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Applied multivariate forecasting model to tourism industry

Abstract

Various forecast models can be adopted for predicting what types of tourism demand are vulnerable to wide fluctuations. This study employs the fuzzy grey model FGM(1,N) and back-propagation neural networks (BPNN) as the multivariate forecasting models. Various benchmark univariate forecasting models are also employed in this study including the naïve method, exponential smoothing model, Holt's method, and linear regression. We find that the multivariate forecasting models generates more accurate forecasts than univariate models in the tourism service industry. More specifically, the GM(1,N) model was applied to choose the critical influences on tourism demand. Then, FGM(1,N) model was applied to forecast tourism demand using officially published annual data which show tourists traveling from Taiwan to the United States and to Japan during the period 1990-2003. The results showed that the FGM (1,N) outperformed the benchmark statistical methods during the out-of-sample period. Moreover, when important determinants including service price, foreign exchange rate, population, and per capita income are ranked and selected, the GM(1,N) model was improved and achieved viable performance. Finally, in terms of deciding which model to use, the general finding that can be drawn from this study appears to be that in situations involving little sampling data the grey model is superior to other traditional forecasting models. Further discussion and managerial implication can be drawn from these findings.

Keywords:
tourism service industry; multivariate forecasting model; service price

Introduction

The tourism industry, which comprises 11.7% of total global economic output and supplies 8% of the total number of jobs worldwide, is one of the largest-scale service industries compared with other competitive industries. Thus, the development of the tourism industry not only supplies numerous job opportunities to local residents but also generates considerable foreign exchange earnings for the economy. The globally accepted definition of the "tourism industry" is of a business with multiple aspects, including hotels, restaurants, transportation, entertainment, craft products, and so on.

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The perishable nature of tourism demand means that it is impossible to satisfy fluctuating tourism demand with a stable supply of resources, equipment and employees. Therefore, forecasts are essential due to the importance of accurate and numerous practical applications, including financial statements, electronic power, international passenger demand, and water resources (Lee, Var & Blaine, 1996), and accurate forecasts would help managers to make better tactical strategic decisions. Furthermore, governments can use such forecasts to efficiently plan the tourism infrastructure.

Turner and Witt (2001) proposed that tourism demand forecasting remains an important research area, and the search continues for more accurate forecasting methods. Witt and Witt (1995) developed two methodologies for forecasting tourism demand: quantitative and qualitative. The former includes econometrics models (Vangegas & Croes, 2000; Li, Song & Witt, 2005), time series (Burger, Dohnal, Kathrada & Law, 2001; Preez & Witt, 2003; Lim & Wang, 2005), neural networks (Law & Au, 1999; Law, 2000; Burger *et al*., 2001; Kon & Turner, 2005), fuzzy time series (Wang, 2004; Yu & Schwartz, 2006), Grey theory (Wang, 2004; Yu & Schwartz, 2006), to name some.

The advantage of the econometrics model (including multiple regressions) is that scholars can identify and analyze variables from numerous affecting factors, and then model the relationship of dependant and independent variables. The drawbacks of the econometrics include high cost, time-consumption, and difficulties in gathering current data. Moreover, time series models including the naïve forecast, moving average, exponential smoothing, and the Box-Jenkings method involves a statistical analysis which employs only the historical data of the univariate being forecast, and this use of easily collected historical data is one of the main attraction features of the model.

However, the above mentioned methods need large amounts of data, normal distribution and stationary data trends. These basic assumptions limit their application validity of forecast modeling. Currently, many scholars are designing new forecasting methods to overcome the limitations of traditional methods. One such method is the artificial intelligence methods that do not require making as many assumptions as traditional statistical methods. An extensive literature exists on methods of forecasting tourism demand. The main aim of this current study is to investigate the feasibility of incorporating influencing multivariate of tourism demand into artificial intelligence, and to rank variables based on their importance.

Morley (1999) argued that modeling tourism demand has become a significant study area in tourism, since it aims to understand what contributes to this growth and occasional breaks in the growth, to assess the impacts of factors on tourism numbers and to produce forecasts. Thus, this investigation constructs five different forecasting methods, including fourteen forecasting models that are tested on the data; namely, the naïve method, exponential smoothing, Holt's model, the regression model, artificial neural network and the grey forecasting model.

