Forecasting Key Indicators of China's Inbound and Outbound Tourism: Optimistic-Pessimistic Method

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ABSTRACT

Purpose – Tourism industry is a highly complex system surrounded by many uncertainties because of its innumerable connections with other supporting systems. Considering tourism a grey system, the current study proposes Optimistic-Pessimistic Method (OPM). This technique can aid in improving the forecast accuracy of four tourism-related indicators, the inbound tourism to China, outbound tourism from China, revenues collected through inbound tourism and expenses incurred on outbound tourism.

Design/methodology/approach – The study integrates OPM into EGM and then using the secondary data collected from the World Bank database, predicts the four tourism-related indicators. The Mean Absolute Percentage Error steered the performance of the models.

Findings – One of the main contributions of the study lies in its overall evaluation of one of the major travel and tourism countries of the world in light of four crucial indicators. The study highlights, for tourism-related indicators' recent information, contains more valuable information about the future. OPM presents a novel application of the concept of whitenization of interval grey number.

Originality/value – OPM represents a novel application of the concept of whitenization of interval grey number in the theory of grey forecasting.

Keywords: Traveling; Inbound Tourism; Outbound Tourism; Grey Forecasting model; Optimistic-Pessimistic Method

Nomenclature

EGM (1,1)	Even Grey Model, first order differential equation containing one variable
GDP	Gross Domestic Product
GM	Grey Model for forecasting

GST	Grey System Theory
MAPE	Mean Absolute Percentage Error
OPM	Optimistic-Pessimistic Method (O/P Method)
O/P-EGM	O/P Method based EGM (1,1)
USD	US Dollars
WTCF	World Tourism Cities Federation
WTTC	World Travel & Tourism Council

1. INTRODUCTION

As the growth in international tourism is slowing down in the mature destinations (e.g., Northern and Western Europe and North America) and is expected to increase in the emerging destinations at twice the rate of those in advanced nations, the tourism in emerging markets is drawing increasing attention (Claveria, 2016). China has witnessed the substantial growth of international tourism over the past twenty years, and today has become a key originator and recipient of tourists (Sun et al., 2016). Today, China has emerged as one of the "major Travel & Tourism economies" of the world (WTTC, 2017a) and not only China itself is reaping benefit from international tourists so do the countries China's "generous" travellers chose to visit. Today tourism has become a vital engine of socio-economic development for countries through export revenues, employment opportunities, and infrastructure development (World Bank, 2018). In 2012, China became the most prominent international tourism spender for the first time, setting a record \$102 billion in tourism expenditure and at the same time got the No. 1 outbound tourism status in the world (Chen, 2018; Chen, Chen & Wei, 2017). In 2016, international inbound tourists spent 114.109 billion USD in China, according to World Bank statistics. As a globally traded service, inbound tourism is recognized for being one of the leading trade categories in the world. In the decade from 1994 to 2004, outbound international travellers from China increased by 17% annually and in the period 2010 to 2014 the China's outbound tourists increased at an average annual of 18% (WTCF, 2018; Keating & Kriz, 2008). Considering the proportion of Chinese outbound tourists to be small as compared to its population, comprising a continually expanding middle class, there is an enormous growth potential for Chinese outbound tourism with positive consequences for the destined countries (Keating & Kriz, 2008). In 2017, 130.5 million outbound tourists from China spent \$258 billion, with a growth of 7% and 5%, respectively (WTCF, 2018). These statistics show the momentum of the Chinese tourism industry, which is bigger than the economies of several countries. It also shows the tremendous potential that China as a destination and source of tourists possess. Also, considering the importance of the international tourism for China and its economy and the significance of the Chinese outbound tourists for the countries they visit, its forecasting has both policy and social implications for the concerned governments and other stakeholders like travel agencies, airline industries, hospitality industry, and even general public.

From 2016 to 2017 even though the amount of foreign visitor exports (spending) rose from \$119.7bn to \$125.3bn however the proportion was a reduction in 5.3% to 5.2% of total exports, with foreign visitor spending reducing from 18% to 13% (WTTC, 2018). Further, even though the total value of tourism trade experienced a geometric increase since 1978 however in 2009, China entered into the deficit period of tourism foreign exchange income, and the deficit period is still not over (Yan, 2017). Thus, the development in Chinese tourism is accompanied by a continuous and expanding deficit in the tourism balance of trade (Dai et al., 2017). Albeit the overall picture of the tourism industry of China is good and the country is on its way to becoming the most attractive tourist destination in upcoming years. However, considering the existing and potential challenges there is a continuous need to restudy and research Chinese tourism sector and its performance especially when China has become one of the most interesting and widely discussed countries in the world not only because of its economy, global influence, technology, food and culture but also because of its tourism-related policies and its consequences. In order to make the right policy and investment decisions, the importance of empirical evidence is immense (WTTC, 2018). Thus the need to empirically study Chinese tourism sector's current status and its future performance is growing which can also be manifested from the increasing number of research publications on Chinese tourism-related phenomenon (see, e.g., Cheng & Zhang, 2019; Gao et al., 2019; Huang & Chen, 2016; Ruhanen et al., 2015). The role of support vector regression, artificial neural networks and fuzzy approaches is well known (Wan & Song, 2018) for tourism-related forecasting; however, the deployment of grey models on tourism-related predictions is still in infancy. Furthermore, given the significance of China as a major tourist destination, and uncertainties surrounding the tourist behaviours when the emerging destinations are outpacing the advanced destinations at a higher speed in terms of international tourism growth, it is crucial for the concerned organizations to study the behaviour of Chinese tourism through an approach that is better equipped to handle uncertain and complex systems like the tourism industry, and is not unfamiliar with the Chinese environment as well.

Considering tourism industry a huge, comprehensive, complex, volatile (sensitive), and uncertain system (Sun et al., 2016; Xu, 2008; Gössling & Hall, 2006), comprising multiple interlinked sub-systems (businesses/sectors) that may differ in "nature, operations, and external environment" (Marais et al., 2017), which becomes more comprehensive, as well as uncertain, in the Chinese context because of the number of factors such as higher number of tourist destinations, variety of seasons, higher considerations like climate change and pollution, increasing ageing population, parallel systems of habits (e.g., eating) and cultures (consider, a nation comprising 56 ethnic groups), parallel systems of payments (online versus cash), parallel systems of governances ('one country, two systems'), a mix of socialistic and market-oriented administrative policies, and diverse actors/stakeholders involved, the current study aims to forecast the inbound tourism to China, outbound tourism from China and, related receipts and expenditures. Based on the data from 2006 – 2016, the predictions for the next 10 years have been made using a grey prediction model, Even GM (1,1). While discussing the model GM(1,1), which is usually synonymous to the model Even GM(1,1) in the literature, Sun et al. (2016) argued that although the model has been broadly studied, it may have unsatisfactory curve-fitting effects for data revealing significant randomness thus it is essential to propose new models to improve its forecast accuracy. Therefore, while making the objective of the current study manifold, a novel and convenient approach, the Optimistic-Pessimistic (O/P) Method (OPM), has also been proposed and successfully tested to improve the forecast accuracy of the original grey model.

