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Realities beyond the Grey-Markov Model for Forecasting International Tourism Demand

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A B S T R A C T

This study applied a forecasting method to forecast Korean tourism demand from three major source countries (Japan, China and United States), which combines the first-order one variable grey differential equation model from grey system theory and Markov chain model from stochastic process theory. Then it tested the real performance of the model in terms of international tourism demand during 2013 through 2017. Even though all of the relative errors of the forecasting values are less than 5% meaning the Grey-Markov chain model gives higher precision in forecasting tourism demand, this study revealed that the real international tourism demand is not closed to the values forecasted by using the mathematical model. There are some other factors which took a role breaking the mathematical forecasting rules based basically upon historical records. This study informs international tourists' movement in terms of Korean tourism demand is heavily influenced by political issues associated with China and Japan.

Keywords: Grey System Theory, Markov Chain Model, Grey-Markov Chain Model, Tourism Demand Forecasting

Ⅰ. Introduction

A manager must plan for the future in order to minimize the risk of failure or, more optimistically, to maximize the possibilities of success. Planning, both operational and strategic, relies on accurate forecasting. Especially, planning in tourism is no less dependent on accurate forecasts (Choi et al., 2011) and no manager can avoid the need for some form of forecasting (Archer, 1987).

Although precise future predictions are virtually impossible, the minimization of errors, i.e. forecasting with minimum variation from the actual, will lend credibility to the procedures. Accordingly, forecasting can certainly give us an idea of what future conditions may be like, and it can provide us with an assessment of the possible outcome of alternative courses of action.

Tourism demand modeling and forecasting methods can be broadly divided into two categories: quantitative and qualitative methods. In their study, Song & Turner (2006) concluded that the majority of the published studies used quantitative methods to forecast tourism demand. Although many quantitative methods have been applied to forecasts of tourism demand, no single forecasting method has been found to outperform all others in all situations (Li et al., 2005). On the contrary,

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empirical studies have shown that combining the forecasts obtained from single models can improve forecasting accuracy. The rationale for combining forecasts is that greater accuracy can be achieved by synthesizing the information contained in different individual forecasts into a composite forecast (Bates & Granger, 1969; Winkler, 1989). Bunn (1989) notes that such combinations improve forecast accuracy by taking advantage of the availability of multiple information and computing resources, and defines this approach as 'data-intensive' forecasting. Another principal motivation for combining forecasts is to avoid the difficulty and risks inherent in model selection. As Zhang (2003) states, ''the final selected model is not necessarily the best for future uses due to many potential influencing factors such as sampling variation, model uncertainty and structure change. By combining different methods, the problem of model selection can be eased with little extra effort''.

In this sense, this study used combining different methods to forecast international tourism demand. The developing trend of the number of tourist arrivals was regarded as a grey system behavior because the relation between the number of tourist arrivals and economic development, social environment and policy, etc., is not necessarily clear, although they influence the number of tourist arrivals.

The grey dynamic model (GM) based upon Grey system theory which was first introduced in early 1980s by Deng(1982) is relatively easy and few calculations are needed. But the accuracy of conventional GM is not satisfactory when the original data show great randomness. Therefore, this study assumed more precise forecasting can be achieved by Grey-Markov Chain Model. In addition, this study conducted further study to verify the accuracy with reality. This is because of a research note conducted by Armstrong & Farley (1969). According to their study on forecasting store choice by Markov model, Markov model showed only slight predictive advantage over the no-change model for short-term forecasting. While this does not imply a blanket rejection of the Markov technique for forecasting, it is important to test the performance of the model by comparing with the realities.

Ⅱ. Literature Review

A. Grey System Theory

Grey system theory is an interdisciplinary scientific area that was first introduced in early 1980s by Deng (1982). Since then, the theory has become quite unknown parameters. As superiority to conventional statistical models, grey models require only a limited amount of data to estimate the behavior of unknown system (Julong, 1989). The essential contents and topics of Grey System theory encompass the following areas: grey relational space, grey generating space, grey forecasting, grey decision making, grey control, grey mathematics, and grey theory. In Grey System theory a dynamic model with a group of differential equation is developed, which is called grey differential model (GM) (Julong, 1987).