This investigation has the following objectives:
(1) To identify the influences on tourism demand, the grey quantitative relationship between the tourism demand and influential factor was established using multidimensional grey assessment theory.
(2) To formulate the grey forecasting procedure using the influences on tourism demand.
(3) To compare the performance of forecasting models using multivariate and univariate approaches and then select the best of these two models.

Determinants of tourism demand and data

The first problem is the selection of a variable to be used as an indicator of tourism demand. In the literature, Gonzalez and Moral (1995) proposed regression forecasting models for international tourism demand using population, income, cost of living, foreign exchange rate, marketing expenditure, and relative prices as independent variables. Lim (1997) surveyed numerous empirical articles on international tourism demand and concluded that the most widely used explanatory variables were income, relative price, and transportation cost. Moreover, Law and Au (1999) and Law (2000) adapted the determinants designed by Gonzalez and Moral (1995). As noted above, the number of Taiwanese tourist arrivals can be calculated as:

$$TD = f(Y, SP, POP, FER) \tag{1}$$

where TD denotes the number of tourist visits from an origin country to a destination country, Y represents per capita income, SP is the relative price, POP denotes the population, and FER represents the currency exchange rate.

Substantial agreement exists regarding the important explanatory variables in the case of international tourism, such as income, population, foreign exchange and price. Income reflects the magnitude of the market because increased income is required to support increased buying power. According Engel's Law, spending on leisure and entertainment will increase as people's incomes increase. Witt and Witt (1995) noted that origin country income or private consumption is generally included as an explanatory variable, and is commonly included in the demand function in per capita form. Crouch (1994) showed that income is the main explanatory variable. Consequently, income is considered the most important determinant of tourism demand (Song, Wong & Chon, 2003; Dritsakis, 2004). National disposable income (NDI), gross domestic product (GDP), gross national product (GNP), and gross national income (GNI), have also been used in many empirical studies (Song & Tuner, 2004). This study investigation uses per capita GNP (US$) as a proxy variable for income level in Taiwan.

In terms of population, Witt and Witt (1995) hypothesized that the level of foreign tourism from a given origin is expected to depend upon the origin population, with demand increasing along with population growth. Sometimes population is a separate explanatory variable but, generally, the influence of population on the consuming market is accommodated by modifying the dependent variable to international tourism demand per capita (Law, 2000; Song & Turner, 2004).

Exchange rate is the price of foreign currency on international money markets. If the exchange rate rises, the buying power will decrease an international commodity markets. A higher exchange rate for the NT dollar to the US dollar thus decreases Taiwanese tourist demand for travel to foreign destinations. The exchange rate is also sometimes used separately to represent tourist living costs, possibly in addition to the exchange-rate-adjusted consumer price index. The justification of varying exchange rate is that consumers are aware of destination travel costs, and thus use the exchange rate as a proxy variable. However, the use of the exchange rates alone can be misleading because, even though the exchange rate for a destination may become more favorable, this could be counterbalanced by a relatively high inflation rate (Song & Witt, 2003; Song & Turner, 2004; Dritsakis, 2004).

Relative price is also an important explanatory variable. Service offering price is more difficult to measure than any other variable. This work cites service price as a proxy for the relative price, as initially used by Law (2000), paid by Taiwanese visitors for services in the USA. and Japan. The formula for calculating service price (SP) is denoted as:

$$SP_i = \frac{CPI_{k,i} / CPI_{k,0}}{CPI_{j,i} / CPI_{j,0}} \tag{2}$$

where SP denotes the service price, and $CPI_{k,0}$ represents the base period CPI of the destination country k. Moreover $CPI_{j,0}$, is the base period CPI of the original country j.

In this study, these four determinants for forecasting tourism demand from Taiwan to Japan and the USA - population, income, foreign exchange rate and service price – were applied. Secondary sources of data, issued by the Taiwan official government and the Taiwan Economic Journal Database, were used in this investigation (Table 1). Tables 2 contains relevant data for forecasting Taiwanese travel demand to the U.S.A. and Japan in the period 1990 to 2003. In each case, annual data from 1990 to 2003 are used with the estimation period 1990–2001 and the post-estimation period 2002–2003.