The structure of the paper is as follows: After the introduction section, there is a section on background. Within it, the review of literature justifying the appropriateness of grey forecasting models for tourism forecasts is also presented. It is followed by the section on research methodology where data collection and analysis methodologies are briefed. The study reveals that tourism data available in major databases contains uncertainty, and thus deployment of the models of the Grey System Theory, an emerging methodology to analyze data containing uncertainty, was a sound move.

2. BACKGROUND

2.1. Chinese Tourism Industry

As one of the biggest economic industries of the world, travel and tourism, which supports one-tenth jobs on the globe, is a dynamic driver of employment opportunity and can absorb surplus labour in a country (WTTC, 2018; Wei, Qu & Ma, 2013). The tourism industry accounts to around 10% of global GDP and is projected to grow at the rate of 4% per annum, thus eclipsing many other industries (Lenzen et al., 2018; WTTC, 2018). One of the key benefits of tourism for the developing countries like China, where unbalanced regional development and increasing regional economic disparities are significant challenges for the balanced national economic growth, is its inherent characteristic to distribute development away from the industrial centres and towards regions that have not been developed (Goh, Li & Zhang, 2015). In the post-Mao period, when uneven regional and economic development started showing up, tourism became an important cornerstone of Chinese national policy to support the national economy. Since the late 1970s, China's appreciation of tourism has become a moderator for economic development and modernization that allowed Chinese tourism sector to develop rapidly and making it the largest sector in the service industry (Wei et al., 2013; Keating & Kriz, 2008). "The success of the economic reforms in China, which has resulted in fast economic growth has also been the main cause of rapid tourism growth in China," states Witt and Turner (2002).

International tourist arrivals surged from 1.18 million in 1978 to 106.6 million in 2011, and foreign exchange revenues from inbound tourism rose from $263 million in 1978 to $48.5 billion in 2011 and then $56.9 billion in 2014 (Keyim, 2017; Yan, 2017). Overall, from 1980 to 2006, the inbound tourist arrivals to China and the resulting tourism receipts grew at a rate of 11% and 14% per annum, respectively (Keyim, 2017). Inbound tourism is an internationally traded service and a major category of trade, and it has an effect on an economy like that of exports. In 2016, international inbound tourists spent 114.109 billion USD in China, according to World Bank statistics.

The tourism statistics place China in a very lucrative position in the world both as a source and the destination country of the tourists. Thus, not only macro-factors are being studied, but micro-factors have also sought scholars' attention to understand the market better. For example, scholars have even begun studying the behaviour of Chinese tourists to serve them better. Cheng and Zhang (2019) investigated the Airbnb hosts' experience with Chinese outbound tourists. Ruhanen et al. (2015) studied the Chinese tourists' perceptions and motivations for a particular (e.g., Australian) tourist destination. In this new era of tourism, where tourism can drive a country's economy, no wise country affords to refuse the tourists who are well-known for their generosity and spending. At the same time, irrespective of the fact that what the people in the West may think of China, the rising number of foreigners visiting China each year demonstrates their curiosity in the country that houses almost everything – from beautiful mountains to well-preserved historic sites, from cold desert nights to hot springs, and from lush green forests to high rising skyscrapers with a sense of safety and security at every mile.

Further, the efforts China's tourism bodies are putting in to manage these cultural, historical and natural sites are not going astray. Zha and Li (2016) note that "the tremendous progress in the Chinese tourism sector has become one of the key factors fueling the growth and advancement of the Chinese economy." Every year the World Travel & Tourism Council (WTTC) disseminates a report of tourism performance of countries. The report is considered influential among the stakeholders associated with the tourism industry all over the world. According to their reports (WTTC, 2017a; 2018), the *direct* contribution of travel and tourism in China's GDP rose from USD275.2bn (2016) to USD402.3bn (2017) with 2.5% (2016) to 3.3% (2017) of total GDP. The *total* contribution, which includes direct and indirect contributions, of Travel & Tourism to GDP rose from USD1000.7bn (2016) to USD1349.3bn (2017), with 9% (2016) to 11.0% (2017) of GDP. These figures make tourism and travel not only a vital part of the Chinese economy but also signifies the importance of China as a worthy place for visitors and travellers. These figures also signify China, which is already the world's second-largest economy, as one of the major travel and tourism economies as well.

2.2. Tourism Industry as a Grey System

Tourism research has become a multidisciplinary field (Faulkner & Goeldner, 1998) since no single theory can explain the tourism system and phenomenon independently because of the relation of tourism systems and tourism industry with almost any other system and industry in the world. For example, the disease of COVID-19 that emerged as a healthcare crisis did not take too long in evolving to the travelling/tourism crisis, affecting not only every stakeholder in the travelling and tourism industries but also in the closely-linked industries. Thus, studying tourism in the context of networks, chaos and complexities, and uncertainty (Wu et al., 2019; Baggio & Sainaghi, 2016; Pavlovich, 2014; Baggio & Sainaghi, 2011; Xu, 2008; Zahra and Ryan, 2007; Gössling & Hall, 2006; Pavlovich, 2003) is an important issue. Travelling is a phenomenon that surrounds much uncertainty for travellers who leave their comfort zones to go abroad. However, if one looks at a tourism industry on the whole one may see a highly complex, open and flexible (self-organizing) system continuously striving to achieve equilibrium in the wake of rising complexities across all businesses directly or indirectly connected with the national or international tourism infrastructures. At least since the late 20th-century tourism as a complex, chaotic and uncertain system is getting exceeding attention by the scholars. Faulkner and Russell (1997) studied chaos and complexity in the tourism system. Zahra and Ryan (2007) discussed the complexity in tourism systems and acknowledged the difficulty in predicting the future of the system, in light of chaos and complexity theory. Xu (2008) forecasted domestic tourism in Hubei using grey system theory. A system might begin from an ultimately ordered and stable state and develop to states characterized by a complex behaviour, or even to completely chaotic situations where long-term forecasts are impossible because the uncertainty in the accurate determination of its initial state evolves exponentially in time (Sainaghi & Baggio, 2017). Therefore, in the current study, tourism has been viewed as an open system, which is both complex and uncertain and continuously interacts with other systems in its surrounding. However, irrespective of the amount of uncertainty and unpredictability surrounding this system it cannot be classified as a *black* system, a system with entirely unknown information. At the same times, these complexities and uncertainties restrict us from considering it as a *white* system, a system with entirely known information. Thus, considering the partially known and partially unknown information associated with it, one can view tourism as a *grey* system. This perspective does not negate the existing theories and their perspectives but rather complements them to understand the tourism system better.

2.3. Tourism Forecasts and Grey Prediction Models

The tourism industry is a hugely complex system, which is a set of multiple sub-systems (or, businesses) like tour guiding, passenger transportation, retailing, hoteling, catering, event management and several support and leisure services (Marais et al., 2017). Since most of the tourism products (e.g., airline seats, hotel rooms, and car rentals) are perishable, and cannot be inventoried, thus considering the fact that the fluctuating demands cannot be met with a stable supply of resources, equipment and workforce, the need for reliable forecasting of tourist arrivals and demands for accurate decision-making becomes a fundamental need (Hadavandi et al., 2011; Hsu & Wang, 2008). Therefore, there is no escape from forecasts, and if forecasts are accurate, then it is a blessing otherwise embarrassment at the global stage! Accurate forecasts can also minimize the need for risk and uncertainty management, and if a risk and uncertainty management is inbuilt in a forecasting technique, the benefits can be manifold.