Grey system theory has been developed rapidly and applied to various system such as social, economic, financial, scientific and technological, agricultural, industrial, transportation, mechanical, metrological, medical, military etc., system (Kayacan et al., 2010). For example, Wang (2002) used the grey theory to predict stock prices and it is shown that the approach is very efficient.

The Grey system theory includes five major parts, which include grey prediction, grey relation, grey decision, grey programming, and grey control (Li et al., 2006). Prediction is to analyze the developing trend in the future according to past facts. Most of the prediction methods need a large number of history data, and will make use of the statistical method to analyze the characteristics of the system. Furthermore, because of additional noise from the outside and the complex interrelations among the system or between the system and its environment, it is more difficult to analyze the system. As a prediction model, the grey dynamic model (GM) has the advantages of establishing a model with few and uncertain data and has become the core of grey system theory.

B. Markov Chain Model

A Markov chain named after Andrey Markov

(1856-1922), is a mathematical system that undergoes transitions from one state to another, between a finite or countable number of possible states. It is a random process usually characterized as memoryless: the next state depends only on the current state and not on the sequence of events that preceded it. This specific kind of 'memorylessness' is called the Markov property. Markov chains have many applications as statistical models of real-world processes. Andrey Markov developed the theory of Markov chains in his paper 'Extension of the Limit Theorems of Probability Theory to a Sum of Variables Connected in a Chain' (Markov, 1971).

A Markov chain is a sequence of random variables $X_1, X_2, X_3, \cdots$ with the Markov property, namely that, given the present state, the future and past states are independent. Formally,

$$P_r = (X_{n+1} = x | X_1 = x_1, X_2 = x_2, \cdots X_n = x_n) \\ = P_r(X_{n+1} = x | X_n = x_n)$$

The possible values of X_i form a countable set Scalled the state space of the chain. Markov chains are often described by a directed graph, where the edges are labeled by the probabilities of going from one state to the other states.

Applying Markov-chain model in tourism first presented by Mednick (1975) and Uysal et al. (1995). Medinick (1975) used it to find travel patterns of US visitors to Ontario, and Uysal et al. (1995) tried to estimate trip-type switching and market share by using the Markov chain model. Also, in Choi et al. (2011), Markov chain model was applied to estimate destination switching and market share. And the result of that study proved that Markov analysis is an acceptable way of forecasting the future movement of international tourist.

C. Grey-Markov Chain Model and its Use

The rationale of Grey-Markov forecasting model is as follows: first a GM grey forecasting model is built to calculate the fluctuating trend curve of the historical data series, then specify some states around the trend curve, a Markov transition matrix can be built to find out the transition probability, finally these two models should be combined to forecast accurately by the historical time series data. This forecasting method can make full use of the information given by historical data, and increase greatly the forecasting precision of random fluctuating sequences.

The applications of Grey-Markov chain model for forecasting problems have resulted in several research papers. Zhan-Li & Jin-Hua (2011) applied Grey-Markov model in forecasting fire accidents. Yan et al. (2012) established a real estate price prediction model of Qingdao city based on the Grey-Markov chain. Chen et al. (2012) used Grey-Markov model to predict traffic accidents in 2012. The application of Grey-Markov model also has been used in forecasting annual maximum water levels at hydrological stations (Dong et al., 2012).

Markov chain requires the prediction object to be stationary process. Since the change of the number of international tourist arrivals is a non-stationary process, it is necessary to combine the two models of prediction. The new Grey-Markov model was expected to forecast tourism demand more accurately than previously used methods. This model combines the first-order one variable grey differential equation model (abbreviated as GM model) from grey system theory and Markov chain model from stochastic process theory.

The main objective of this study is to find a way to forecast future tourism demand. Since empirical studies have shown that combining the forecasts obtained from single models can improve forecasting accuracy, Markov chain based on statistical method was incorporated with the original grey dynamic model (GM) to further enhance the predicted accuracy. Once it shows the predicted values, this study conduct further research to verify the accuracy with reality.