Table 1
DATA SOURCE

Variables	Sources of data
Tourism demand	Yearly Statistics, Tourism Bureau Ministry of Transportation and Communications, R.O.C. (Taiwan)
Populations	Directorate General of Budget Accounting and Statistic
Per capita income	Executive Yuan, R.O.C. (Taiwan)
Exchange rate	Central Bank of China (Taiwan) (http://www.cbc.gov.tw/EngHome/statistics.asp)
Consumer price index	Directorate General of Budget Accounting and Statistic Executive Yuan, R.O.C. Taiwan Economic Journal Database

Table 2
HISTORICAL DATA ON TAIWANESE TOURIST ARRIVALS IN THE USA AND JAPAN

Year	Taiwanese tourists to:		Service price		Foreign exchange rate		Taiwanese population	Taiwanese per capita
	USA	JAPAN	USA	JAPAN	TW$/ US$	TW$/ Yen	(1,000)	GNP (US$)
1990	239,325	591,495	1.021	0.829	26.890	144.79	20,401	8,111
1991	267,584	653,242	1.016	0.833	26.809	134.71	20,606	8,982
1992	286,966	748,112	1.030	0.855	25.163	126.65	20,803	10,506
1993	371,750	737, 100	1.030	0.869	26.382	111.20	20,995	10,964
1994	453,924	676,944	1.045	0.898	26.455	102.21	21,178	11,806
1995	522,910	498,565	1.053	0.932	26.476	94.06	21,357	12,686
1996	579,488	600,146	1.055	0.960	27.458	108.78	21,525	13,260
1997	588,916	651,597	1.040	0.952	28.662	120.99	21,743	13,592
1998	577,178	674,089	1.042	0.962	33.445	130.91	21,929	12,360
1999	563, 991	720,903	1.021	0.967	32.266	113.91	22,092	13,235
2000	651,134	811,388	1.000	0.985	31.225	107.77	22,277	14,188
2001	532,010	765,247	0.972	0.991	33.800	121.53	22,406	12,876
2002	532,180	797,460	0.955	1.000	34.575	125.39	20,401	12,916
2003	479,264	731,330	0.932	1.000	34.418	115.93	20,606	13,156

Forecasting models

As already noted, there are many forecasting models proposed and used. In this section two multivariate models – grey forecasting model and back-propagation neural networks (BPNN) and univariate models selected for comparison in this study will be described in more details.

MULTIVARIATE MODELS

Grey forecasting model

Grey system theory was initially developed by Deng in early 1980s for considering systems involving uncertainties and information insufficiency. This had extensive applications, including systems analysis, data processing, modeling, forecasting, decision making and control. A forecasting model designed using grey theory is called a grey model (GM). Grey models are provided by grey differential equations, which are groups of abnormal differential equations with variable behavior parameters. Consequently, GM(n,m), where n denotes the order of the differential equation and m represents the number of type of observed data, is defined as a higher-order multivariable differential equation. The GM(1,1) is a single variable first-order grey model that is widely applied to various fields (Hsu & Wen, 1998; Hsu & Wang, 2002; Wang, 2004). However, development and formulation of GM(1,N) in the tourism industry have seldom been investigated.

In grey forecasting, the grey model exploits the accumulated generating operating (AGO) technique to outline system behavior. Assume an original series to be

$$\begin{aligned} x_1^{(0)} &= \{x_1^{(0)}(1), x_1^{(0)}(2), \cdots, x_1^{(0)}(k)\} \\ x_2^{(0)} &= \{x_2^{(0)}(1), x_2^{(0)}(2), \cdots, x_2^{(0)}(k)\} \\ &\vdots \\ x_N^{(0)} &= \{x_N^{(0)}(1), x_N^{(0)}(2), \cdots, x_N^{(0)}(k)\},\ k = 1, 2, \cdots, n. \end{aligned} \tag{3}$$

where $x_1^{(0)}$ is the predicted series, $x_j^{(0)}$, $j = 2,3,\cdots,N$ is the associated series.

