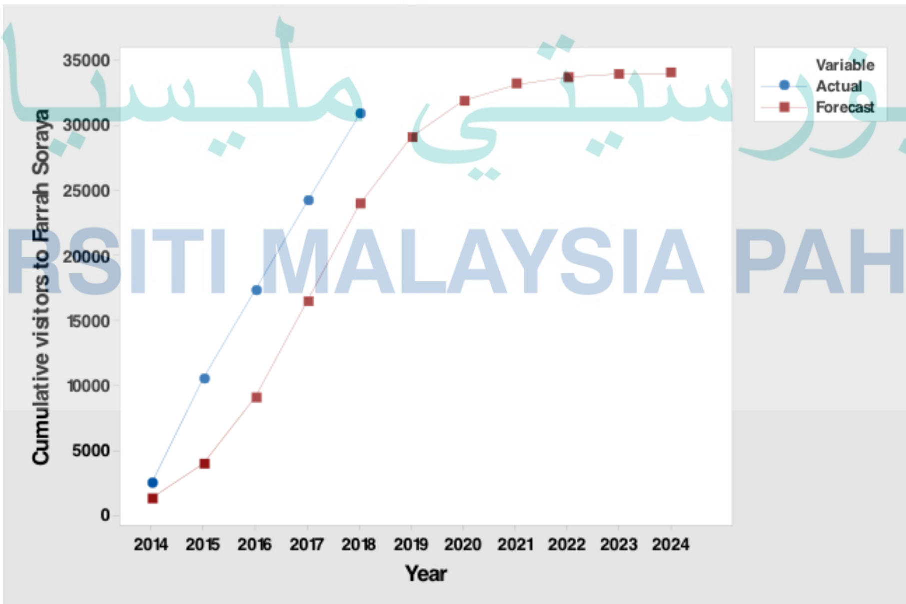

Figure 4.8 Actual and forecasted cumulative number of visitors to Tanah Aina Farrah Soraya using BDM

Figure 4.7 shows actual and forecasted current visitors to Tanah Aina Farrah Soraya. Figure 4.8 plots the cumulative of the actual and forecasted visitors to Tanah Aina Farrah Soraya, hence, a better comparison can be seen. Based on the forecast in Figure 4.7, the number of visitors increase rapidly during the first four years (2014-2017). In 2018, there is a slight increment of visits to the place where the maximum number of visitors are displayed. Then, the value starts to drop in 2019. Comparing both actual and forecasted visitors, the forecast take four years for the number of visitors to reach its maximum value. Based on the Figure 4.8, as the number keeps decreasing approaching 2020, new innovation need to be made in Tanah Aina Farrah Soraya.

4.7 Forecast Evaluation for Bass Diffusion Model Application

As explained in Section 3.10, forecast evaluation are used to compare the accuracy in forecasting. In this study, mean absolute percentage error (MAPE) is used. The data from 2014 until 2017 is used for in-sample data while 2018 for out-sample data for both products. The results from the forecast evaluation are presented in Table 4.5.

Table 4.5 MAPE results for Tanah Aina Fahad and Tanah Aina Farrah Soraya for BDM

Products	**MAPE(%)**	
	In-Sample	**Out-Sample**
Fahad	44	44
Farrah Soraya	37	12

From Table 4.5, MAPE results for Tanah Aina Fahad show that both in-sample and out-sample data give the same value which is 44%. While, for Tanah Aina Farrah Soraya, the MAPE are 37% and 12% for in-sample and out-sample respectively, which reveals that the value of MAPE out-sample is smaller than in-sample data. We mentioned in Section 3.10 that the model with the lowest value from forecast evaluation is considered as the best forecasting model. Based on Table 3.1 which categorised the MAPE, the forecast of Tanah Aina Fahad using BDM is considered reasonable, meanwhile for Tanah Aina Farrah Soraya is considered good. Therefore, comparing the MAPE value of out-sample data, we conclude that BDM is more accurate in forecasting the number of visitors to Tanah Aina Farrah Soraya compared to Tanah Aina Fahad.

4.8 Grey Bass Forecasting Model for Tanah Aina Fahad

In BDM, the parameter of potential market, m is determined using ordinary least square (OLS) estimation meanwhile in grey Bass forecasting model, m is determined manually. Therefore, m = 5891 in BDM is employed and substituted into Step 4 in Section 3.9. The values of p and q are estimated using MATLAB software as detailed in Appendix C. Then, p = 0.1681 and q = 0.5397 are obtained. These parameters are summarised in Table 4.6 and the results of forecast using grey Bass forecasting model are presented in Table 4.7.

Table 4.6 Results of parameters estimation for Tanah Aina Fahad in Grey Bass forecasting model

Parameter	Value
m	5891
p	0.1681
q	0.5397

Table 4.7 Actual and forecasted number of visitors to Tanah Aina Fahad using grey Bass forecasting model

Year	Actual current visitors	Forecast current visitors	Actual cumulative visitors	Forecast cumulative visitors
2014	260	260	260	260
2015	1288	1229	1548	1489
2016	1266	1351	2814	2840
2017	1259	1171	4073	4011
2018	972	823	5045	4834
2019		497		5331
2020		273		5604
2021		142		5746
2022		72		5818
2023		36		5854
2024		18		5872

Table 4.7 displays an actual and forecasted current and cumulative visitors to Tanah Aina Fahad by using grey Bass forecasting model with m = 5891. The results show that for current visitors, the forecast increases from 2014 until 2016 and starts to decrease in 2017. The number of visitors continue to decrease after 2017. The results of forecast is displayed in Figure 4.9.

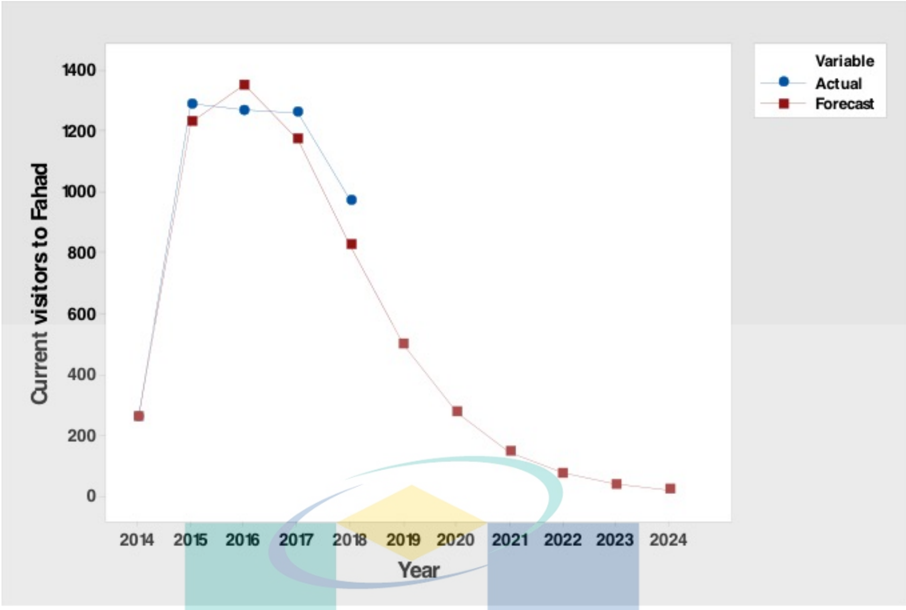

Figure 4.9 Actual and forecasted current number of visitors to Tanah Aina Fahad using grey Bass forecasting model

Figure 4.9 displays the actual and forecasted number of current visitors to Tanah Aina Fahad using grey Bass forecasting model. It is clearly seen that Tanah Aina Fahad is expected to receive its maximum number of visitors which is 1351 in 2016 while the actual maximum number happened in 2015 with 1288 visitors. The number of forecasted visitors will decrease after the peak time visitors. The cumulative plot is shown in Figure 4.10. It displays the actual and forecasted cumulative visitors to Tanah Aina Fahad. From the figure, the rate of increment after 2018 is slower compared to the increment before 2018 because it has reached its saturation level. Besides, there are small differences between actual and forecasted cumulative number of visitors to Tanah Aina Fahad.