Ⅲ. Methodology

A. Building the GM Forecasting Model

Grey-Markov chain model was proposed to forecast tourist arrivals to Korea from Japan, USA, and China. This model consists of GM model and Markov chain model. Grey-Markov model was established based on the advantage of both methods, which adopts GM model to study development regulation of data sequence and uses Markov Model to study vibrating regularities of data sequences (Huang et al., 2007). The GM forecasting model was built as follows:

Step 1: Assume the original data sequence to be:

$$x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)\} \quad \text{(Eq. 1)}$$

Step 2: Then $x^{(1)}$ is viewed as 1-AGO (one time accumulated generating operation) generation series for $x^{(0)}$, if $x^{(1)}(j) \in x^{(1)}$ can satisfy $x^{(1)}(j) = \sum_{i=1}^{j} x^{(0)}(i)$;

Then $x^{(1)}$can be obtained as:

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

Step 3: The grey differential equation of GM and its whitening equation are obtained as:

$$\frac{dx^{(1)}}{dt} + a\,x^{(1)} = b \quad \text{(Eq. 3)}$$

$$x^{(o)}(i) + az^{(1)}(i) = b, \qquad i = 2,3 \ldots n \quad \text{(Eq. 4)}$$

Where, a denotes the developing coefficient, b denotes grey input.

Step 4: Let $\hat{u}$ be the parameters vector, $\hat{u} = (\hat{a}, \hat{b})^T = (A^T A)^{-1} A^T X_N$, B denotes the accumulated matrix and Y is the constant vector, so $a$and b can be obtained by using least square method. Where

$$A = \begin{bmatrix} -z^{(1)}(1) & 1 \\ -z^{(1)}(2) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \qquad X_n = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}$$

$$z^{(1)}(i) = \frac{1}{2}(x^{(1)}(i) + x^{(1)}(i+1)), \quad i = 2,3,4,... n \quad \text{(Eq. 5)}$$

Step5: The solution of Eq. (4) can be obtained as follows:

$$\hat{x}^{(1)}(t+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-at} + \frac{b}{a} \quad \text{(Eq. 6)}$$

Step 6: Applying the inverse accumulated generating operation (IAGO), and then the predicted equation is,

$$\hat{x}^{(0)}(i+1) = \hat{x}^{(1)}(i+1) - \hat{x}^{(1)}(i) = \left(x^{(0)}(1) - \frac{b}{a}\right)(1 - e^{a})e^{-ai} \quad \text{(Eq. 7)}$$

B. Building the Grey-Markov Chain Model

The original data were first modeled by the GM, and then the residual errors between the predicted values and the actual values for all previous time steps are obtained. The idea of the MCGM was to establish the transition behavior of those residual errors by Markov transition matrices, and then the possible correction for the predicted value can be made from those Markov matrices.

The detailed procedure is shown as follows.

Step 1. The division of state

For original data series, use GM model to obtain the predicted value $\hat{x}^{(0)}(i)$. Then, the relative error $e(i) = (x^{(0)}(i) - \hat{x}^{(0)}(i))/x^{(0)}(i)$ can also be obtained.

Then $\hat{x}^{(0)}$is a Markov chain, we can divide it into n states according to the relative error, its any state can be denoted as:

$$\otimes_j = [\otimes_{j-}, \otimes_{j+}] \quad \otimes_{j-} = \hat{x}^{(0)}(j) + a_j \quad \otimes_{j+} = \hat{x}^{(0)}(j) + b_j \quad \text{(Eq. 8)}$$