Knowing the fact that tourism is a very comprehensive industry representing a very complicated, uncertain and huge system (Xu, 2008), which comprises dozens of sub-systems, the tourism industry-related forecasts need a non-traditional approach like Grey System Theory that allows the tourism-related forecasts to be nearer to reality. Grey models are an integral part of Grey System Theory, which is an intelligent, multifaceted field, which was pioneered by Deng (1982) to handle problems associated with poorly understood (uncertain) systems (Mahmoudi et al., 2020). One of the earliest studies using a grey model to forecast tourism demand was executed by Wang (2004). He argued that in order to obtain low forecast errors from Autoregressive integrated moving average (ARIMA) and neural network models one constraint is the necessity of large sample, which is difficult to obtain in the environment that is dramatically changing in a short period. Therefore, he preferred grey system theory and fuzzy theory for the prediction of tourists' arrival to Taiwan from Hong Kong, Germany and the United States. Later several scholars used grey models independently or with other models in a tourism environment, see, e.g., Huang et al. (2004), Liu, Sun and Yuan (2008), Hsu and Wang (2008), Xu (2008), Lin, Lee and Huang (2009), Chen and Qiu (2009), Huang, Yang and Chen (2009), and Kan, Lee and Chen (2010). Among the recent studies, Liu et al. (2014) used an optimized GM (1,1) model to forecast the number of domestic tourists to Zhejiang. Pirthee (2017) used two grey models to predict the tourist arrivals to Mauritius. Ma, Liu and Wang (2019) used a non-linear multivariate grey Bernoulli model to forecast the tourist income of China.

Here it should be noted that currently, many forecasting methods are in use for tourism forecast; however, they have different limitations. For example, the ARIMA models are usually used for time series forecasting where the historic times series data is used to construct a mathematical function (Wang, 2004), which is being used to predict the future data values. However, in order to reduce the forecasting error, ARIMA and other time series models require a large number of data, which is not always and readily available for time series data when the environment is dynamically changing with time or the cost of data collection is not affordable (Sun et al., 2016; Wang, 2004). To overcome these issues, the researchers proposed Neural Networks based models; however, they require a larger sample size in order to get reliable forecasts. On the other hand, grey forecasting models are neither subject to large sample size nor any particular distribution of data (Liu et al., 2020; Javed & Liu, 2018b; 2019; Ng

& Deng, 1995). Hsu and Wang (2008) in their study on tourism demand forecasting also concluded that "in situations involving little sampling data, the grey model is superior to other traditional forecasting models." Liu and Liu (2010) in their study on predicting red tourism through the model GM(1,1) also stated that the application of grey models could solve the problem of insufficient and uncertain data even when the tourism growth is not stable. In Table 1, adapted from Dang et al. (2016), an overview of the comparative analysis of grey forecasting models and other forecasting models has been presented.

Table 1. Historical data requirement of different models

Forecasting models	Data Requirement	Time horizon for forecasting
Box-Jenkins	50	Long
Moving average	2 to 30	Short
Simple exponential smoothing	5 to 10	Short
Neural network	Large number	Short
Trend models	10 to 20	Short, medium
Casual regression models	10 observations per independent variable	Short, medium, long
Grey models	4	Short, medium, long

3. METHODOLOGY

3.1. Data collection and analysis techniques

Secondary data concerning international tourism (receipts; the number of arrivals; the number of departures; expenditures) were collected from the World Bank (2018) for the period 2006 – 2016. Even Model GM (1,1) was used for data analysis and forecasting. The original model was executed at the Chinese language *Grey System Modelling* software. The EGM parameters (*a* and *b*) were also calculated through the software package. For O/P-EGM, Microsoft Excel was also used. For the Exponential Regression Analysis, Microsoft Excel was used.

Here the current study wants to offer a very serious proposition. The data reported by an organization (or databank) considered unreliable may be unreliable; however, the data reported by an organization (or databank) considered reliable may or may not be reliable. It happens because of the uncertainty in the data that can make the reliability of the data questionable (Javed, 2019). For example, on 11th November 2018, the database of World Bank (data.worldbank.org) was showing that "International tourism, expenditures (current US$)" were 261,129,000,000$ in 2017. However, on 10th July 2019, the same database was revealing the expenditures to be 250,112,000,000$ (while the figure for 2018 was 257,733,000,000$). During the Pandemic I, the COVID-19 pandemic, the international community, witnessed several instances on the global stage when different parties revisited their databases on different occasions to reflect the reality more accurately. Other than underscoring reliability of data as a function of time these facts signify the relevance, and significance, of the latest information over the older one. Thus, if a forecasting methodology is unable to consider the uncertainty in data, the accuracy of the forecasts can be tainted. Therefore, an approach like Grey System Theory, which was primarily introduced to deal with the problems containing uncertain data or poor information, is equally suitable when the data (or information) does not apparently contain uncertainty. When new information is available, the value of old information may change (degrade) prompting the database administrators to revise their earlier datasets.

3.2. The model Even GM (1,1)

Grey System Theory (GST) is an interdisciplinary and intelligent approach to analyze data associated with a "grey system", an uncertain system with incomplete or partially known information (Mahmoudi et al., 2019; Javed et al., 2018; Javed & Liu, 2018a). One of the key advantages of GST and its models are its superior decision making and forecasting even when the sample size is small (Ofosu-Adarkwa et al., 2020; Javed et al., 2019; Carboni & Russu, 2014). For grey forecasting models, the sample size can be as small as four values (see, Table 1). Grey forecasting models (GMs) are the most popular time-series prediction models of GST. Grey forecasting models, as time-series analysis techniques, have been used in various fields only with partly known distribution information (Wei, Xie & Hu, 2018). The models assume that the original time series is partially quasi-exponential (Wei et al., 2020). Deployment of different kinds of grey models in tourism forecasting is not unknown in the literature (see, e.g., Pirthee, 2017; Liu et al., 2014). There are four basic forms of the model GM (1,1) from which Even GM (1,1) is the most popular one and is almost synonymous to GM (1,1) in the communications of grey systems scholars (Javed & Liu, 2018b; Liu, Yang & Forrest, 2017), i.e. when the grey systems scholars refer "GM (1,1)" they usually mean Even GM (1,1). In the following part, the model EGM, adapted from Liu et al. (2017) and Liu and Yang (2017), is summarized.

Let the actual data sequence is $X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \dots x^{(0)}(n)\right)$ and its 1-AGO sequence is $X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \dots x^{(1)}(n)\right)$ where, $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)\,, k = 1,2,\dots,n$. The even form of GM (1,1) will be defined as, $x^{(0)}(k) + az^{(1)}(k) = b$ where, $z^{(1)}(k) = \frac{x^{(1)}(k)+x^{(1)}(k-1)}{2}$. The *parameter vector* $\hat{v} = [a,b]^T$ can be estimated through the least square method i.e.,

$$\hat{v} = [a,b]^T = [B^T B]^{-1} B^T Y$$

where,

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \text{ and } \quad Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}$$

The time response function of the model is expressed as

$$\hat{x}^{(1)}(k) = \left(x^{(0)}(1) - \frac{b}{a}\right) e^{-a(k-1)} + \frac{b}{a} \ , k = 1,2,\dots,n$$

The regressive reduction formula is expressed as

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), \qquad k = 1,2,\dots,n$$

And the time-response function of $X^{(0)}$ is given by

$$\hat{x}^{(0)}(k) = (1 - e^{a}) \left(x^{(0)}(1) - \frac{b}{a}\right) e^{-a(k-1)}\,, k = 1,2,\dots,n$$

Here it should be noted that in most grey models the first value of the simulated (forecasted) sequence is the first value of the actual data (see, e.g., Xie & Liu, 2005). Even GM (1,1) model exploits the first-order differential equation to describe the variable to be forecast (Sun et al., 2016) and is suitable for non-exponential increasing data sequence (Liu et al., 2016: pp. 153). For the complete detail on the model Even GM (1,1), its parameters and characteristics, Liu et al. (2017) and Liu and Yang (2017) can be referred.