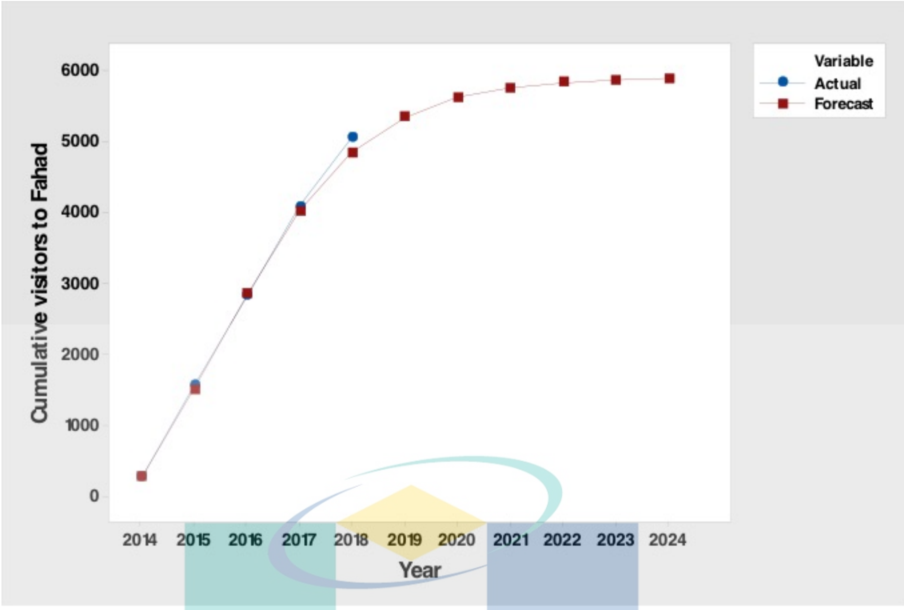

Figure 4.10 Actual and forecasted cumulative number of visitors to Tanah Aina Fahad using grey Bass forecasting model

4.9 Grey Bass Forecasting Model for Tanah Aina Farrah Soraya

Based on the OLS estimation in BDM, the parameters m, p and q are calculated to be 34076, 0.0229 and 0.8860 respectively. The same step applied in forecasting Tanah Aina Fahad using grey Bass forecasting model is applied for Tanah Aina Farrah Soraya. In Tanah Aina Farrah Soraya case, the value of $m = 34076$ is used. From MATLAB software, the values of $p = 0.1986$ and $q = 0.4406$ are obtained and are listed in Table 4.8. The results of forecast for Tanah Aina Farrah Soraya using grey Bass forecasting model are presented in Table 4.8.

Table 4.8 Results of parameters estimation for Tanah Aina Farrah Soraya in grey Bass forecasting model

Parameter	**Value**
m	34076
p	0.1986
q	0.4406

Table 4.9 lists both current and cumulative visitors to Tanah Aina Farrah Soraya based on the forecast from grey Bass forecasting model. The forecast reveals there is rapid increment of visitors from first year, 2014 to 2015. It reaches its maximum number of visitors in 2015 with 7709 visitors. Then, the number slowly decreasing. The current

Table 4.9 Actual and forecasted number of visitors to Tanah Aina Farrah Soraya using grey Bass forecasting model

Year	Actual current visitors	Forecast current visitors	Actual cumulative visitors	Forecast cumulative visitors
2014	2418	2418	2418	2418
2015	8080	7709	10498	10127
2016	6810	7562	17308	17689
2017	6873	6135	24181	23824
2018	6682	4255	30863	28079
2019		2640		30719
2020		1527		32246
2021		847		33093
2022		459		33552
2023		246		33798
2024		131		33929

and cumulative visitors are plotted in Figures 4.11 and 4.12 respectively.

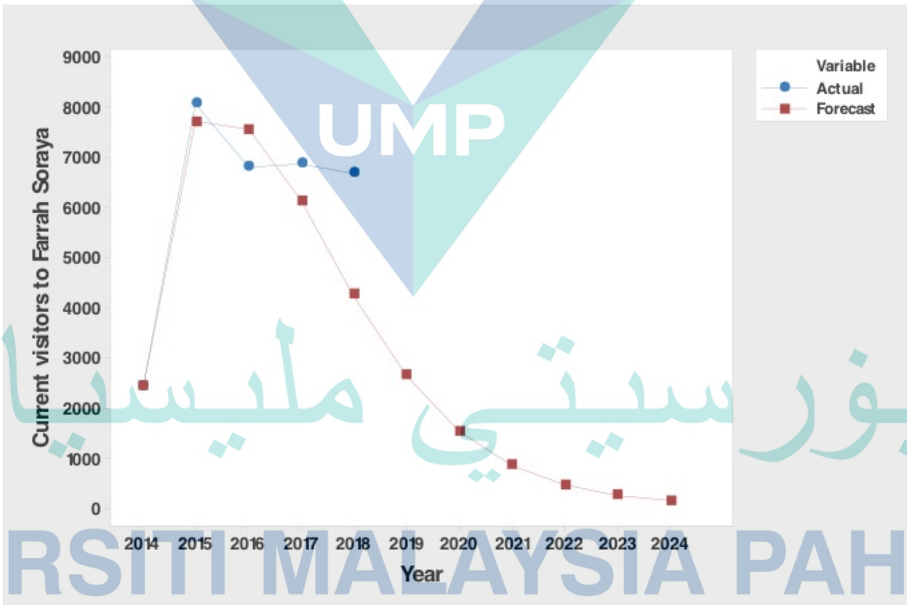

Figure 4.11 Actual and forecasted current number of visitors to Tanah Aina Farrah Soraya using grey Bass forecasting model

Based on Figure 4.11, the comparison between actual and forecast can be clearly seen. In 2015, the number of visitors are forecasted to be slightly lower than the actual visitors. The trend of forecast keep decreasing after 2015. On the contrary, Tanah Aina Farrah Soraya received 6810 visitors in 2016 and an unexpected increased in the number of visitors in the following year based on the actual data.

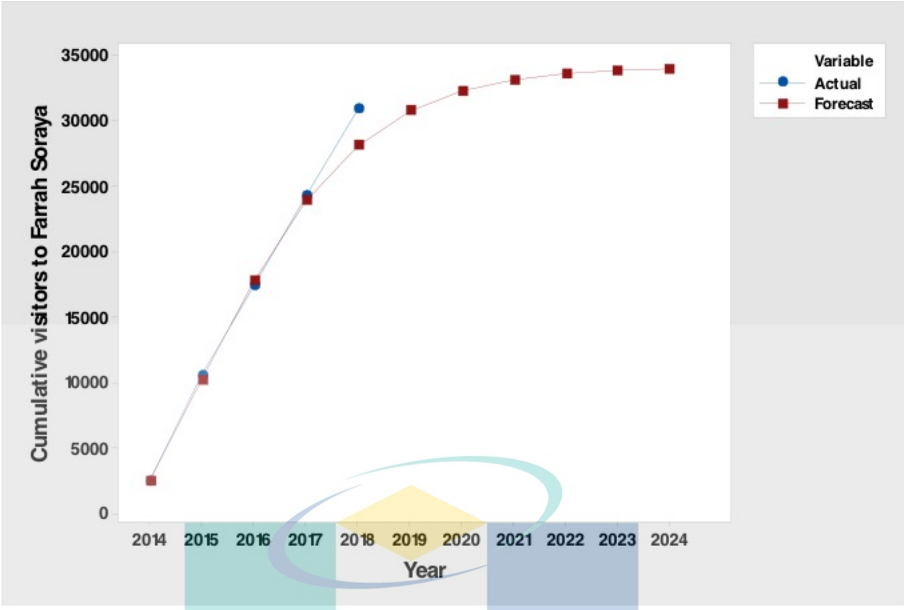

Figure 4.12 Actual and forecasted cumulative number of visitors to Tanah Aina Farrah Soraya using grey Bass forecasting model

Based on Figure 4.12, cumulative forecasted visitors of Tanah Aina Farrah Soraya shows as the time increases, the rate of increment is slower. Therefore, the management is expected to experience in the dropping number of visitors if there is no improvement of attractions in the place.

4.10 Forecast Evaluation for Grey Bass Forecasting Model Application

This section will explain the forecast evaluation using mean absolute percentage error (MAPE). In-sample dataset and out-sample dataset for both Tanah Aina Fahad and Tanah Aina Farrah Soraya are split as the same as in Section 4.7 which are; by years 2014 until 2017 as in-sample dataset meanwhile year 2018 as out-sample dataset. The results of MAPE are presented as in Table 4.10.

Table 4.10 MAPE results for Tanah Aina Fahad and Tanah Aina Farrah Soraya for grey Bass forecasting model

Products	**MAPE(%)**	
	In-Sample	**Out-Sample**
Fahad	5	15
Farrah Soraya	7	36

Based on Table 4.10, the values of MAPE for out-sample data are 15% for Tanah Aina Fahad and 36% for Tanah Aina Farrah Soraya. The value of out-sample dataset is lower for Tanah Aina Fahad than Tanah Aina Farrah Soraya. Comparing the two cases, we can conclude that grey Bass forecasting model is more suitable to forecast Tanah Aina Fahad than Tanah Aina Farrah Soraya.

4.11 Comparison between Bass Diffusion Model and Grey Bass Forecasting Model

This section analyses the performance between BDM and grey Bass forecasting model when using the same potential market, m generated from BDM for both cases of Tanah Aina Fahad and Tanah Aina Farrah Soraya.

4.11.1 Comparison for the Case of Tanah Aina Fahad

The comparisons of both BDM and grey Bass forecasting model are important in order to decide which model perform the best to forecast Tanah Aina Fahad. Mean absolute percentage error (MAPE) is again used to measure the forecast evaluation. The data for Tanah Aina Fahad of 2014 until 2017 are considered as in-sample data and 2018 as out-sample data. MAPE results are listed in Table 4.11.