Assume $n^i$is the data number of original sequence, the transition probability from $\otimes_i$to $\otimes_j$can be established:

$$P_{ij}^{(k)} = \frac{n_{ij}^{(k)}}{n_i}, \qquad i = 1,2,\cdots n \qquad \text{(Eq. 9)}$$

where $P_{ij}^{(k)}$is the transition probability of state $\otimes_j$ transferred from state $\otimes_i$ for k steps, k is the number of transition steps each time, n_i is the number of data in state $\otimes_i$, $n_{ij}^{(k)}$ is the number of original data of state $\otimes_j$ transferred from state $\otimes_i$ for k steps, its transition probability matrix can be expressed as follows:

$$P^{(k)} = \begin{bmatrix} P_{11}^{(k)} & P_{12}^{(k)} \cdots & P_{1r}^{(k)} \\ P_{21}^{(k)} & P_{22}^{(k)} \cdots & P_{2r}^{(k)} \\ \vdots & \ddots & \vdots \\ P_{n1}^{(k)} & P_{n2}^{(k)} \cdots & P_{nn}^{(k)} \end{bmatrix} \qquad \text{(Eq. 10)}$$

The transition probability matrix of states $P^{(k)}$ reflects the transition rules of the system. The transition probability of states $P_{ij}^{(m)}$ reflects the probability of transition from initial state i to probable state j by m steps. It is the foundation of prediction by the Markov probability matrix. Then select the closest times from the prediction time, the transfer steps are defined as 1 steps, 2steps and n steps respectively in terms of the distance to the predict time, in the transition probability matrix, the corresponding row vectors of the initial states are the probability that every state appears, then calculate the sum of every probability, the relative error zone $[\otimes_{j-},\otimes_{j+}]$ is obtained, the median in $[\otimes_{j-},\otimes_{j+}]$ is selected as the relative error, so forecasting value of original data sequence is obtained according to the above explanation.

$$\hat{y}^{(0)} = \hat{x}^{(0)}(1 + \frac{\otimes_{j-} + \otimes_{j+}}{2}\%) \qquad \text{(Eq. 11)}$$

Ⅳ. Results

The original data sequence of tourists arrivals from selected countries to Korea from 2004 to 2012 are listed in Table 1. Then, Grey-Markov forecasting model was applied to forecast the tourist arrivals. The methodology proposed in this paper and its outcomes are as follows.

A. Forecasted International Flows by Model

1. GM Forecasting Model

Based on the original data of Japanese tourist arrivals from 2004 to 2012；

$$x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(9)\}$$

Table 1. Tourist Arrivals from Japan, China and US to Korea (2004-2012)

Year	Japanese tourist arrivals	Chinese tourist arrivals	US tourist arrivals
2004	2,443,070	627,264	511,170
2005	2,440,139	710,243	530,633
2006	2,338,921	896,969	555,704
2007	2,235,963	1,068,925	585,212
2008	2,378,102	1,167,891	610,083
2009	3,053,311	1,342,317	611,327
2010	3,023,009	1,875,157	652,889
2011	3,289,051	2,220,196	661,503
2012	3,518,792	2,836,892	697,884

=(2,443,070, 2,440,139, 2,338,921, 2,235,963, 2378102, 3,053,311, 3,023,009, 3,289,051, 3,518,792)

is an original series of real numbers with irregular distribution.

Then $x^{(1)}$ is viewed as AGO generation series for $x^{(0)}$, according to Eq. 2,

Then $x^{(1)}=\{\sum_{i=1}^{1}x^{(0)}(i),\sum_{i=1}^{2}x^{(0)}(i),\cdots,\sum_{i=1}^{n}x^{(0)}(i)\}$
=(2,443,070, 2,440,139, 2,338,921, 2,235,963, 2,378,102, 3,053,311, 3,023,009, 3,289,051, 3518792)

$z^{(1)}(k)$ is the generated mean sequence of consecutive neighbors of $x^{(1)}$,

$$z^{(1)}(k)=\frac{1}{2}(z^{(1)}(k)+z^{(1)}(k-1),k=2,...,9$$

So $z^{(1)}(k)=\{z^{(1)}(1),\cdots,z^{(1)}(8)\}$
=(3,663,139.5, 6,052,669.5, 8,340,111.5, 1,064,7144, 1,336,2850.5, 1,647,144, 1,955,7040.5, 22,960,962)