Then one-order AGO is defined as:

$$\begin{aligned} x_1^{(1)} &= \{x_1^{(1)}(1), x_1^{(1)}(2), \cdots, x_1^{(1)}(k)\} \\ x_2^{(1)} &= \{x_2^{(1)}(1), x_2^{(1)}(2), \cdots, x_2^{(1)}(k)\} \\ &\vdots \\ x_N^{(1)} &= \{x_N^{(1)}(1), x_N^{(1)}(2), \cdots, x_N^{(1)}(k)\},\ k = 1, 2, \cdots, n \end{aligned} \tag{4}$$

where , $x_i^{(1)}(k) = \sum_{j=1}^{k} x_i^{(0)}(j)$, $i = 1, 2, \cdots, N$.

A grey differential equation with N variables is called GM(1,N) and can be expressed as follows:

$$\frac{dx_1^{(1)}(k)}{dt} + a_1 z_1^{(1)}(k) = \sum_{i=2}^{N} b_i x_i^{(1)}(k),\ k = 1,2,\cdots,n \tag{5}$$

where the value of a_1 indicates the coordinate degree between index x_1 and various factors. Moreover, b_i is the *i*th influence coefficient, which means that x_i influences x_1 (the behavior variable) and $z_1^{(1)}(k) = 0.5x_1^{(1)}(k) + 0.5x_1^{(1)}(k-1)$, $k \geq 2$.

The parameter of GM(1,N) is $\hat{a} = [a_1, b_2, \cdots, b_N]^T$, based on the least squared method, is denoted as follows:

$$\hat{a} = (B^T B)^{-1} B^T Y_N, \tag{6}$$

where, $B = \begin{bmatrix} -z_1^{(1)}(2) & x_2^{(1)}(2) \cdots x_N^{(1)}(2) \\ -z_1^{(1)}(3) & x_2^{(1)}(3) \cdots x_N^{(1)}(3) \\ \vdots & \vdots \\ -z_1^{(1)}(n) & x_2^{(1)}(n) \cdots x_N^{(1)}(n) \end{bmatrix}$ and $Y_N = \begin{bmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(n) \end{bmatrix}$

The optimal a_1 and b_i are then determined and their correlation is illustrated in Eq. (6). The value of a_1 indicates the developing coefficient for $x_1^{(1)}$. These coefficients $|b_i|$ display the degree of correlation between indices and factors.

For forecasting purpose, FGM(1,N) is derived from GM(1,N), the FGM(1,N) whitened differential equation is denoted by: $\frac{dx_1^{(1)}(k)}{dt} + a_1 x_1^{(1)} = \sum_{i=2}^{N} b_i x_i^{(1)}(k)$, and $k = 1, 2, \cdots, n$. Then the forecasting function of FGM(1,N) is defined as (Deng and Guo, 1996):

$$x_1^{(0)}(k) = \sum_{i=2}^{N} \beta_i x_i^{(1)}(k) - \alpha x_1^{(1)}(k-1), \quad k = 2, 3, \cdots, n \tag{7}$$

where $\alpha = \frac{a}{1+0.5a}$, $\beta_i = \frac{b_i}{1+0.5a}$, $i = 2, 3, \cdots, N$.

When N=1, Eq. (7) is transformed into a multivariate model GM(1,1), is used to forecast the time series with one variable.. Then the forecasting function of GM(1,1) is rewritten as (Hsu, 2003; Wang, 2004):

$$\hat{x}_1^{(0)}(k) = \left[x^{(0)}(1) - \frac{b}{a} \right] (1 - e^{a}) e^{-a(k-1)}, \quad k = 2, 3, \cdots, n \tag{8}$$

where a, b is a parameter, which is estimated using OLS.

Back-propagation neural networks (BPNN)

Artificial neural networks (ANNs) are a class of nonlinear models inspired by studies of the brain and nerve system. The advantage of ANNs over other conventional statistical models is that they can model complex, possibly nonlinear relationships without requiring any prior assumptions regarding the underlying data generating process. Back propagation neural networks (BPNN) are one sub-class of ANNs. The BPNN is a supervised feed-forward neural network that uses training data as a basis for identifying patterns representing input and output variables.

The BPNN has been widely applied in various fields, particularly for forecasting tourism demand (Law, 2000; Burger *et al*., 2001). BPNN is comprised of two processes: learning and recalling. During the learning stage, certain variables and referent output are calculated based on the processing data embedded in the learning sample. The amending weight and bias are then iterated using the gradient steepest descent method, and converging finally to an allowance output. To summarize, ANNs are expected to outperform traditional statistical methods in forecasting due to better recognition of the high-level features of processing the data, and using a small-sized training set.