Table 4.11 Comparison of MAPE for Tanah Aina Fahad forecast

Products	MAPE(%)	
	In-Sample	Out-Sample
BDM	44	44
GBFM	5	15

Table 4.11 shows the value of MAPE for the forecast of Tanah Aina Fahad's visitors using BDM and grey Bass forecasting model. BDM gives the same high value of 44% for both in-sample and out-sample. While, for grey Bass forecasting model, in-sample value is 5% and out-sample value is 15%. The values of MAPE for both samples, for grey Bass forecasting model are lower than BDM. Therefore, grey Bass forecasting model reveals that the model gives a better forecast for Tanah Aina Fahad compared to the forecast using BDM. The number of actual visitors and from BDM and grey Bass model's forecasts are presented in Figures 4.13 and 4.14 for a clearer comparison.

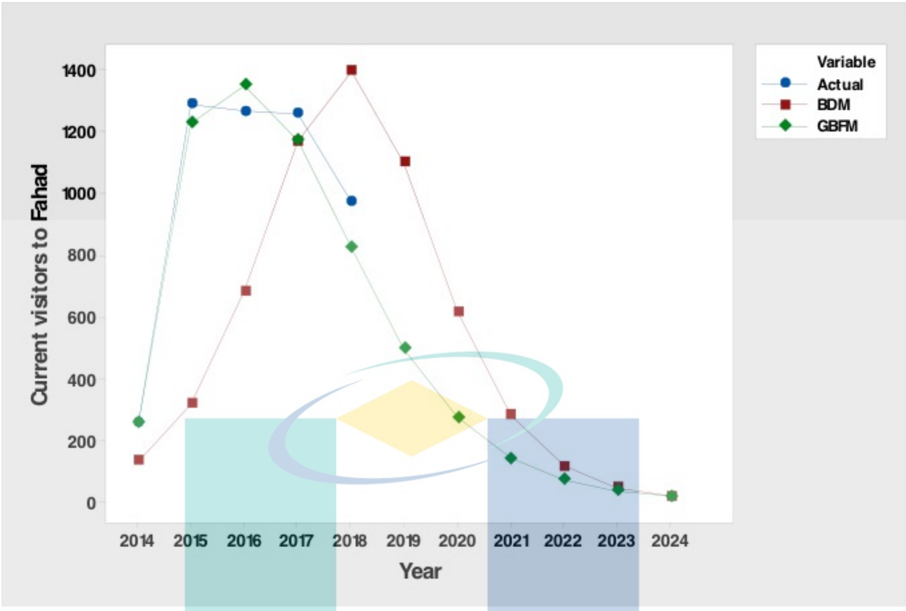

Figure 4.13 Comparison of actual number of visitors to Tanah Aina Fahad with forecasted number using BDM and grey Bass forecasting model

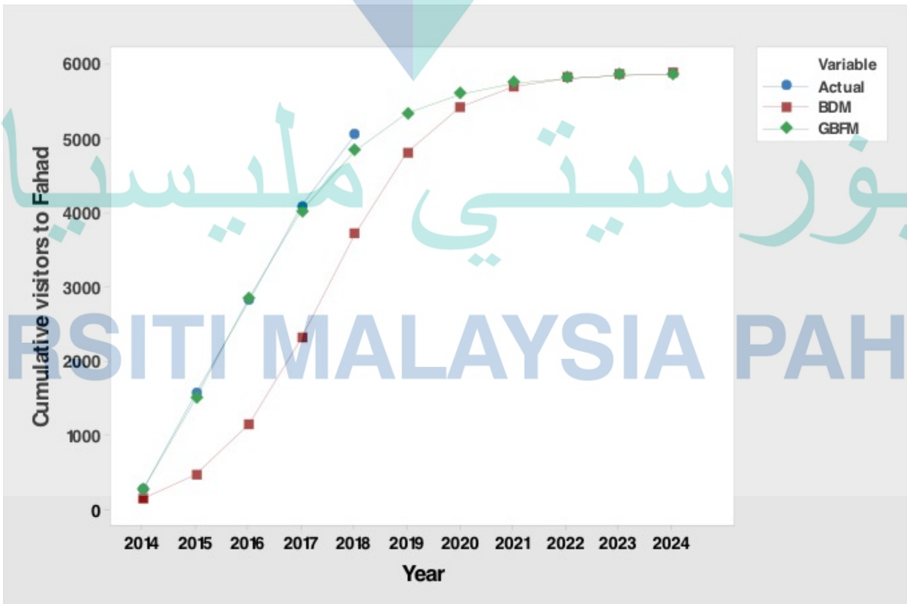

Figure 4.14 Comparison of cumulative number of visitors to Tanah Aina Fahad with fore-casted number using BDM and grey Bass forecasting model

Figure 4.13 shows the comparison of actual current value and the forecasts from BDM and grey Bass forecasting model meanwhile Figure 4.14 shows the cumulative of actual value and cumulative forecasts from both models. Based on Figure 4.13, Tanah Aina Fahad is forecasted to reach its peak visitors earlier in 2016 from grey Bass forecasting model meanwhile later in 2018 for BDM. Then, grey Bass forecasting model's plot in both graph have a small difference with the actual number of visitors compared to BDM. Hence, this provides us with a better observation that among the two models, grey Bass forecasting model has a more accurate performance than BDM in the case of Tanah Aina Fahad. In addition, we could see the number of forecasted visitors in year 2024 reach similar value for both BDM and grey Bass forecasting model.

4.11.2 Comparison for the Case of Tanah Aina Farrah Soraya

This subsection will discuss the comparison of both models with the actual values for the case of Tanah Aina Farrah Soraya. The results for MAPE of Tanah Aina Farrah Soraya for both models are written in Table 4.12.

Table 4.12 Comparison of MAPE for Tanah Aina Farrah Soraya forecast

Products	**MAPE(%)**	
	In-Sample	**Out-Sample**
BDM	37	12
GBFM	7	36

Table 4.12 shows the comparison of MAPE values for Tanah Aina Farrah Soraya's forecast for both models. BDM has a higher value of MAPE which is 37% for in-sample dataset while 12% for out-sample dataset. Besides, the grey Bass forecasting model has a lower value for in-sample and higher value for out-sample which are 7% and 36%, respectively. From the MAPE values, it shows that the BDM have a better forecast in this tourism product due to lower out-sample MAPE value compared to grey Bass forecasting model. We plot the actual, BDM and grey Bass forecasting model in Figures 4.15 and 4.16 in order to compare which model gives a better forecast to the actual data.

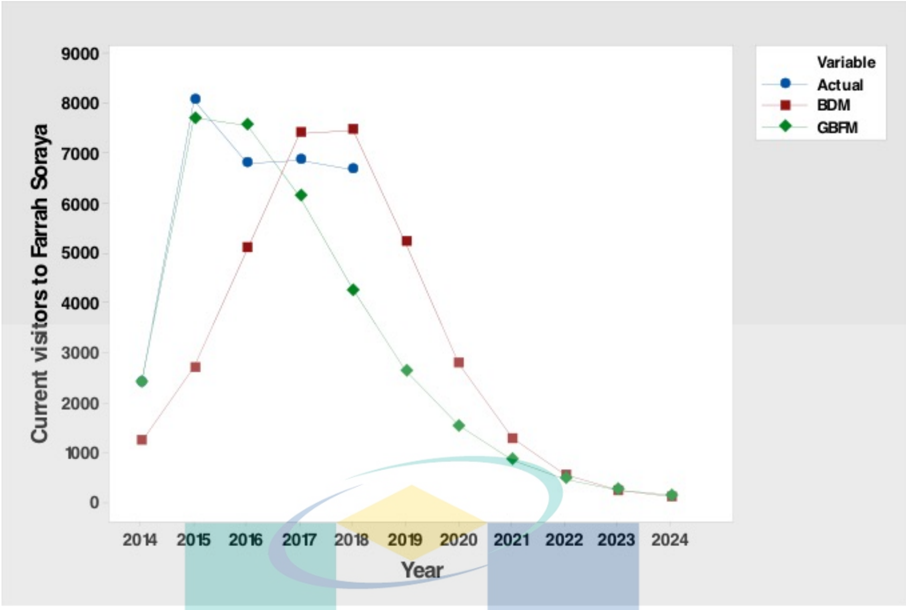

Figure 4.15 Comparison of actual number of visitors to Tanah Aina Farrah Soraya with forecasted number using BDM and grey Bass forecasting model

Figure 4.15 gives the comparison of actual and forecasted current visitors to Tanah Aina Farrah Soraya using BDM and grey Bass forecasting model. The actual visitors increased rapidly in its first year. However, Tanah Aina Farrah Soraya faced actual downfall of the number of visitors after 2015 and have a slight increment in 2017. For the forecast, it can be clearly seen that grey Bass forecasting model follows closely the actual data trend from 2014 until 2018 which explains the lower value of MAPE for in-sample dataset. In 2018, the forecast from BDM gives higher number, 7469 and grey Bass forecasting model's forecast gives lower number, 4255 compared to actual number, 6682. The big difference in the actual number of visitors to the forecast using grey Bass forecasting model is the reason why out-sample data gives a higher value. The forecast also reaches its peak in year 2018 for BDM and in the year 2016 for grey Bass forecasting model. The comparison of cumulative visitors are shown in Figure 4.16.