3.3. The Optimistic-Pessimistic Method (OPM)

Here it should be noted that the integration of two different approaches/algorithms to boost the forecasting of a model or to enhance the forecasting accuracy of a model is well-known in applied studies. Li, Yang and Li (2018) argued that "a single prediction model cannot accurately fit a data sequence with large fluctuations" followed by proposing the integration of linear regression and Discrete GM(1,1). Different scholars tried to improve the performance of grey models in different ways. One of the earliest studies to provide solid grounds for the improvement of GM (1,1) was by Feng (1997). Later different scholars tried to improve the grey models in various ways, see, e.g., Wang (2004), Hsu (2010), Shan et al. (2012) and Huang (2012). Zhang et al. (2019) discussed the possibility of improving the accuracy of GM (1,1) model through various optimization methods, which includes "the optimization of both parameter estimation method and initial condition for GM (1,1) model, the optimization of combination with other model and the function transformation of the modelling sequence." However, these optimization methods require small to extensive tailoring in the original algorithm of the grey model. The method proposed in the current study is simple and can be applied with confidence without much tailoring of the original algorithm of grey models.

Further, considering the fact that old information can also increase the forecast error in grey models (Juan, 2011; Liu et al., 2014), a new method to confirm it has been proposed. The proposed approach can be easily integrated into any forecasting technique, and the increase or decrease in the forecast accuracy resulting from this integration reveals the extent of influence of old information on the forecasts. The proposed Optimistic-Pessimistic Method (OPM) reduces the forecast error without altering the original algorithm of the grey forecasting model. Here, instead of altering the *process* (core algorithm) that yields *output* (forecast), merely *input* (historical data) is altered, i.e., first of all, the input is decomposed and then passed through the same process followed by the synthesis of the resultant outputs. It allows the integration of OPM in any appropriate forecasting algorithm very convenient while preventing the increase in computational cost. The prediction accuracy is achieved by reducing the historic data's *noise*, an inherent property of a piece of information that determines its usefulness (or uselessness) for decision making (e.g., forecasting) relative to another piece of information. This noise can also be called *inherent randomness* in the sequence of data representing an observed behaviour of a phenomenon or the *inherent randomness* existing in the observational values of individual variables of the model (Liu et al., 2017: pp. 184-186). It has been well-known that new information contains less noise than the old information. One approach of reducing the influence of noise on the prediction accuracy is to increase the overall influence of new information in the predictions. If the *pessimistic* data sequence is the data sequence containing both relatively older and relatively recent information, then the study argues, the *optimistic* data sequence contains only the recent information. Thus, a method that incorporates both of these sequences intrinsically incorporates greater say of recent information in prediction than the older information. It is the underline concept on which the Optimistic-Pessimistic Method (OPM) is developed.

3.3.1. Axiom - I

The integration of OPM in a forecasting method reveals superior performance only when the latest information contains greater insight than older information about the future pattern.

3.3.2. Definition

Let's say X = ($x(1)$, $x(2)$,…, $x(k)$,…, $x(m\text{-}2)$, $x(m\text{-}1)$, $x(m)$) is the set of historical (actual) data that is used to produce *pessimistic* set of forecasted data X_F = ($x(m+1)$, $x(m+2)$,…, $x(m+n)$). Here, $x(m)$ represents last data value of the original data and $x(m+n)$ represents the last forecasted value, e.g., if $x(m)$ is for 2016, then $x(m+n)$ could be any year after 2016.

Let us say X'= ($x(k)$, ,…, $x(m\text{-}2)$, $x(m\text{-}1)$, $x(m)$) is the subset containing *recent* values of the set X, such that $X' \subset X$. Using this recent subset of X, the *optimistic* forecasted set is X'_F = ($x'(m+1)$, $x'(m+2)$,…, $x'(m+n)$). The decision to select $x(k)$ is up to the decision-maker. If priority is on extremely new information $x(k)$ would move toward $x(m)$ otherwise, it would move away from $x(m)$. Rule of thumb could be the consideration of not more than half of the recent historical data for optimistic predictions. The data sets X_F and X'_F represent pessimistic and optimistic predictions, respectively. If one's objective is long-term predictions, then two points should be considered carefully. In OPM-based grey models: 1) long term forecasts from a long term historical data are more likely to be accurate; 2) long term forecasts from short term historical data are less likely to be accurate. Therefore, it is recommended that X' should not be too small; it should contain at least four values, i.e., $m \geq k+3$. This assumption is in line with the minimum data requirement for grey forecasting models (Deng, 2005).

According to OPM, the synthetic set of both optimistic (X'_F) and pessimistic (X_F) forecasted sets is represented as $\tilde{X}_F$ and is given by

$$\tilde{X}_F = \left(\tilde{x}(m+1), \tilde{x}(m+2), \ldots, \tilde{x}(m+n)\right)$$

where,

$$\tilde{x}(m+1) = \alpha . x'(m+1) + (1-\alpha). x(m+1)$$

$$\tilde{x}(m+2) = \alpha . x'(m+2) + (1-\alpha). x(m+2)$$

$$\ldots$$

$$\tilde{x}(m+n) = \alpha . x'(m+n) + (1-\alpha). x(m+n)$$

Similarly, the synthetic simulation of actual data $\tilde{X}$ can also be obtained. Here, $\alpha \in [0,1]$ is the *weighting coefficient*, or positioned coefficient, which can be tailored as per the situation and need. If decision-makers consider the pessimistic predictions (X_F) more realistic, then α should be lower ($\alpha <$ 0.5) and if they consider optimistic predictions (X'_F) more reliable then α should be greater ($\alpha > 0.5$). In general, $\alpha = 0.5$ can be chosen, provided Axiom – I is satisfying.

From above discussion, it can be seen that OPM is an application of the concept of whitenization of interval grey number (Liu, Yang and Forrest, 2017: pp. 30 - 31) to the grey forecasting theory. To summarize the discussion, it is argued that in OPM, "Optimism" implies a preference for new information (recent data) over old information, and "Pessimism" implies a preference for the entire information irrespective of the fact information is old or new.