UNIVARIATE MODELS

In addition to non-traditional procedures, various benchmark statistical approaches are employed in this study, namely the naïve method, exponential smoothing model, Holt's method, and linear regression. The four models are types commonly used in the tourism industry (Law & Au, 1999; Law, 2000).

The naïve method is very simple (Law & Au, 1999; Law, 2000), stating that the value of the period to be forecast equals the value of the last period for which information is available: $F_t = A_{t-1}$ The simplest form of exponential smoothing is the single exponential smoothing model (Gaynor and Kirkpatrick, 1994; Law and Au, 1999), formally started as: $F_t = F_{t-1} + \alpha(A_{t-1} - F_{t-1})$, where $\alpha =$ smoothing constant, $F =$ forecast value, and $A =$ actual value.

Another frequently used exponential smoothing model is Holt's method. The data series values are smoothed by weighting the current level and the previous smoothed adjusted estimate of the trend: $\tilde{A}_t = \alpha A_t + (1-\alpha)(\tilde{A}_{t-1} - \tilde{B}_{t-1})$ Moreover, the trend estimates are provided by the weighted differences of two smoothing series and the previous trend, $t-1$: $\tilde{B}_t = \beta(\tilde{A}_{t-1} - \tilde{A}_t) + (1-\beta)\tilde{B}_{t-1}$. Moreover, the i -period-ahead forecast is given by: $F_{t+i} = \tilde{A}_t + i\tilde{B}_{t+i}$. The values of both α and β are allowed to vary to enable the identification of the optimum values of these parameters; that is, this study attempts to identify the values of α and β that minimizes the mean square error.

The function of simple linear regression (LR) is: $\hat{TD}_t = a + bt$, where a , b are the parameters to be estimated, t denotes time, TD is the sample value, and $\hat{TD}_t$ denotes the prediction value of period t .

Multiple regression is widely used in tourism research for estimating tourism demand functions (Ong, 1995), which are required for planning police making, and also for budgeting purposes by tourism operators, investors and government bureaus. The main studies employing multiple regression analysis of linear models were performed by Morley (1997), Lim (1997) and Law (2000). Multiple linear regression models have the following general form: $TD_t = a + b_1 Y_t + b_2 SP_t + b_3 POP_t + b_4 FER_t$, where $a =$ the intercept constant, and $b_1, b_2, \cdots, b_4 =$ slope coefficient.

MAGNITUDE OF FORECASTING ERROR

The forecasting accuracy of the models are measured mainly using Theil inequality coefficient (TIC), mean absolute percentage error ($MAPE$) and root mean square error ($RMSE$). These measures have already been presented in detail by others, including Law (2000), Song *et al*. (2000), Kon and Turner (2005). The is defined as

$$TIC = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\hat{F}_t - A_t\right)^2} \Bigg/ \left(\sqrt{\frac{1}{n}\sum_{t=1}^{n}\hat{F}_t^2} + \sqrt{\frac{1}{n}\sum_{t=1}^{n}A_t^2}\right).$$

The Theil inequality coefficient (TIC) lie between [0,1] where 0 is represents a perfect fit, 1 is represents a poor prediction. Mean absolute percentage error is defined as

$MAPE = \left\{\sum_{t=1}^{n}\left[(A_t - \hat{F}_t)/A_t\right] \Big/ n\right\} \times 100\%$; and root mean square error is defined as

$RMSE = \sqrt{\sum_{t=1}^{n}(A_t - \hat{F}_t)^2 \Big/ n}$, where $\hat{F}_t$ denotes the predicted number of visitors,

and A_t represents the actual number of visitors. The model yielded plausible prediction values when $MAPE$ was low, and vice versa. Lewis (1982) summarized the criteria of $MAPE$ in Table 3.