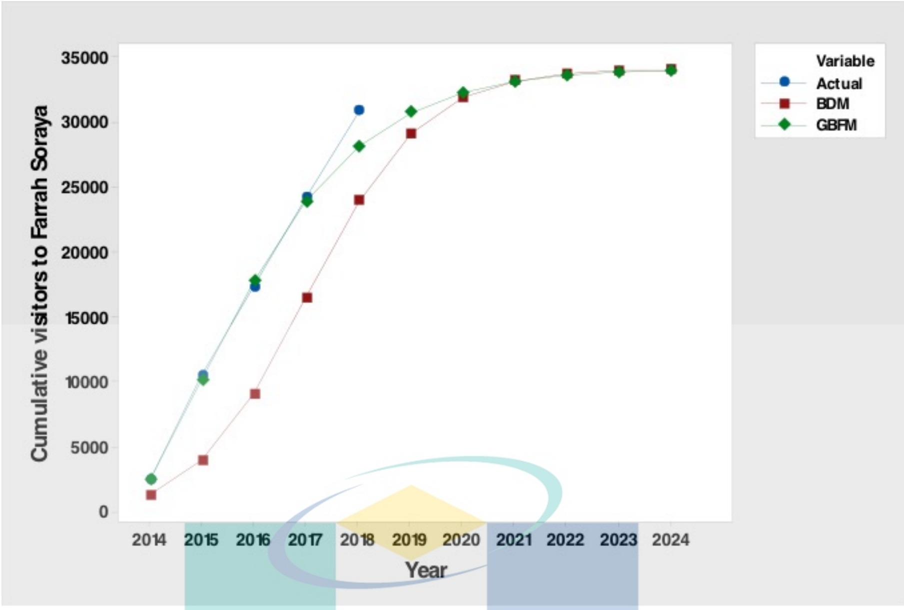

Figure 4.16 Comparison of cumulative number of visitors to Tanah Aina Farrah Soraya with forecasted number using BDM and grey Bass forecasting model

Figure 4.16 shows clearly that the forecast from grey Bass forecasting model follows the actual data compared to BDM. Even though the MAPE for grey Bass forecasting model gives a high value for out-sample dataset, the observation of overall forecast shown in Figures 4.15 and 4.16 reveal that the forecast follows the actual data better than forecast from BDM. From the plot, grey Bass forecasting model has a better forecast compared to BDM. However, the best model is chosen based on the comparison of MAPE values. Then, it can be concluded that Tanah Aina Farrah Soraya perform better using BDM than grey Bass forecasting model. Outperformance of grey Bass forecasting model by BDM might be affected by the choice of potential market. As stated by Abu and Ismail (2018), the value of peak level changes as market potential change. As the peak level of number of visitors changes, hence, causing different value of forecast's outcome. Therefore, different potential market will be used for both cases and will be discussed further in Chapter 5.

4.12 Summary

This chapter applies the methodology of Bass diffusion model (BDM) and grey Bass forecasting model to the new tourism products; Tanah Aina Fahad and Tanah Aina Farrah Soraya. Annual data from 2014 until 2018 are categorised as limited data case because there were five data available. In grey Bass forecasting model, since potential value m is being selected manually, the values of m estimated from BDM are used. The values of p and q are estimated using OLS using MATLAB software.

Both Tanah Aina Fahad and Tanah Aina Farrah Soraya show that BDM can be used in forecasting the new tourism products due to the graph pattern of the new product diffusion. Other than that, when comparing the forecasting accuracy of both products using MAPE, Tanah Aina Farrah Soraya shows a better performance compared to Fahad because its value of out-sample data is lower than Tanah Aina Fahad.

Based on BDM forecast, Tanah Aina Fahad is estimated to receive its maximum number of visitors in 2018, after four years of opening. However, the number declines rapidly in the consecutive years. Tanah Aina Farrah Soraya is also estimated to receive its peak number of visitors in the same year, 2018. The same declining pattern in the following year is also expected for Tanah Aina Farrah Soraya if there is no new plans made. The managements' new plans in terms of investing in advertisement or upgrading facilities in the locations can be attempted in order to fulfil relative demand in the future.

In grey Bass forecasting model, for Tanah Aina Fahad, the value of m is 5891. Based on the MAPE values, BDM presents higher value compared to grey Bass forecasting model. This means that the combined model results in a better forecast for Tanah Aina Fahad. Using the grey Bass forecasting model, Tanah Aina Fahad is expected to receive 1351 visitors in 2016. In 2017, the number of visitors starts to decline after its peak visitors in 2016.

For Tanah Aina Farrah Soraya, the potential market used is 34076. MAPE value of BDM and grey forecasting model are 12% and 36%, respectively. Therefore, BDM outperformed grey Bass forecasting model in the case of Tanah Aina Farrah Soraya. From BDM's forecast, Tanah Aina Farrah Soraya is expected to received 7469 visitors in 2018, which is its peak visitors. Then, the number of visitors starts to decline.

CHAPTER 5

FORECASTING USING DIFFERENT MARKET POTENTIAL

5.1 Selection of Potential Market for Grey Bass Forecasting Model

When introducing a new product to the market, marketers always face the problem of unknown potential market. Potential market plays a pivotal role in expecting future demand but unknown potential market complicates the process. Z. X. Wang (2013) stated that parameter of potential market, m is specified by expert's prediction or analogy. In previous application of grey Bass forecasting model, the value of m from ordinary least square (OLS) estimation of Bass diffusion model (BDM) is used. Otherwise, in this section, different value of m will be used. Parameter m is determined from the number of visitors to Pahang, specifically Raub because both Tanah Aina Fahad and Tanah Aina Farrah Soraya are located in Raub district.

The data from Tanah Aina Fahad and Tanah Aina Farrah Soraya are collected from 2014 until 2018. Consequently, the number of visitors to Raub district are used to determine the potential market, m for Tanah Aina Fahad. The number of visitors to Raub were collected from Tourism Pahang and are displayed in Table 5.1.

Table 5.1 Number of visitors to Raub, Pahang

Year	Number of visitors
2014	46443
2015	55919
2016	65959
2017	65257
2018	71454

Table 5.1 shows the yearly number of visitors to Raub. The average number of visitors from 2014 until 2018 to Raub is calculated to be 61006. It is important to calculate the average number of visitors to Raub to estimate the expected visitors to both Tanah Aina resorts. The selection of best parameter m for Tanah Aina Fahad and Tanah Aina Farrah Soraya are discussed further in the Section 5.1.1 and Section 5.1.2, respectively.

5.1.1 Selection of Potential Market for Tanah Aina Fahad

Overall visitors of Tanah Aina Fahad in the range year 2014 until 2018 are compared to the average number of arrivals. It was found that only 2% of arrivals to Raub accommodate Tanah Aina Fahad. Therefore, we take 2%, 5%, 10%, 20%, 30%, 40% and 50% from the average number of visitors to calculate the potential market of people staying in Tanah Aina Fahad. Then, from Step 4 in Section 3.9, we estimate the value of coefficient of innovation, p and coefficient of imitation, q using OLS estimation. The lists of potential markets, m calculated based on the percentages of visitors to Raub, Pahang, parameters p and q are presented in Table 5.2. The best parameters chosen for a successful diffusion, both p and q have to be positive and $p \leq q$. In addition, the value for both parameters must be in the interval of [0,1]. Parameters m is accepted or rejected according to these two conditions. Therefore, the acception and rejection of the potential market are written in the last column in Table 5.2.

Table 5.2 List of percentages and parameters for Tanah Aina Fahad

Percentage (%)	*m*	*p*	*q*	Remarks
2	1220	0.0372	-0.2443	Reject
5	3050	1.0248	-1.0978	Reject
10	6100	0.1676	0.4986	Accept
20	12201	0.1029	0.1407	Accept
30	18302	0.0700	0.0764	Accept
40	24402	0.0528	0.0502	Reject
50	30502	0.0424	0.0359	Reject

Based on Table 5.2, the potential market from 2% and 5% are rejected because q give negative values. For 40% and 50%, the value of $q < p$, hence, rejected. Accepted m are highlighted as shown in the Table 5.2. Potential market of 10%, 20% and 30% percentages with values of 6100, 12201 and 18302, respectively are accepted as they satisfy the conditions mentioned in choosing the best parameter.

Then, mean absolute error percentage (MAPE) is used to decide which potential market gives the most accurate forecast among the three values. The result from the forecast evaluations of grey Bass forecasting model for each parameters m is listed in Table 5.3.

Table 5.3 Comparison of MAPE for different market potential of Tanah Aina Fahad

m	**In-sample (%)**	**Out-sample (%)**
6100	4	12
12201	1	21
18302	0	25

Table 5.3 presents the comparison of MAPE values for different market potential values. Larger potential market of 12201 and 18302 give higher values for out-sample. This means that the values give a weak forecast. Hence, the potential market of m = 6100 is chosen to forecast Tanah Aina Fahad. The parameters p and q estimated using MATLAB are summarised as in Table 5.4. Then, 10 years demand forecast for Tanah Aina Fahad using grey Bass forecasting model are shown in Table 5.5.