3.4. Performance evaluation of the model

Chopra and Meindl (2016: pp. 178) states, "Forecasts are always inaccurate and should thus include both the expected value of the forecast and a measure of forecast error." Mean Absolute Percentage Error (MAPE) is a popular method of estimating the performance of a forecasting model. It also allows comparative analysis of two models, e.g., improved versus the original one, where lower MAPE value implies higher forecast accuracy. MAPE, usually reported in percentage, is given by the following formula,

$$MAPE(\%) = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{x(k) - \hat{x}(k)}{x(k)}\right| \times 100$$

where, $x(k)$ and $\hat{x}(k)$ are representing actual (expected) observation and forecast value (simulated value obtained through the model), respectively. The effectiveness of MAPE has already been reported in multiple studies involving prediction making using grey models (see, e.g., Javed & Liu, 2018b; Pirthee, 2017). Scholars use Lewis's scale of MAPE results as a mean to judge the accuracy of the forecast (Ding, 2018; Lee and Shih, 2011; Chen, Bloomfield & Fu, 2003). This scale is given below.

$$MAPE(\%) = \begin{cases} < 10 & Highly\ accurate\ forecast \\ 10 \sim 20 & Good\ forecast \\ 20 \sim 50 & Reasonable\ forecast \\ > 50 & Inaccurate\ forecast \end{cases}$$

4. RESULTS AND DISCUSSION

4.1. Pilot Testing of the OPM based model and Performance appraisal

Before applying OPM based grey forecasting models on the case under the study, it is worthwhile to measure the performance of OPM on the secondary data, available to us from some published studies. For this purpose, a case has been taken from Chen et al. (2010) 's study that presents data of tourists to Taiwan from three different destinations (Hong Kong, USA and Germany) over the period 1989 to 2003. This data was divided into two parts; 1989 to 1998 (10 years) was considered as historical/actual data and 1999 to 2003 (5 years) was considered as a forecast horizon and was left for out-of-sample testing. The complete historical data (1989 to 1998) was considered as the pessimistic data sequence, which an analyst would usually consider for the prediction. A recent subset from this data, 1994 to 1998 data, was taken as the optimistic data sequence, which is prerequisite for executing OPM. MAPE(%) was considered as a performance evaluation tool. As can be seen from Table 2, OPM-based EGM(1,1) outperformed the original EGM(1,1) in most cases. OPM reduced the prediction error from 3.82% to 3.12% for Hong Kong tourists, 2.47% to 1.99% for American tourists and from 2.76% to 2.11% for German tourists. The prediction accuracy on the future forecasts is also visible from the lower MAPE(%) value for the American and German tourists to Taiwan, and for Hong Kong tourists the MAPE(%) values are almost comparable. The results indicate that the integration of OPM in a forecasting model is likely to boost the forecast accuracy.

Table 2. Forecasting of Inbound Tourists to Taiwan based on the data by Chen et al. (2010)

	Hong Kong to Taiwan			USA to Taiwan			Germany to Taiwan		
Year	**Actual Data**	EGM (1,1)	O/P-EGM	**Actual Data**	EGM (1,1)	O/P-EGM	**Actual Data**	EGM (1,1)	O/P-EGM
1989	211,804	211,804	211,804	220,594	220,594	220,594	25,002	25,002	25,002
1990	193,544	183,780	183,780	224,915	236,791	236,791	24,320	25,404	25,404
1991	181,765	193,985	193,985	240,375	245,487	245,487	25,798	26,582	26,582
1992	193,523	204,758	204,758	259,145	254,504	254,504	28,969	27,815	27,815
1993	213,953	216,129	216,129	269,110	263,851	263,851	28,644	29,104	29,104
1994	241,775	228,131	234,953	286,713	273,542	280,127	31,334	30,454	30,894
1995	246,747	240,799	244,324	290,138	283,589	285,680	32,944	31,866	32,450
1996	262,585	254,172	255,673	289,900	294,004	294,247	33,914	33,343	33,576
1997	259,664	268,287	267,569	303,634	304,802	303,083	34,660	34,889	34,745
1998	279,905	283,185	280,039	308,407	315,997	312,197	35,343	36,507	35,959
MAPE (%)		3.82%	3.12%		2.47%	1.99%		2.76%	2.11%
1999	319,814	298,911	293,112	317,801	327,603	321,599	34,190	38,200	37,221
2000	361,308	315,511	306,817	359,533	339,635	331,299	34,829	39,971	38,531
2001	392,552	333,032	321,187	348,808	352,110	341,305	33,716	41,824	39,893
2002	456,554	351,526	336,254	377,470	365,042	351,628	33,979	43,763	41,307
2003	323,178	371,047	352,054	272,858	378,449	362,279	28,577	45,792	42,777
MAPE (%)		14.44%	15.38%		10.31%	10.16%		27.91%	21.81%

*Pessimistic Data is from 1989 to 1998 (5 years);
**Optimistic Data is from 1994 to 1998 (5 years);

***Forecasting horizon is from 1999 to 2003 (5 years).

The pilot testing case, as shown in Table 2, is revealing that based on historic/actual data in all of the cases, OPM has improved the accuracy of the grey models. Even in the forecasted horizon, in most of the cases, OPM based predictions are nearer to actual values. Further, both *in-sample forecasting* (N = 10) and *out-of-sample forecasting* (N = 5) was used to measure the performance of the forecasting model through MAPE (%). Out-of-sample forecasting performance is measured using five years' data from 1999 to 2003. The decrease in MAPE (%) value, which is clearly observable in most cases, showed that with the integration of OPM in EGM (1,1), the accuracy of the model is very likely to increase for both in-sample and out-of-sample data. Thus, the feasibility and effectiveness of OPM are evident.

Here it should be noted that in the entire 'in-sample' testing the integration of OPM into EGM (i.e., O/P-EGM) resulted in improvement in forecast accuracy. However, in the 'out-of-sample' testing, in two cases O/P-EGM's based forecast was relatively more accurate than that of the original EGM, and in one case EGM based forecast was slightly better than that of O/P-EGM. This behaviour is explainable in the light of Axiom – I, i.e., the integration of OPM in a forecasting method may only reveal superior performance if the latest dataset contains greater insight than entire dataset about future projections. Therefore, this pilot testing reveals, the data of inbound tourists' data from USA and Germany contain greater uncertainty and, thus, exists a more considerable variation between new and older information.

4.2. Application on China's Tourism Indicators

After the successful pilot testing of the model O/P-EGM, it was deemed fit for practical use. First of all, the model EGM(1,1) was deployed to forecast the inbound tourism (A) and related receipts (R), and outbound tourism (D) and related expenditures (E), as shown in Table 3. The discussion is presented in the following sections.

Table 3. EGM(1,1) based Forecasting of Tourists and Financials

	A (Unit: 1000 persons)		D (Unit: 1000 persons)		R (Unit: 100,000 current US$)		E (Unit: 100,000 current US$)	
Year	Actual data	EGM-based Simulated Data	Actual data	EGM-based Simulated Data	Actual data	EGM-based Simulated Data	Actual data	EGM-based Simulated Data
2006	49913	49913	34524	34524	339490	339490	243220	243220
2007	54720	53237	40954	40321	372330	413417	297860	331433
2008	53049	53771	45844	46448	408430	420588	361570	425580
2009	50875	54311	47656	53507	396750	427884	437020	546469
2010	55664	54856	57386	61639	458140	435306	548800	701699
2011	57581	55407	70250	71007	484640	442858	725850	901023
2012	57725	55963	83182	81798	500280	450540	1019770	1156966
2013	55686	56525	98185	94229	516640	458355	1285760	1485613
2014	55622	57092	116593	108549	440440	466306	2273440	1907615
2015	56886	57666	127860	125046	449690	474395	2498310	2449490
2016	59270	58244	135130	144050	444320	482624	2611290	3145290
2017		58829		165942		490996		4038739
2018		59420		191161		499513		5185979
2019		60016		220213		508178		6659103

2020		60619		253680		516993		8550682
2021		61227		292233		525961		10979580
2022		61842		336645		535085		14098430
2023		62463		387806		544367		18103216
2024		63090		446743		553809		23245599
2025		63723		514637		563416		29848722
2026		64363		592848 (592.9 million)		573190 ($57.3 billion)		38327522
Parameters		a = -0.0100;		a = -0.1415;		a = -0.0172;		a =-0.250;
		b = 52472.7881;		b = 32651.1784;		b = 404033.6231;		b = 230912.957;
		Coefficient = 52707.6773		Coefficient = 35001.2452		Coefficient = 406367.7848		Coefficient =258113.5325
MAPE (%)		2.64%		4.50%		7.67%		17.40%

A: International tourism, number of *arrivals* (overnight visitors);
D: International tourism, number of *departures*;
R: International tourism, *receipts*;
E: International tourism, *expenditures*.