Then, by least-squares method, the coefficients a and b can be obtained as

$$A=\begin{bmatrix}-3,663,139.5 & 1\\ -6,052,669.5 & 1\\ -8,340,111.5 & 1\\ -10,647,144 & 1\\ -13,362,850.5 & 1\\ -16,401,010.5 & 1\\ -19,557,040.5 & 1\\ -22,960,962 & 1\end{bmatrix}\quad X_n=\begin{bmatrix}2,440,139\\ 2,338,921\\ 2,235,963\\ 2,378,102\\ 3,053,311\\ 3,023,009\\ 3,289,051\\ 3,518,792\end{bmatrix}$$

So the value ($a=-0.068, b=1,930,171.92$) can be obtained after calculating, then the grey forecasting model is established according to Eq. 5 as follows:

$$\frac{dx^{(1)}}{dt}-0.068x=1,930,171.92$$

Then according to Eq. 6, the forecasting model is:

$$\hat{x}^{(1)}(t+1)=30,827,951.18e^{0.068t}-28,384,881.18$$

By the same method, the forecasting model of Chinese tourist arrivals and the forecasting model of US tourist arrivals also can be obtained like:

$$\hat{x}^{(1)}(t+1)=2,915,236.49e^{0.203t}-2,287,972.49$$
$$\hat{x}^{(1)}(t+1)=14,276,252.69e^{0.037t}-13,765,082.69$$

2. Dividing States by Markov Forecasting Model

According to relative error from 2004 to 2012, four states are divided as follows, and the circumstances that relative error lays in the state are listed in Table 2.

Table 2. GM Forecasting Values and State Prediction

Year	Japan			China			US		
	Forecast Value	Relative error (%)	State	Forecast Value	Relative error (%)	State	Forecast Value	Relative error (%)	State
2004	2,443,070	0	3	627,264	0	3	511,170	0	2
2005	2,169,218	11.10	4	656,139	7.62	1	538,115	-1.41	4
2006	2,321,856	0.73	3	803,818	10.39	1	558,398	-0.48	3
2007	2,485,234	-11.15	1	984,736	7.88	1	579,446	0.99	1
2008	2,660,108	-11.86	1	1,206,373	-3.30	3	601,287	1.44	1
2009	2,847,289	6.75	4	1,477,894	-10.10	4	623,951	-2.07	4
2010	3,047,638	-0.82	2	1,810,527	3.45	2	647,470	0.83	1
2011	3,262,086	0.82	3	2,218,027	0.10	3	671,875	-1.57	4
2012	3,491,624	0.77	3	2,717,244	4.22	2	697,200	0.10	2

For Japanese tourist arrivals:
$\otimes_1 = [-11.86, -6.12)$, $\otimes_2 = [-6.12, -0.38)$,
$\otimes_3 = [-0.38, 5.36)$, $\otimes_4 = [5.36, 11.10]$

For Chinese tourist arrivals:
$\otimes_1 = [10.39, 5.2675)$, $\otimes_2 = [5.2675, 0.145)$,
$\otimes_3 = [0.145, -4.9775)$, $\otimes_4 = (-4.9775, -10.10]$

For US tourist arrivals:
$\otimes_1 = [1.44, 0.5625)$, $\otimes_2 = [0.5625, -0.315)$,
$\otimes_3 = [-0.315, -1.1925)$, $\otimes_4 = [-1.1925, -2.07]$

3. Calculating Transition Probability Matrix

Transition probability matrix can be calculated according to the method introduced in this paper:

For Japanese tourist arrivals:

$$P(1) = \begin{bmatrix} \frac{1}{2} & 0 & 0 & \frac{1}{2} \\ 0 & 0 & 1 & 0 \\ \frac{1}{3} & 0 & \frac{1}{3} & \frac{1}{3} \\ 0 & \frac{1}{2} & \frac{1}{2} & 0 \end{bmatrix} \quad P(2) = \begin{bmatrix} 0 & \frac{1}{2} & 0 & \frac{1}{2} \\ 0 & 0 & 1 & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 \end{bmatrix}$$

$$P(3) = \begin{bmatrix} 0 & \frac{1}{2} & \frac{1}{2} & 0 \\ 0 & 0 & 0 & 0 \\ \frac{1}{2} & 0 & 0 & \frac{1}{2} \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 \end{bmatrix} \quad P(4) = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \\ \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Due to four states are divided, so latest four years near to prediction time are selected to make state prediction table (Table 3), the transition steps are defined as 1, 2, 3 & 4.