Table 5.4 Results of parameters estimations for Tanah Aina Fahad using different potential market

Parameter	**Value**
m	6100
p	0.1676
q	0.4986

Table 5.5 Actual and forecasted number of visitors to Tanah Aina Fahad using different market potential in grey Bass forecasting model

Year	**Actual current visitors**	**Forecast current visitors**	**Actual cumulative visitors**	**Forecast cumulative visitors**
2014	260	260	260	260
2015	1288	1236	1548	1496
2016	1266	1343	2814	2839
2017	1259	1181	4073	4020
2018	972	860	5045	4880
2019		544		5424
2020		314		5738
2021		172		5910
2022		91		6001
2023		48		6049
2024		25		6074

Table 5.5 displays actual and forecasted current and cumulative number of visitors to Tanah Aina Fahad by grey Bass forecasting model using parameters m = 6100, p = 0.1676, q = 0.4986. The results show that for current visitors, the forecast increases from 2014 until 2016 and starts to decrease in 2017. The visitors continue to decrease after 2017. This situation will happen because as the number of visitors reach its peak in 2017, no new adopters will visit the place if there is no new attractions or advertisement made about the locations. Hence, the number drops. Besides, there are small differences between actual and forecast number of visitors. This forecast is displayed in Figure 5.1.

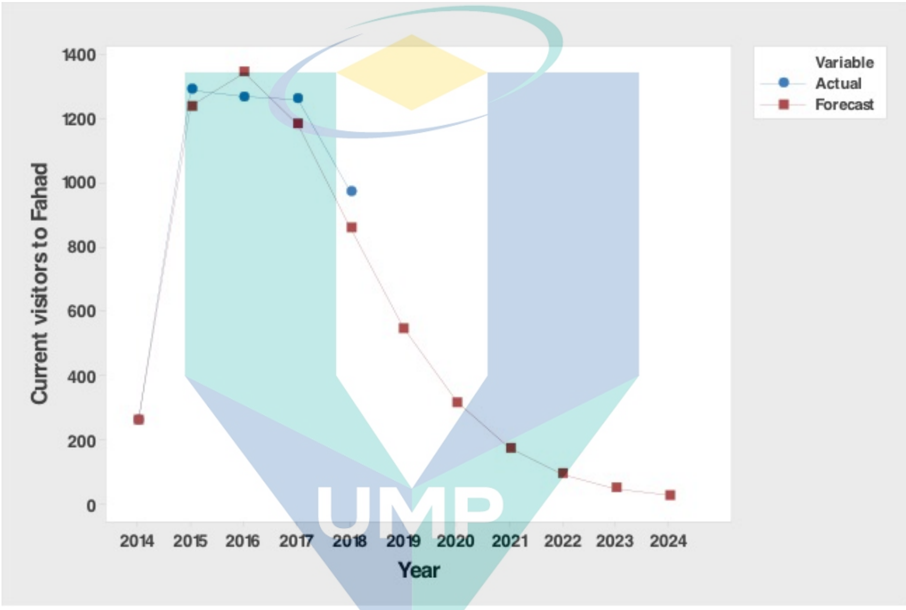

Figure 5.1 Actual and forecasted current number of visitors to Tanah Aina Fahad using different market potential

Besides, cumulative number of visitors show as the time increases, the number of visitors increase. However, after 2016, the rate of increment is slower compared to the increment before 2016 because it has reached its saturation level. Year 2016 is the maximum with 1343 number of visitors. The comparison of actual and forecasted cumulative number of visitors are shown in Figure 5.2.

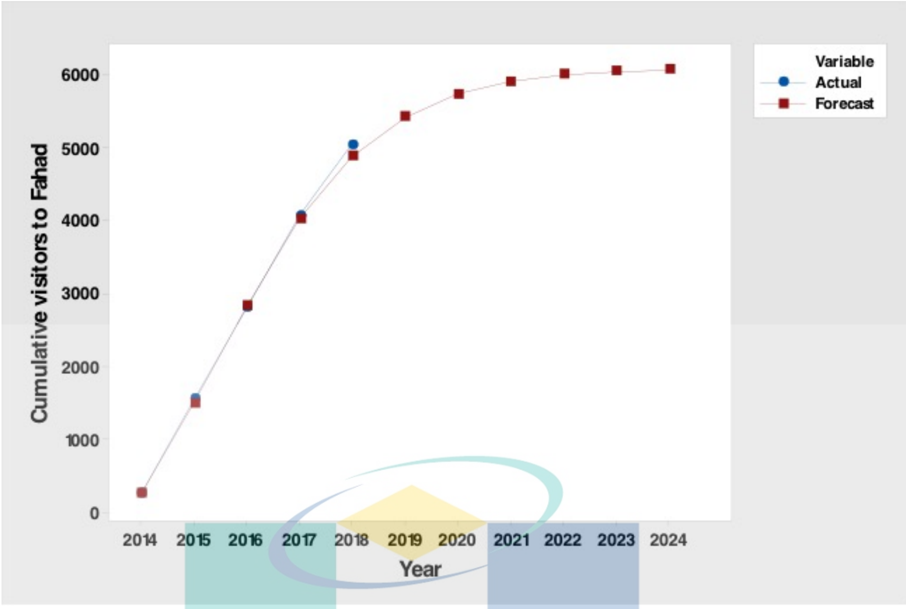

Figure 5.2 Actual and forecasted cumulative number of visitors to Tanah Aina Fahad using different market potential

5.1.2 Selection of Potential Market for Tanah Aina Farrah Soraya

This section will apply grey Bass forecasting model to Tanah Aina Farrah Soraya. The same steps in choosing potential market parameter m as in Tanah Aina Fahad are used. The percentage of people accommodated Tanah Aina Farrah Soraya to average number of visitors to Raub, Pahang is calculated to be 11%. Therefore, we take the same values of percentages as in Tanah Aina Fahad which are 2%, 5%, 10%, 20%, 30%, 40% and 50%. The parameters m, p and q are presented in Table 5.6.

Table 5.6 List of percentages and parameters for Tanah Aina Farrah Soraya

Percentage (%)	*m*	*p*	*q*	Remarks
2	1220	-1.4577	-0.0671	Reject
5	3050	-1.8241	-0.2171	Reject
10	6100	-2.0001	0.4544	Reject
20	12201	2.1930	-1.8132	Reject
30	18302	1.3235	-1.5544	Reject
40	24402	0.0849	1.2785	Reject
50	30502	0.1913	0.6167	Accept
60	36604	0.1961	0.3581	Accept
70	42704	0.1815	0.2324	Accept
80	48805	0.1647	0.1600	Reject

Table 5.6 shows that the percentages from 2% until 40% parameters are rejected due to not satisfying the conditions stated earlier. Percentages of 2%, 5%, 10%, 20%, 30% and 40% are rejected because they do not satisfy the conditions of interval between [0,1]. Then, we extended the values to 60%, 70% and 80% from the average value to calculate the potential market of people staying in Tanah Aina Farrah Soraya. Meanwhile, 80% with m = 48805 is rejected because p > q. Therefore, the only values accepted are 50%, 60% and 70% with value of m = 30502, 36604, and 42704, respectively, as highlighted in the Table 5.6.

Comparing the percentage and the value of m in Tanah Aina Farrah Soraya to Tanah Aina Fahad, the accepted value of m is higher, which is 42704 to 6100. Although the value of 60% and above are considered large for potential market, we still take the values into consideration assuming that as the time increases, the value of potential market will increase. Besides, the location of Tanah Aina Farrah Soraya closer to Kuala Lumpur could influence people's choice when choosing Tanah Aina Farrah Soraya as their accommodation. The decision whether the potential market is accepted or rejected are also noted in Table 5.6. Consequently, among the three values, MAPE values are calculated, so the best potential market value will be chosen to forecast the new tourism demand. The values of MAPE are shown in Table 5.7.

Table 5.7 Comparison of MAPE for different market potential of Tanah Aina Farrah Soraya

m	**In-sample (%)**	**Out-sample (%)**
30502	9	48
36604	6	31
42704	5	22

Based on Table 5.7, it is obvious that m = 42704 has the smallest value for both in-sample and out-sample of MAPE values. This means that using this parameter will give a better forecast compared to the other values. Therefore, m = 42704 is chosen with p = 0.1815 and q = 0.2324 as listed in Table 5.8, are used in the application of grey Bass forecasting model for Tanah Aina Farrah Soraya. The results of forecast are displayed in Table 5.9.

Table 5.8 Results of parameters estimations for Tanah Aina Farrah Soraya using different potential market

Parameter	Value
m	42704
p	0.1815
q	0.2324

Table 5.9 Actual and forecasted number of visitors to Tanah Aina Farrah Soraya using different market potential in grey Bass forecasting model

Year	Actual current visitors	Forecast current visitors	Actual cumulative visitors	Forecast cumulative visitors
2014	2418	2418	2418	2418
2015	8080	7827	10498	10245
2016	6810	7373	17308	17618
2017	6873	6416	24181	24034
2018	6682	5208	30863	29242
2019		3995		33237
2020		2933		36170
2021		2085		38255
2022		1448		39703
2023		990		40693
2024		669		41362

Table 5.9 shows the actual and forecasted visitors for Tanah Aina Farrah Soraya with the value of potential market, m = 42704. Based on the forecast, it is revealed that the visitors will reach its maximum at 7827 in 2015. Then, the number of visitors will decrease gradually. Besides, there is a noticeably small difference between the actual and forecasted number of visitors. The actual and forecasted current visitors to Tanah Aina Farrah Soraya are plotted as shown in Figure 5.3 and their cumulative are plotted as given in Figure 5.4. Based on Figure 5.4, it can be seen that the rate of increment of the number of visitors is slower after 2019 compared to before 2019.