4.2.1. Forecasting Inbound Tourism to China through Grey Models

The first part (A) of Table 3 shows the actual data from 2006 to 2016 for the inbound tourism (overnight visitors) to mainland China and predicted inbound tourists from 2017 to 2026 using Even Grey model. All values of inbound and outbound tourism are in thousands (1,000 persons), and revenue and expenditures from inbound and outbound tourism are in hundred thousand ($100,000), in the tables. As far as inbound tourism (overnight visitors) to China is concerned, even the grey model's accuracy was around 97.4%. According to the model EGM (1,1), around 64,363,000 (64.4 million) persons are increasingly expected to travel to China in 2026.

4.2.2. Forecasting Outbound Tourism through Grey Models

The second part (D) of Table 3 shows the actual data from 2006 to 2016 for the outbound tourism (number of departures) from mainland China to abroad and predicted outbound tourists from 2017 to 2026 using Grey models. All values of outbound tourism are in thousand (1,000 persons). As far as outbound tourism from China to other countries is concerned, the even grey model's accuracy was around 95.5%. According to EGM (1,1), around 592,848,000 (592.9 million) people are expected to travel to other countries from China in 2026. The trend is increasing. Deng (2018) quoted Jane Sun for predicting the number of potential Chinese outbound tourists to be 240 million by 2020. According to our projections, this milestone is expected to be achieved somewhere between 2019 and 2020, and in 2020 the Chinese outbound tourists are predicted to exceed 253 million.

4.2.3. Forecasting Revenue from Inbound Tourism

The third part (R) of Tables 3 shows the actual data from 2006 to 2016 for the revenue from the inbound tourism to China and predicted the revenue from 2017 to 2026 using the grey models. All values of revenue from inbound tourism are in hundred thousand ($100,000). As far as the revenue from inbound tourism to China is concerned, the accuracy of both grey models was comparable. The accuracy in the predictions through grey models turned out to be around 92.3%. According to EGM (1,1), China's revenue from inbound tourism is expected to reach $57,319,000,000 ($57.3 billion) till 2026. The trend is increasing.

4.2.4. Forecasting Outbound Tourism Expenditures

The fourth part (E) of Tables 3 shows the actual data from 2006 to 2016 for the expenditures incurred by the outbound tourism from China to abroad and predicted the expenditures from 2017 to 2026 using Grey models. All values of the expenditures are in a hundred thousand ($100,000). The results reveal, as far as the expenditures made by outbound tourists from China is concerned, the model EGM's accuracy was 82.6%. According to EGM, expenditures made by outbound tourists from China are expected to reach $3,833 billion until 2026. The trend is increasing. These expenditures are the source of revenue for other countries that the outbound tourists from China are choosing to be their travel destinations.

4.2.5. Improved Forecasting through OPM

One advantage of OPM is that it can easily be integrated into a forecasting model without altering the core portion of the algorithm of the original model. Table 4 shows the execution of O/P-EGM, for outbound tourists' expenditure. The visual illustration of the actual data revealed that the recent data starting from 2013/2014 onward have bit different trend as compared to the preceding data. On this convenient basis, the actual data was divided into two parts, pessimistic data (actual data; histroric dataset) and optimistic data (latest sub-set of pessimistic data).

Table 4. Forecasting International tourism, expenditures (current USD; $100,000) through O/P-EGM

Year	Pessimistic Data (X)	Optimistic Data (X')	X-based EGM	X'-based EGM	O/P-EGM
2006	243,220		243,220		243220
2007	297,860		331,433		331433.0
2008	361,570		425,580		425579.6
2009	437,020		546,469		546469.3
2010	548,800		701,699		701698.9
2011	725,850		901,023		901022.8
2012	1,019,770		1,156,966		1156966.4
2013	1,285,760	1,285,760	1,485,613	1,285,760	1,265,882
2014	2,273,440	2,273,440	1,907,615	2,294,541	1,957,505
2015	2,498,310	2,498,310	2,449,490	2,456,234	2,281,853
2016	2,611,290	2,611,290	3,145,290	2,629,322	2,685,080
2017			4,038,739	*2,814,607*	3,189,578
2018			5,185,979	*3,012,949*	3,824,380
2019			6,659,103	*3,225,268*	4,627,146
2020			8,550,682	*3,452,549*	5,646,745
2021			10,979,580	*3,695,846*	6,946,623
2022			14,098,430	*3,956,288*	8,609,170
2023			18,103,216	*4,235,083*	10,741,407
2024			23,245,599	*4,533,525*	13,482,380
2025			29,848,722	*4,852,997*	17,012,776
2026			38,327,522	*5,194,982*	21,567,420

Parameters			a =-0.250;	a =-0.0681;	
			b = 230912.957;	b = 2129745.7768;	
			Coefficient =258113.5325	Coefficient = 2143491.2070	
MAPE (%)			17.35%		14.64%

Similarly, OPM based forecasting for the other three cases (receipts from inbound tourists, inbound tourism and outbound tourism) can also be executed. The final results of this exercise for each case have been summarized in tabular form, as shown in Table 5.

Table 5. Forecasting the Receipts, Tourists' Arrivals and Departures through O/P-EGM

	R			A			D		
Year	Pessimistic Data (X)	Optimistic Data (X')	O/P-EGM	Pessimistic Data (X)	Optimistic Data (X')	O/P-EGM	Pessimistic Data (X)	Optimistic Data (X')	O/P-EGM
2006	339490		339490	49913		49913	34524		34524
2007	372330		413417	54720		53237	40954		40321
2008	408430		420588	53049		53771	45844		46448
2009	396750		427884	50875		54311	47656		53507
2010	458140		435306	55664		54856	57386		61639
2011	484640		442858	57581		55407	70250		71007
2012	500280		450540	57725		55963	83182		81798
2013	516640	516640	487497	55686	55686	56105	98185	98185	96207
2014	440440	440440	454597	55622	55622	56263	116593	116593	112963
2015	449690	449690	459604	56886	56886	57450	127860	127860	125646
2016	444320	444320	464685	59270	59270	58669	135130	135130	139917
2017			469842			59921			155992
2018			475076			61207			174119
2019			480388			62528			194579
2020			485779			63885			217694
2021			491251			65279			243835
2022			496805			66712			273424
2023			502443			68185			306946
2024			508165			69698			344955
2025			513974			71254			388088
2026			519870			72853			437074
$MAPE^{O/P}$ (%)			6.11 %			2.30 %			3.57 %

R: Forecasting International tourism, receipts (current USD; $100,000) through O/P-EGM
A: Forecasting International tourism, number of arrivals (1000 persons) through O/P-EGM
D: Forecasting International tourism, number of departures (1000 persons) through O/P-EGM

The OPM-based model reveals reasonable forecasting while considering both optimistic and pessimistic perspectives to predict the future pattern of the data. For example, for the case of "international tourism - expenditure" using EGM model, the position of O/P-EGM forecast against actual data (X) based forecasts and optimistic data (X') based forecasts can be seen from Figure 1.