For Chinese tourist arrivals:

$$P(1) = \begin{bmatrix} \frac{2}{3} & 0 & \frac{1}{3} & 0 \\ 0 & 0 & 1 & 0 \\ \frac{1}{3} & \frac{1}{3} & 0 & \frac{1}{3} \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad P(2) = \begin{bmatrix} \frac{1}{3} & 0 & \frac{1}{3} & \frac{1}{3} \\ 0 & 1 & 0 & 0 \\ \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$P(3) = \begin{bmatrix} 0 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ 0 & 0 & 0 & 0 \\ \frac{1}{2} & 0 & \frac{1}{2} & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad P(4) = \begin{bmatrix} 0 & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ 0 & 0 & 0 & 0 \\ 0 & \frac{1}{2} & \frac{1}{2} & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Due to four states are divided, so latest four years near to prediction time are selected to make state prediction table (Table 4), the transition steps are defined as 1, 2, 3 & 4.

For US tourist arrivals:

$$P(1) = \begin{bmatrix} \frac{1}{3} & 0 & 1 & \frac{2}{3} \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 \end{bmatrix} \quad P(2) = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & 0 & \frac{1}{3} \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ \frac{1}{2} & 0 & 0 & \frac{1}{2} \end{bmatrix}$$

Table 3. State Prediction of Japanese Tourist Arrivals

	Initial state	Transition	State 1	State 2	State 3	State 4
2012	3	1	1/3	0	1/3	1/3
2011	3	2	1/2	0	1/2	0
2010	2	3	0	0	0	0
2009	4	4	0	0	0	1
Sum			5/6	0	5/6	4/3

Table 4. State Prediction of Chinese Tourist Arrivals

	Initial state	Transition	State 1	State 2	State 3	State 4
2012	2	1	0	0	1	0
2011	3	2	1/2	1/2	0	0
2010	2	3	0	0	0	0
2009	4	4	0	0	0	0
Sum			1/2	1/2	1	0

$$P(3)=\begin{bmatrix}\frac{1}{2} & 0 & 0 & \frac{1}{2}\\ 1 & 0 & 0 & 0\\ 0 & 0 & 0 & 1\\ \frac{1}{2} & \frac{1}{2} & 0 & 0\end{bmatrix} \quad P(4)=\begin{bmatrix}0 & \frac{1}{2} & 0 & \frac{1}{2}\\ 1 & 0 & 0 & 0\\ 1 & 0 & 0 & 0\\ 0 & 0 & 0 & 1\end{bmatrix}$$

Due to four states are divided, so latest four years near to prediction time are selected to make state prediction table (Table 5), the transition steps are defined as 1, 2, 3 & 4.

4. Calculating Forecasting Values

According to the State prediction, the forecast values from 2004 to 2012 are also calculated by Grey-Markov model (Table 6).

5. Results of the Grey-Markov Chain Forecast Values

The GM forecasting model of Japanese, Chinese and the US tourist arrivals to Korea can be obtained like follows:

$$\hat{x}^{(1)}(t+1)=30{,}827{,}951.18e^{0.068t}-28{,}384{,}881.18$$
$$\hat{x}^{(1)}(t+1)=2{,}915{,}236.49e^{0.203t}-2{,}287{,}972.49$$
$$\hat{x}^{(1)}(t+1)=14{,}276{,}252.69e^{0.037t}-13{,}765{,}082.69$$

So the GM forecast values from 2013 to 2017 can be obtained (Table 7). Take the Japanese tourist arrivals for example, according to Table 4 (State Prediction), the relative error of 2013 is in state 4: [5.36, 11.10]. The forecast value of 2013 obtained by GM is 3737313, so the forecast value obtained by Grey-Markov is 4044894, that is $3737313\times(1+\frac{5.36+11.10}{2}\%)=4044894$, By the Same method, the relative error of 2014 to 2017 can also be obtained. So the Grey-Markov chain forecast values can be calculated (Table 7).