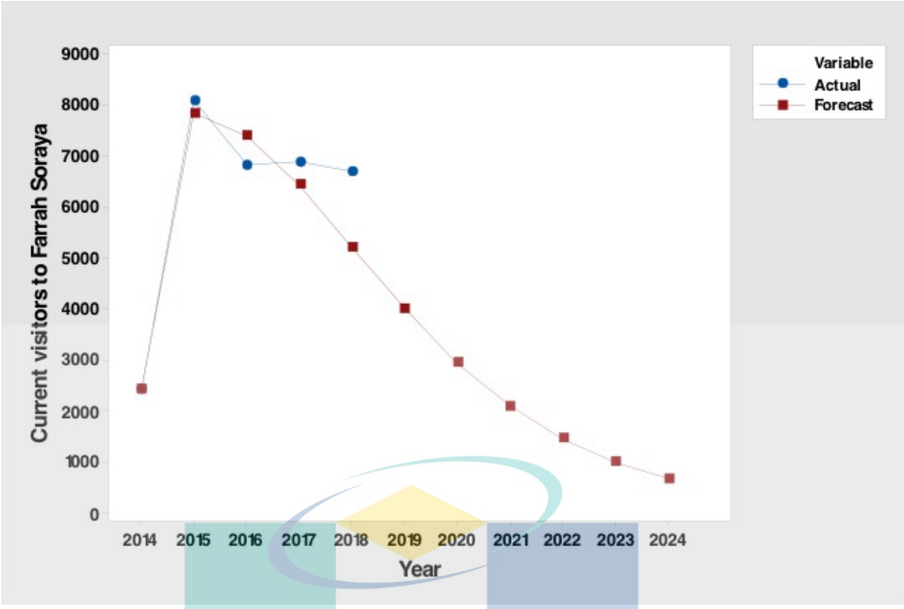

Figure 5.3 Actual and forecasted current number of visitors to Tanah Aina Farrah Soraya using different market potential

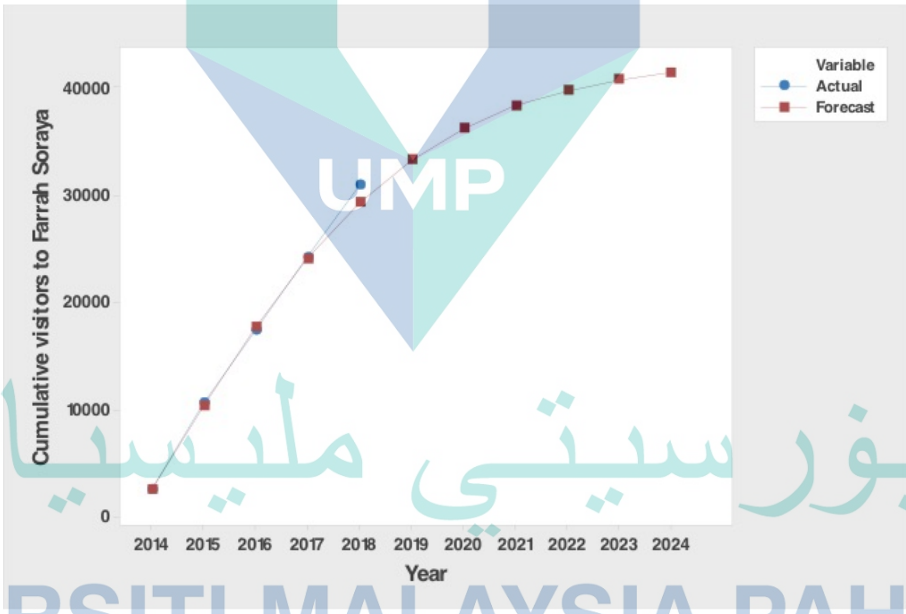

Figure 5.4 Actual and forecasted cumulative number of visitors to Tanah Aina Farrah Soraya using different market potential

5.2 Comparison of Forecast using Different Potential Market

As mentioned earlier, different potential market, m will give different results to the forecast. Hence, this section will show the performance of forecast of grey Bass forecasting model when using different potential market. The potential markets are specified from all accepted values of m when choosing potential market in the previous section.

Then, the analysis for each cases of Tanah Aina Fahad and Tanah Aina Farrah Soraya are being elaborated in the Subsections 5.2.1 and 5.2.2, respectively.

5.2.1 Tanah Aina Fahad

Based on Section 5.1, the accepted percentages of potential markets are 10%, 20% and 30% for Tanah Aina Fahad. The values of 10% is 6100, 20% is 12201 and 30% is 18302. Besides, the value of m generated from BDM, where m = 5891 are also included in this section. These values of m are substituted into grey Bass forecasting model to generate their forecast output. Hence, a better comparison can be interpreted. We presented graphically the forecast using different potential values in Figures 5.5 and 5.6.

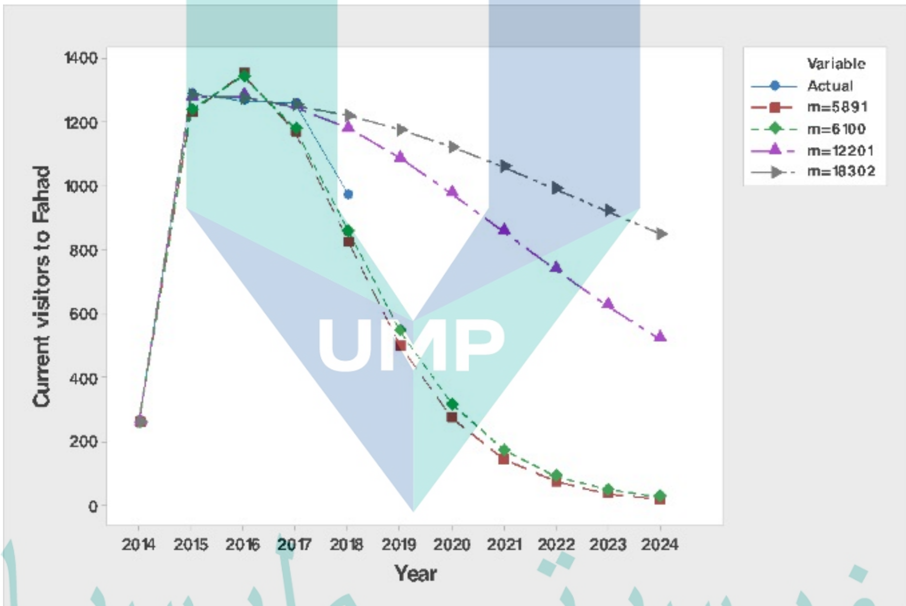

Figure 5.5 Comparison of current number of visitors to Tanah Aina Fahad using different market potential

Figure 5.5 is the comparison of actual and forecasted current number of visitors using different market potential value for Tanah Aina Fahad. Figure 5.6 compares their cumulative actual and forecasted visitors. Among the four values, m = 6100 and m = 5891, noted in the green line and red line, respectively, have small differences with the actual value compared to the others. The visitors are expected to reach the maximum value in the year 2016. After that, the number of visitors start to decline as it has reached its saturation state.

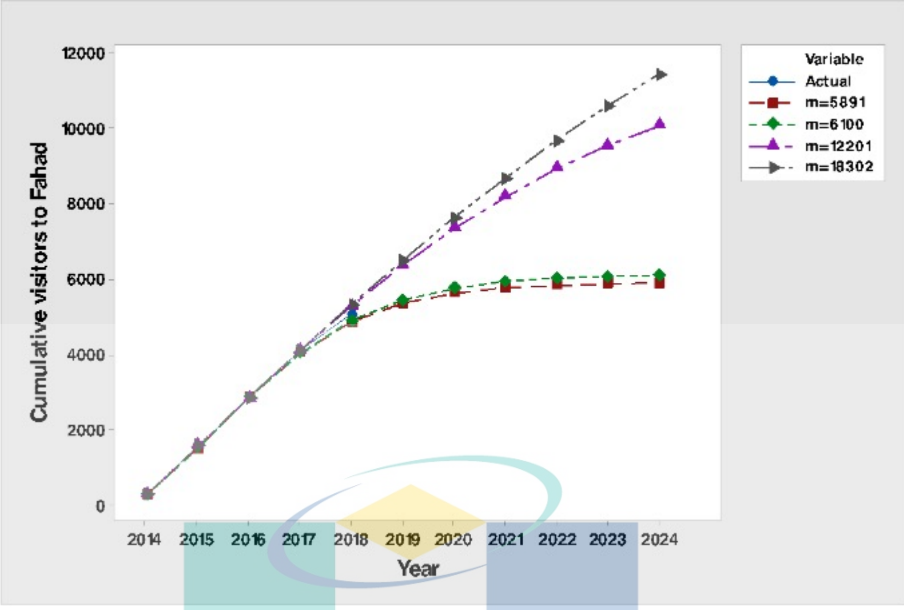

Figure 5.6 Comparison of cumulative number of visitors to Tanah Aina Fahad using different market potential

5.2.2 Tanah Aina Farrah Soraya

In the case of Tanah Aina Farrah Soraya, the selected percentages of potential markets are 50%, 60% and 70% with the values of 30502, 36604 and 42704 respectively. The same case of m = 34076 estimated from BDM is also included. Figure 5.7 plots the actual and forecasted current number of visitors meanwhile Figure 5.8 plots the actual and forecasted cumulative number of visitors to Tanah Aina Farrah Soraya.