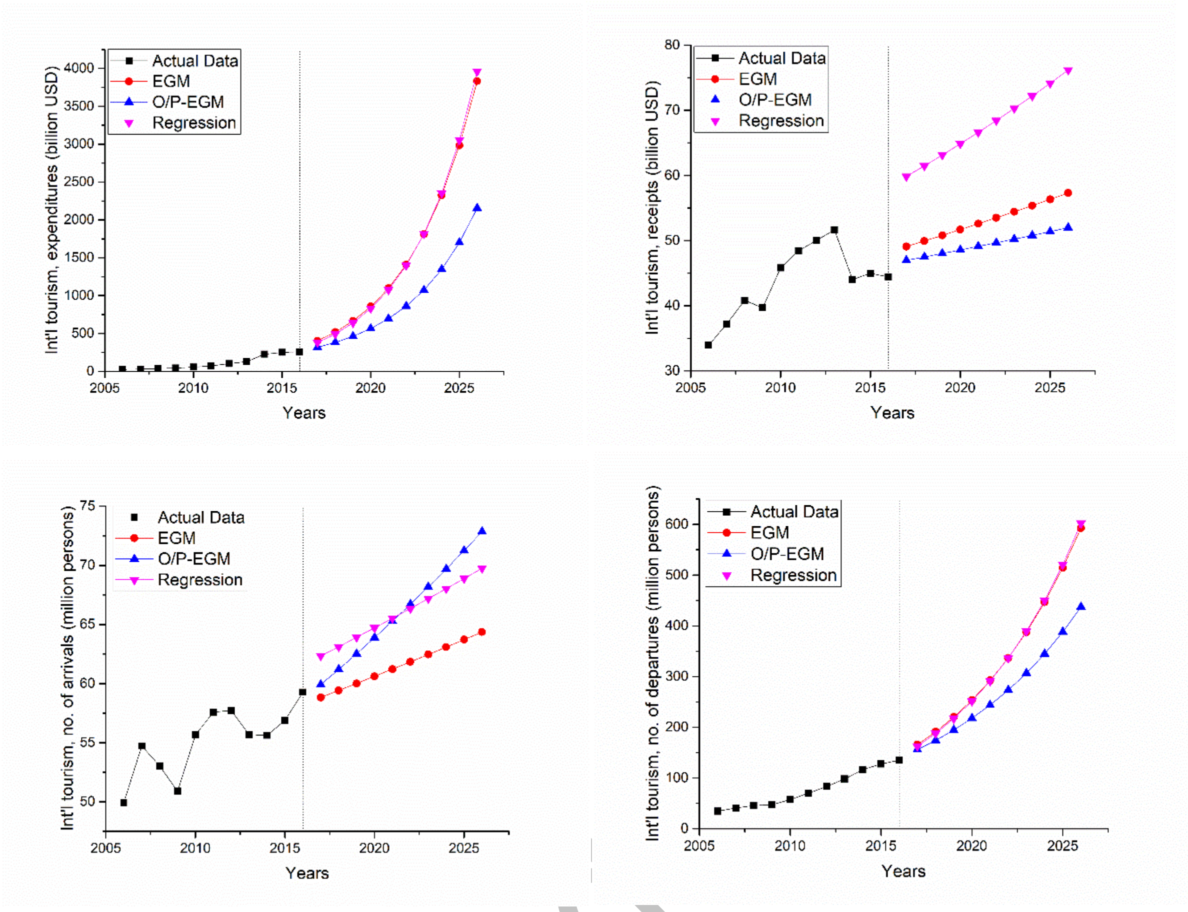

Fig 1. Forecasting the four tourism indicators through EGM, O/P-EGM and Regression models

4.2.6. Performance Evaluation of the Models with recently available data

The out-of-sample testing was performed on the 2017 and 2018 datasets, and the results from the EGM, O/P-EGM, and Exponential Regression analysis are shown in Table 6. MAPE(%) [2017, 2018] for the three models was [12.89%, 17.99%], [6.99%, 9.32%] and [19.29%, 21.77%], respectively. One can see that the performance of O/P-EGM is finest among these models.

Along with the pilot testing, Table 6 reconfirms the feasibly of OPM. Considering Axiom – I in mind, it can be argued that decrease in the error measure (e.g., MAPE) for OPM-based forecast implies that the forecasted data is more explainable by recent (optimistic) data than by the complete set of data (pessimistic). One can see from Table 6 that in all cases, OPM-based grey models' MAPE (%) values are lower that is signifying that the model is likely to produce reliable tourism-related predictions, which can be better explained by the recent data than by the entire data set. Thus, the findings suggest that the integration of OPM significantly improves the performance of grey prediction models, as can been seen from Figure 2 as well. In Figure 2, the y-axis shows the four tourism indicators and the x-axis shows the forecast accuracy in percentage, deduced from MAPE (%) values.

Table 6. Performance Evaluation of the Models against 2017 and 2018's actual data

	International tourism expenditure (current US$:100,000)								International tourism, receipts (current US$:100,000)							
	Actual Data		EGM		O/P-EGM		Regression		Actual Data		EGM		O/P-EGM		Regression	
	2017	*2018*	*2017*	*2018*	*2017*	*2018*	*2017*	*2018*	*2017*	*2018*	*2017*	*2018*	*2017*	*2018*	*2017*	*2018*
	2,578,750	2,772,450	4,038,739	5,185,979	3,189,578	3,824,380	3,795,993	4,926,092	385,590	403,860	490,996	499,513	469,842	475,076	598,520	614,777
Variation			1,459,989	2,413,529	610,828	1,051,930	1,217,243	2,153,642			105,406	95,653	84,252	71,216	212,930	210,917
Variation (%)			56.62%	87.05%	23.69%	37.94%	47.20%	77.68%			27.34%	23.68%	21.85%	17.63%	55.22%	52.23%
MAPE (%)			28.31%	43.53%	11.84%	18.97%	23.60%	38.84%			13.67%	11.84%	10.93%	8.82%	27.61%	26.11%
	Outbound tourism from China (1000 persons)								Inbound Tourism to China (1000 persons)							
	Actual Data		EGM		O/P-EGM		Regression		Actual Data		EGM		O/P-EGM		Regression	
	2017	*2018*	*2017*	*2018*	*2017*	*2018*	*2017*	*2018*	*2017*	*2018*	*2017*	*2018*	*2017*	*2018*	*2017*	*2018*
	143,035	149,720	165,942	191,161	155,992	174,119	72,616	83,947	60,740	62,900	58,829	59,420	59,921	61,207	62,337	63,121
Variation			22,907	41,441	12,957	24,399	70,419	65,773			1,911	3,480	819	1,693	1,597	221
Variation (%)			16.01%	27.68%	9.06%	16.30%	49.23%	43.93%			3.15%	5.53%	1.35%	2.69%	2.63%	0.35%
MAPE (%)			8.01%	13.84%	4.53%	8.15%	24.62%	21.97%			1.57%	2.77%	0.67%	1.35%	1.31%	0.18%