Table 5. State Prediction of U.S. Tourist Arrivals

	Initial state	Transition	State 1	State 2	State 3	State 4
2012	2	1	0	0	0	1
2011	4	2	1/2	0	0	1/2
2010	1	3	1/2	0	0	1/2
2009	4	4	0	0	0	1
Sum			1	0	0	3

Table 6. Grey-Markov Forecasting Values

Year	Japanese tourist arrivals			Chinese tourist arrivals			US tourist arrivals		
	Real Value	Forecast Value	Relative error (%)	Real Value	Forecast Value	Relative error (%)	Real Value	Forecast Value	Relative error (%)
2004	2,443,070	2,443,070	0	627,264	511,170	0	511,170	511,170	0
2005	2,440,139	2,347,745	3.79	710,243	530,633	0.39	530,633	529,337	0.24
2006	2,338,921	2,380,018	-1.76	896,969	555,704	3.37	555,704	554,189	0.27
2007	2,235,963	2,261,811	-1.16	1,068,925	585,212	0.66	585,212	585,248	0
2008	2,378,102	2,420,964	-1.80	1,167,891	610,083	-0.80	610,083	607,307	0.46
2009	3,053,311	3,081,621	-0.92	1,342,317	611,327	-1.80	611,327	613,772	-0.40
2010	3,023,009	2,948,590	2.46	1,875,157	652,889	0.83	652,889	653,953	-0.16
2011	3,289,051	3,343,703	-1.66	2,220,196	661,503	2.51	661,503	660,915	0.09
2012	3,518,792	3,579,089	-1.71	2,836,892	697,884	1.62	697,884	698,063	-0.03

Table 7. Forecasting Values of Tourism Demand from Selected Countries.

Year	Japanese tourist arrivals			Chinese tourist arrivals			US tourist arrivals		
	GM	State	Grey-Markov	GM	State	Grey-Markov	GM	State	Grey-Markov
2013	3,737,313	4	4,044,894	3,328,821	3	3,248,388	723,480	4	711,678
2014	4,000,290	1	3,640,644	4,078,047	2	4,188,409	750,750	2	751,679
2015	4,281,772	1	3,896,841	4,995,903	3	4,875,189	779,048	4	766,340
2016	4,583,060	1	4,171,043	6,120,343	2	6,285,975	808,413	1	816,507
2017	4,905,548	4	5,309,274	7,497,863	3	7,316,696	838,884	4	825,200

Table 8. Discrepancy between Forecasted Value of the Model and Reality

Year	Japanese tourist arrivals			Chinese tourist arrivals			US tourist arrivals		
	Real Value	Forecast Value	Relative error (%)	Real Value	Forecast Value	Relative error (%)	Real Value	Forecast Value	Relative error (%)
2013	2,747,750	4,044,894	-47.21	4,326,869	3,248,388	24.93	722,315	711,678	1.47
2014	2,280,434	3,640,644	-59.65	6,126,865	4,188,409	31.64	770,305	751,679	2.42
2015	1,837,782	3,896,841	-112.04	5,984,170	4,875,189	18.53	767,613	766,340	0.17
2016	2,297,893	4,171,043	-81.52	8,067,722	6,285,975	22.08	866,186	816,507	5.74
2017	2,311,447	5,309,274	-129.69	4,169,353	7,316,696	-75.49	868,881	825,200	5.03

B. Real International Tourists' Flows to Korea

1. Discrepancy between Forecasted Value of the Model and Reality

Table 8 shows the real international tourist's flows to Korea and Grey-Markov chain forecast values which were presented on Table 7. As it is presented on the table, it is quite clear that model works only for the USA, which has error range from 0.0017 to 0.0574 during the year 2013 through 2017. For Japan and China, the model performed not even closed to the reality. Interestingly, the real Japanese tourists' inflow was way below the forecasted one for those years. However, the real Chinese tourists' inflow was above the forecasted one for those years but year 2017.