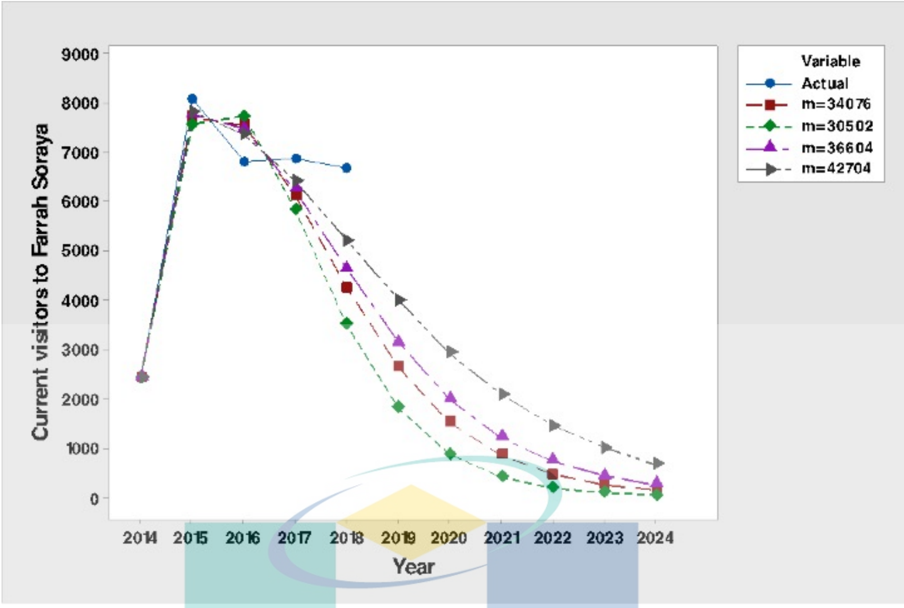

Figure 5.7 Comparison of current number of visitors to Tanah Aina Farrah Soraya using different market potential

Figure 5.8 Comparison of cumulative number of visitors to Tanah Aina Farrah Soraya using different market potential

Based on Figure 5.7, the actual number faced slight inclination in 2017 after facing a declining visitors in 2016. Meanwhile, all forecasted values show that the number of people accommodating Tanah Aina Farrah Soraya continues to decline when the maximum visitors happen in the year 2016. Obvious observation can be seen that potential market value of 42704 follow the actual value better than the other values. Then, among all four percentages, 70% visitors from the average visitors to Raub is the best potential market to be chosen as it give the best forecast for Tanah Aina Farrah Soraya.

5.3 Summary

Generally, potential market is important in predicting the diffusion of products in the market. For grey Bass forecasting model, the value of potential market, m is determined manually. The author uses the potential market based on the percentages from the average visitors to Raub, Pahang which is collected from Tourism Pahang. This is because the values are the closest comparison to the visitors of the attractions. The estimated accommodators in Tanah Aina Fahad are found to be 2% from the average number of yearly visitors from 2014 until 2018 and 11% for Tanah Aina Farrah Soraya. Different percentages ranging from 2% until 80% are used and are substituted into grey Bass forecasting model. Based on MAPE values, the best value of m is found to be 6100 which is 10% from average Raub's visitors and 42704 which is 70%, for Tanah Aina Fahad and Tanah Aina Farrah Soraya, respectively. MAPE values of out-sample data for Tanah Aina Fahad is 12% meanwhile 22% for Tanah Aina Farrah Soraya.

Then, Section 5.2 compares the forecast using all accepted potential markets for each cases. The value of m obtained from BDM estimation is also included and the forecast is analysed using grey Bass forecasting model. The comparison presents that among all values, m = 6100 give the best forecast for Tanah Aina Fahad. For Tanah Aina Farrah Soraya, m = 42704 yields the best prediction. Both values give the smallest differences between actual and forecasted number of visitors in their respective tourism products. The overall results in Chapter 4 and Chapter 5 will be discussed further in proceeding chapter. Besides, the best performing model will also be suggested in Chapter 6.

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

This chapter will conclude on the results from preceding chapters. Besides, the overall findings of the research will be summarised in this chapter. Based on the results and discussion, a conclusion of the study will be made. Besides, the suggestion and improvement for future research are elaborated at the end of this chapter.

6.2 Discussion

Monthly data from November 2014 until December 2018 from two tourism products; Tanah Aina Fahad and Tanah Aina Farrah Soraya were collected. Then, this data is converted to yearly data for forecast without considering seasonal number of visitors to the locations. The data is categorised as limited data because there is only five years data available from the source. One of the objectives of this study is to apply the readily proposed models to the new tourism product forecasting. Two models; Bass diffusion model and Bass diffusion model with grey theory (grey Bass forecasting model) were used in forecasting of the new tourism products. These two models are compared to find which model perform best in forecasting the new tourism product. In order to make the decision on the best model performed, forecast evaluation was measured using mean absolute percentage error (MAPE). As there are only five years data available, the data is split to in-sample data (from year 2014 until 2017) and out-sample data (year 2018).

This section will compare the basic BDM with grey Bass forecasting model for Tanah Aina Fahad and Tanah Aina Farrah Soraya. The forecast using BDM, three parameters are estimated, which are potential market, coefficient of innovation, and coefficient of imitation, m, p and q, respectively. Ordinary least square method (OLS) is used to estimate these mentioned parameters using MATLAB software. Then, the values of parameters are substituted into the BDM model for forecast. Besides, the value of potential market for grey Bass forecasting model is determined by the researcher. At first, same value of m from BDM are used in grey Bass forecasting model. Then, different potential market are employed in grey Bass forecasting model, so the effect on the different values of m on the forecast can be seen.

For Tanah Aina Fahad data set, the potential market value is estimated to be 5891 in BDM. The out-sample data yields the value of 44% in BDM forecast and 15% from the forecast using grey Bass forecasting model. Using different value of m= 6100, which is 10% from average value of the number of visitors to Raub district, Pahang, better forecast is achieved with lower MAPE is yielded using grey Bass forecasting model compared to BDM. MAPE values of out-sample forecast based on the potential market are summarised as in Table 6.1.

Table 6.1 Comparison of MAPE values for Tanah Aina Fahad based on potential market in BDM and grey Bass forecasting model

m	**BDM**	**GBFM**
5891	44	15
6100	-	12

Based on Table 6.1, it can be concluded that the grey Bass forecasting model gave a better forecast for Tanah Aina Fahad. Among the two values of potential market, the best value is m = 6100. Overall, based on Table 3.1 (Lewis's judgment scale), grey Bass forecasting model shows a good forecast for Tanah Aina Fahad for both values of potential market, m compared to BDM forecast. This support the fact in Section 5.1.1 where visitors to Tanah Aina Fahad is 2% from the number of overall visitors and the choice of value for potential market suits the forecast of grey Bass forecasting model which is 10% from the overall average visitors. With 12% MAPE values, there are small differences between both actual and forecasted number of visitors. As a conclusion, grey Bass forecasting model is suitable and providing good forecast for Tanah Aina Fahad.

For Tanah Aina Farrah Soraya data set, the potential market value is estimated to be 34076 in BDM. The out-sample data yields the value of MAPE is 12% in BDM forecast and 36% from the forecast using grey Bass forecasting model. Different value of m = 42704 which is 70% from average value of the number of visitors to Raub district is repeated in grey Bass forecasting model. The MAPE value is 22% which is higher than the forecast using BDM. In fact, both MAPE values are higher in grey Bass forecasting model's forecast compared to BDM. All out-sample values are summarised as in Table 6.2.

Table 6.2 Comparison of MAPE values for Tanah Aina Farrah Soraya based on potential market in BDM and grey Bass forecasting model

m	**BDM**	**GBFM**
34076	12	36
42704	-	22

For the case of Tanah Aina Farrah Soraya data set, BDM shows a better forecast for m = 34076 because of its lower MAPE value. Among the two values of m, grey Bass forecasting model shows a better performance for m = 42704, meanwhile between the two models, BDM performed better than the grey Bass forecasting model. The argument arises when both values of m = 34076 and m = 42704 are employed in the forecast using both models. These values contradicts with the actual percentage of visitors to Tanah Aina Farrah Soraya to the visitors of Raub, Pahang which is 11%. It seems impractical to use the potential market value as high as 70% because very high number of visitors is expected to accommodate Tanah Aina Farrah Soraya. While this argument might be true, this study use the potential market value estimated from BDM and also follows the conditions in choosing the best value from different potential market as explained in Section 3.3. It can be concluded that the values of m, gives significant effect in the forecast of the new tourism product.