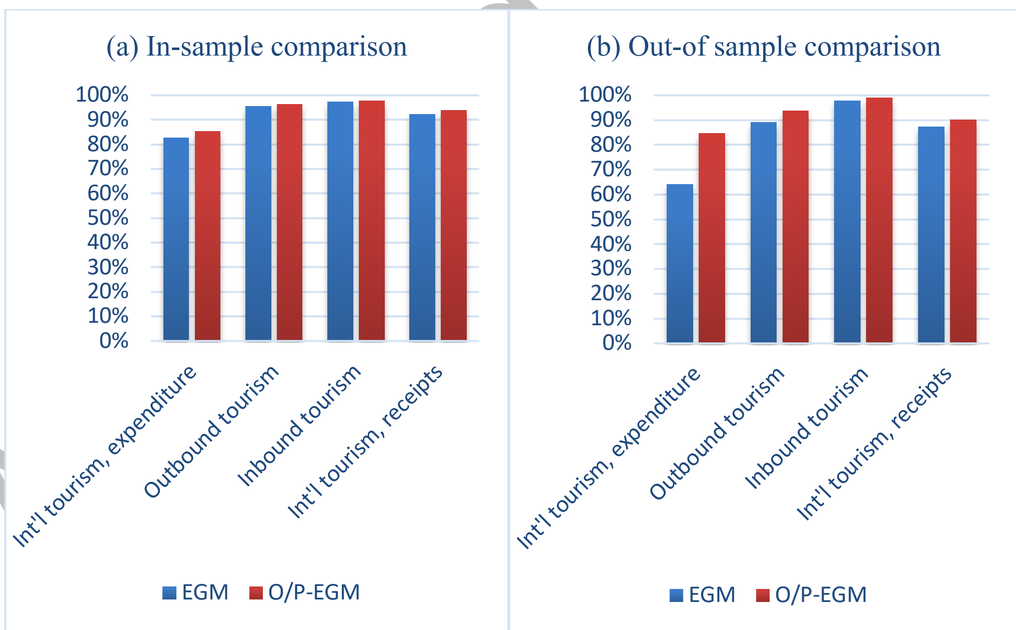

Fig 2. Forecast Accuracy (%) of the models (a) EGM and (b) O/P-EGM

Further, the study reveals that for tourism-related forecasting recent data contains more insight (concerning future) than the older data because of the dynamic and evolutionary nature of the tourism system that's why OPM-based grey model generally performed better than the original model. The average annual growth rate of "International tourism, number of arrivals" was 1.84% from 2006 to 2016 and, according to O/P-EGM, is likely to increase to 2.2% from 2017 to 2026. The average annual growth rate of "International tourism, receipts" was 3.04% from 2006 to 2016 and is likely to reduce to 1.13%

in the next ten years. The average annual growth rate of "International tourism, number of departures" was 14.8% from 2006 to 2016 and is likely to reduce to 12.1% in the next ten years. The average annual growth rate of "International tourism, expenditures" was 28% from 2006 to 2016 and is likely to reduce to 22.8% in next ten years, provided Chinese government's tourism policy or China's international relations do not see any drastic change.

5. CONCLUSION AND RECOMMENDATIONS

Tourism forecasting is a topic gaining exceeding attention in all those countries, who are either the primary source or recipient of tourists. The time-series models have shown to have strengths in forecasting tourism demand (Morley, 2009). Even GM (1,1) is one of the most popular grey forecasting models which uses time-series data as input to generate forecasts. The study shows when the proposed approach, Optimistic-Pessimistic Method (OPM), was integrated into the original model Even GM (1,1), the Mean Absolute Percentage Error of the resultant model, O/P-EGM, was generally decreased that demonstrated the increase in prediction accuracy. Thus, the study not only stresses the suitability of grey prediction models for the tourism-related phenomenon but also shows (through a pilot case and real-world application) if OPM is integrated into grey models their performance can marginally be enhanced. Also, the study suggests for the compelling predictions of Chinese tourism-related indicators the new data is more likely to be insightful than the historical data. The recently available data (out-of-sample testing) on the four cases confirmed the reliability of the predictions made by the proposed approach.

The benefits of the growth of the travel and tourism industry are at least three folds. It creates revenues for the country, its corporate sector and its domestic economy, enhances employment opportunity in the country and creates a positive (hospitable) image of the country and its people abroad. According to the World Travel & Tourism Council (WTTC, 2017a; WTTC, 2017b), even though the U.S. emerged as the strongest country in 2016 (followed by China), "a drop in inbound travel because of anti-foreign sentiment" is expected to reduce the growth rate of travel and tourism in the U.S., which faced a decline from 2.8% to 2.3% from 2016 to 2017. Being the strongest competitor of the U.S. (in *absolute* terms of both direct and total contributions to GDP, travel & tourism investment, and visitor exports, in 2016-2017) and the leader of the world (in terms of total contribution to employment) (WTTC, 2017a; WTTC, 2018), China has both opportunity and potential to attract the foreign tourists through the promotion of tourists-friendly sentiments and policies. The study outlines that Chinese tourism research is likely to seek more attention in future because of the positive growth in all important indicators. Further, because of the rising wave of "protectionism" in the competing economies, China has both resources and opportunities to make maximum gains by projecting itself as a tourist-friendly country.

The study suggests the future researchers to use OPM in other areas as well to enhance the validity of the approach. Further, the impact of OPM's integration on forecasting techniques' long-term verses short-term prediction accuracy is an area of future research. Also, OPM-based grey models' suitability for other tourism indicators, and in other sectors of the economy, can also be gauged in future. Considering China to be one of the major travel and tourism countries of the world this study focused itself to China nevertheless the future scholars can replicate the proposed method in other countries as well with a view to comparatively analyze different economies while considering the increasing role of tourism in supporting several countries' national economies and absorbing their surplus labour. For example, the rapidly developing countries that are going through the uneven distribution of development despite abundant of natural or historic resources can particularly benefit from these proposals.

No development is free from shortcomings. OPM is a modest effort to make the forecasting more accurate when the robust forecasting methods cannot be applied because of limited resources e.g., when time constraint or higher computation cost of a forecasting method prevents a decision-maker from using it, and thus a convenient methodology is needed. Thus, OPM provides the decision-makers with a convenient technique to saturate the accuracy of the forecasting model they are already familiar with. However, convenience comes at a cost. OPM based results should only be trusted when Axiom – I is satisfying. Further, the value of the coefficient α should be determined based on the guidelines discussed in this paper, and its value should be altered when needed to bring forecast nearer to the truth. In the future, a robust algorithm to estimate the optimum value of α can be developed. An approach that can inconsistently distribute the value of α considering the recency of data at each point of time can better serve the purpose. Also, how the integration of OPM in other forecasting methods would influence the accuracy of those methods is yet to be seen. Moreover, gauging the short-term and long-term impacts of the COVID-19 pandemic on the travel and tourism industries is a topic requiring systematic investigations in future.

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