Ⅴ. Discussion and Practical Implications

Since the Russian mathematician Andrei Andreyevich Markov (1856-1922) developed the theory of Markov chains, it has been applied in various fields. Mednick (1975), Uysal et al. (1995), and (Choi et al., 2011) applied it in tourism field and they proved that Markov analysis is an acceptable way of forecasting the future movement of international tourist. Grey system theory on the other hand has been developed rapidly and applied to various systems.

In order to overcome the influence of random fluctuation data on forecasting precision and widens the application scope of the grey forecasting, Grey-Markov chain model was introduced as a new methodology which combines the advantages of both grey forecasting method and Markov chain forecasting method. Zhan-Li & Jin-Hua (2011), Yan et al. (2012), and Chen et al. (2012) are researchers who used the Grey-Markov model. This study established a prediction model of tourism demand by using Grey-Markov Chain Model. Using the statistic data of the number of tourist arrivals from Japan, China and the United States, the effectiveness of the proposed model was verified.

However, this study wanted to verify the accuracy of the performance of the model with reality. The results are somewhat mixed as they were presented

on Table 8. For the Japanese tourists' inflow to Korea the mathematical model overestimated as a result even though the model itself has no any problem. For the Chinese tourists' inflow to Korea the mathematical model underestimated as a result even though the model itself has no any problem. However, the model forecasted the tourists' inflow from the United States within acceptable range.

These discrepancies for those years might not be explained by sole reason. Measuring the future level of international demand for tourism is compounded by a number of factors and those factors are difficult to identify and quantify. However, as we look into events happened for those periods some clues can be achieved. Although there are so many macro-environmental factors influencing on tourists' inflow, it is somewhat clear that international tourists' movement in terms of Korea tourism demand is heavily influenced by political issues associated with China and Japan. Struggling with conflict zone named Dokdo Island and Japanese comfort women issue, Korea and Japan had been very bad political relationships before 2013. Japanese tourists' inflow was frozen dramatically. The weakened Yen in 2013, increased consumer spending tax in 2014, MERS in 2015, North Korea's hydrogen bomb testing in 2016, and invalidating 2015 agreement for the Japanese comfort women by new Korea government in 2017 are some of the events unexpected by the mathematical forecasting model. The overflow of Chinese tourists to Korea for the year 2013 through 2016 was also unexpected by the model. While Korea was struggling with Japan politically, Korea was in good relationship with China until they had an event named THAAD deployment.

The results tell us we should be aware of using forecasted values produced by mathematical model. As it is reported on Table 6, all of the relative errors of the forecasting values are less than 5%, meaning the Grey-Markov chain model gives higher precision in forecasting tourism demand. Therefore, it is very necessary to use the forecasted values in part and consider some other issues changing the values.

In order to take valuable information from the model especially from the Grey-Markov chain model, the rationales of Grey-Markov forecasting model should be understood. Further, it is necessary to understand that there are some other factors taking a certain role of breaking the mathematical forecasting rules based basically upon historical records.

In Korea, the tourism industry is now being highlighted because of its substantial contribution to the balance of payments and its influence on related industrial sectors. In the recent decade, tourist receipts increased from 3, 559 million to 12,396.9 million dollars. In order to cope with this increasing international demand for tourism in Korea, an integrated and sustainable approach to tourism planning and development is required for the benefit of both tourists and residents. In this context, it is important to be able to forecast the future level of international demand, as an initial stage of tourism planning and development.

This study applied a forecasting method to forecast Korean tourism demand from three major source countries (Japan, China and United States), which combines the first-order one variable grey differential equation model from grey system theory and Markov chain model from stochastic process theory. This study also tested the performance of the model and found that using single information from mathematical forecasting model is not enough. Getting right information does not come from a source but many ways.

Although this study verified the accuracy of the model forecasting, the results might be different as future study tests it for tourists' inflows to other countries in different time frame. Further, it is to articulate that macro-environmental variables almost clearly override the forecasting values derived by mathematical model. Thus, more detailed event analysis along with mathematical forecasting is required.

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