Besides, MAPE value can be improved under two conditions. First, the choice of split point between in-sample and out-sample data. Since the split point is chosen from 2014 until 2017 as in-sample dataset and only 2018 as out-sample dataset, it presumably affects the MAPE value calculated. Secondly, the selection of the value of parameter of potential market m influence the forecast performance. It is advised to not only follows the conditions stated but also to consider the value that is rational for the tourism products in expecting their visitors.

Since grey Bass forecasting model shows a slight improvement than the forecast using BDM in the case of Tanah Aina Fahad data set, we conclude that grey Bass forecasting model is suitable and can be applied for forecasting the new tourism product with limited data case. However, several improvements need to be made. Therefore, based on the best performing model, the forecast for each tourism products are as follows:

For Tanah Aina Fahad, the best forecast is based on grey Bass forecasting model. The best potential market, m estimated is 6100 with coefficient of innovation, p = 0.1676 and q = 0.4986. The number of visitors increase in the first three years. The peak number of visitors is in 2016 with 1343 visitors. Then, the visitors start to decline and approaching zero in the future.

For Tanah Aina Farrah Soraya, using BDM, $m = 34076$, $p = 0.0229$ and $q = 0.8860$. Tanah Aina Farrah Soraya is expected to receive its maximum visitors in 2018 with 7469 visitors. Then, the number of visitors start to decrease if there is no further planning or development are made. Thus, the management needs to take action in advertising the place to the public, realising that the number of visitors declining for both places.

6.3 Conclusion

This research focuses in the forecasting of the new tourism products using Bass diffusion and grey Bass forecasting models. In overall, this study has achieved all three of its objectives. Firstly, the analysis of the number of visitors to the new tourism product in Malaysia shows its peak visitors after several years of their openings. The number of visitors are forecasted to decline in the future if there is no new development in terms of upgrading facilities or new attractions made to the products. The management can advertise the place to get recognised by the public or lower the fees as to attract more accommodators. Besides, the government also needs to play the vital role in allocating suitable budget for the tourism products.

Secondly, two models which are BDM and grey Bass forecasting model are applied to forecast the number of visitors. Thirdly, since there are two products, Tanah Aina Fahad and Tanah Aina Farrah Soraya, the findings differ for each cases as the forecasts are affected by the potential market values. For Tanah Aina Fahad, the forecast using grey Bass forecasting model shows an improvement compared to Bass diffusion model. In addition, the potential market used for forecast has a slight difference with the real value. For the case of Tanah Aina Farrah Soraya, the parameter m estimated has a large difference compared to the real percentage of visitors to the place. It is found that the forecast using Bass diffusion model is better than grey Bass forecasting model as it is decided by out-of-sample MAPE value.

As a conclusion, even though grey Bass forecasting model performs better in one case study; Tanah Aina Fahad, it can be suggested that the forecast using grey Bass forecasting model is improved compared to Bass diffusion model in forecasting the new tourism product. The author also advise that the forecast and decision is affected by the choice of potential market. This study also supports the forecast using limited number of data (as low as four data) in grey Bass forecasting model. Further improvements can also be added to improve the study in future, as suggested. The forecasts' findings may help the management to plan for the developments to receive continuous visitors in the future.

6.4 Future Research

Despite the findings and conclusion achieved in this study, there are several improvements need to be made for future references. First, data collected from Tanah Aina Sdn. Bhd. is monthly data, for the data analysis, yearly data is used as explained in Section 3.11. Tourist arrivals to the country are affected by the seasonal variations. For example, number of visitors to tourism products are higher during holiday seasons and the rainy weather in east region of Peninsular Malaysia affects the movement of the visitors. Future research involving the tourism products and arrivals, quarterly data or monthly data need to be considered. Hence, correlation between the seasonality and tourism products can be justified.

Secondly, only one method is applied in estimating parameters in Bass diffusion model which is ordinary least square (OLS). Other methods for parameters estimation can be considered and compared in the future study, for example, genetic algorithm and non-linear least square method. This might improve the findings. Other than the best values of different market potential, the best values of coefficients of innovation and imitation can be also considered in this study.

Generally, there are many other models can be applied other than BDM and grey Bass forecasting model in forecasting such as time series model, econometric model or using artificial intelligence method. Apart from that, this study concentrates only on the number of visitors. The length of stay of visitors are neglected and might affected the forecast, which also can be considered in the future.

Future study can be done by combining qualitative and quantitative studies also need to be considered in order to arrive at the judgement of the decision of visitors in choosing the tourism destination. This will indirectly help the management to acknowledge visitors' reason to choose the destination in terms of price per night of the place, the types facilities served to the crowds or others. In this study, the type of tourism products used are accommodations. The ideas can be expanded in other types of tourism products such as theme parks, sports tourism place and religious buildings.

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APPENDICES

APPENDIX A

PUBLICATIONS / CONFERENCES / SYMPOSIUMS

(a) Sarah Mohd Khaidi, Noratikah Abu and Noryanti Muhammad. *Tourism Demand Forecasting: A Review on The Variables and Models*. 2nd International Conference on Applied and Industrial Mathematics and Statistics 2019 (ICoAIMS 2019), Zenith Hotel, Kuantan, Pahang, 23 - 25 July 2019. (Presenter)

(b) Sarah Mohd Khaidi, Noratikah Abu and Noryanti Muhammad. *A Case Study For New Tourism Product In Malaysia*, AIMS Postgraduate Poster Symposium, 12 December 2018, Pahang, Malaysia. (Presenter)

(c) Sarah Mohd Khaidi, Noratikah Abu and Noryanti Muhammad. *New Tourism Product Demand Forecasting: An Integration of Bass and Grey,* AIMS Postgraduate Poster Symposium, 11 December 2019, Pahang, Malaysia. (Presenter).

(d) Noratikah Abu, Noryanti Muhammad and Sarah Mohd Khaidi. *New Tourism Product Demand Forecasting: An Integration of Bass and Grey*, 10th Creation, Innovation, Technology & Research Exposition 2020 (CITREX 2020), 12 - 13 February 2020, Pahang, Malaysia (Team Member and Presenter), Bronze Medal.

(e) N. Abu, S.M Khaidi and N. Muhammad. 2020. *New tourism product forecasting – application of Bass Diffusion Model and Grey Forecasting Model*, Data Analytics And Applied Mathematics (DAAM). Vol. 1, pp. 37 - 43.

(f) Noratikah Abu, Sarah Mohd Khaidi and Noryanti Muhammad. *New tourism product forecasting - a study of different potential markets*, Monthly Mathematical Colloquium (MMC), Centre for Mathematical Sciences, Universiti Malaysia Pahang. 6 October 2020, Pahang, Malaysia. (Presenter).

(g) Noratikah Abu, Sarah Mohd Khaidi and Noryanti Muhammad. *New tourism product forecasting - a study of different potential markets*, International Conferences on Mathematical Sciences and Technology (MathTech 2020). 8 - 10 December 2020. (Presenter).

APPENDIX B

MATLAB CODE FOR BASS DIFFUSION MODEL

```
clear all
format shortg
m = 5891;
p = 0.0138;
q = 0.9397;

for i=1;
Y(i) = m*((1-exp(-(p+q)*i))/(1+(q/p)*exp(-(p+q)*i)));
S(i) = Y(i);
end
for i = 2:12;
Y(i) = m*((1-exp(-(p+q)*i))/(1+(q/p)*exp(-(p+q)*i)));
S(i) = Y(i) - Y(i-1);
end
format shortg

disp (' t Y(t) S(t)');
disp (' ');
x = [[0:11]', [Y]', [S]'];
disp (x)

subplot(2,1,1); plot(0:11, S)
subplot(2,1,2); plot(0:11, Y)
```

APPENDIX C

MATLAB CODE FOR GREY BASS FORECASTING MODEL

```
clear all
format shortg

a(1) = 260;
a(2) =1288;
a(3) =1266;
a(4) =1259;

m = 5891;
for i = 1:3
x(1) = a(1);
x(i+1)=x(i)+a(i+1);
end

disp (x)
for i =2:4
z(1) = 0;
z(i) = (x(i)+x(i-1))*0.5;
end

disp (z)
for i = 2

b = [m-z(i) z(i)*(1-((z(i))/m)); m-z(i+1) z(i+1)*(1-((z(i+1))/m)); m-z(i+2) z(i+2)*(1-((z(i+2))/m))];
y = [a(2) ;a(3); a(4)];
A = ((inv(b'*b))*b')*y;
end

p = A(1)
q = A(2)
disp (A)
g = 5891;
for i = 1:4;
```

```
s(1) = 5891;
s(i+1) = ((m*((p+((q/m)*g))/(m-g)))-(p*(exp(-i*(p+q)))))/(((q/m)*(exp(-i*(p+q))))+
((p+((q/m)*g))/(m-g)));
end

disp (s);
for i = 1:4;
v(1) = 5891;
v(i+1) = s(i+1)-s(i);
end
disp (v);
```