Table 3

***MAPE* CRITERIA FOR MODEL EVALUATION**

$MAPE$	Forecasting power
<10%	Highly accurate forecasting
10%~20%	Good forecasting
20%~50%	Reasonable forecasting
>50%	Weak and inaccurate forecasting

Source: Lewis (1982)

Empirical results

To test these forecasting models data from Taiwan will be used. Taiwanese economy has grown significantly during the past decade, leading to increasing per capita income, improved living standards, and increased leisure and tourism consumption. Since 1981, the government of Taiwan permitted its residents to travel abroad. Gradually, Taiwanese tourists turned into major tourist sources of other countries. According to the publications of the World Travel and Tourism Council (WTTC), the rate of tourist arrivals from Taiwan has grown faster than that from other countries in Asia. Apart from Hong Kong, the USA and Japan are the two main destination countries. In addition, the significant growth of 0.203 million inbound tourists annually from Taiwan to Japan far exceeded the growth rate for other destination countries. According to official Taiwanese data published in 2003, the United States and Japan are the main markets for Taiwanese tourists in the area of America and Asia, respectively.

Fourteen forecasting models were employed to forecast Taiwanese tourist arrival in USA and Japan based on data from the period of 1990-2001 (i.e., in-sample data). The forecast accuracy is inspected using the out-of-sample data for the 2002-03 periods.

The difference between the actual and the forecast for 2002-03 were used to evaluate the accuracy of the forecasting model.

EMPIRICAL RESULTS OF THE GREY FORECASTING MODEL

GM(1,5) attempts to identify the relevant variables and estimate the relationship between the independent and dependent variables in terms of parameters. All of the models considered in this section operate within an Excel spreadsheet environment. To build the GM(1,5) model of U.S.A., we first obtain original series as follows.

$$
\begin{aligned}
x_1^{(0)} &= \{239325,\ 267584,\ \cdots,\ 532010\} \\
x_2^{(0)} &= \{20401,\ 20606,\ \cdots,\ 22406\} \\
&\ \ \vdots \\
x_5^{(0)} &= \{1.021,\ 1.016,\ \cdots,\ 0.972\}.
\end{aligned}
$$

From Eq. (4), one-order AGO sequence is defined as follows:

$$
\begin{aligned}
x_1^{(1)} &= \{239325,\ 506909,\ \cdots,\ 5635176\} \\
x_2^{(1)} &= \{20401,\ 41007,\ \cdots,\ 257312\} \\
&\ \ \vdots \\
x_5^{(1)} &= \{1.021,\ 2.037,\ \cdots,\ 12.325\}.
\end{aligned}
$$

Additionally, matrix B and constant vector Y_N are accumulated as follows:

$$
B = \begin{bmatrix} -373117 & 41007\cdots & 2.037 \\ -650392 & 61810\cdots & 3.067 \\ \vdots & & \vdots \\ -5369171 & 257312\cdots & 12.325 \end{bmatrix}, \quad Y_N = \begin{bmatrix} 267584 \\ 286966 \\ \vdots \\ 532010 \end{bmatrix}.
$$

From Eq. (6), the parameters are estimated using the OLS method, yielding the following matrix.

$$
\hat{a}_{U.S.A.} = [a_1, b_2, \cdots, b_5]^T = [0.695, -58.33,\ 46.12, 10373.73, 741148.47]^T \quad (9)
$$

The relationship between the TD sequence and the influence sequence (Pop, Y, FER, SP) can be found by comparing the value of $b_2, \cdots, b_5$. Following the same procedures as the abovementioned steps, we can calculate the parameters of Japan. The parameters ($\hat{a}$) are estimated using the OLS method, yielding the following matrix.

$$
\hat{a}_{JP} = [a_1, b_2, \cdots, b_5]^T = [0.15,\ -17.05, -0.07, 8037.16, 891054.68]^T \quad (10)
$$

Eq.(9) yielded the same ranking result as that of Eq.(10), that is, $|b_5| > |b_4| > |b_2| > |b_3|$. The sequential function demonstrates that the relative importance of factors is ranked based on service price (x_5) $\succ$ exchange rate (x_4) $\succ$ populations (x_2) $\succ$ per capita income (x_3). Clearly, the service price has more impact than any of the other factors considered. Regarding forecasting, the parameter matrix of $\hat{a}_{U.S.A.}$ and $\hat{a}_{JP}$ are transformed into a α value and a matrix of β. The fitted models used for export forecasting of tourist arrivals from Taiwan are as follows.

$$\hat{x}_{1,U}^{(0)}(k) = -43.29x_2^{(1)}(k) + 34.23x_3^{(1)}(k) + 7698.9x_4^{(1)}(k) + 550046.5x_5^{(1)}(k) - 0.516x_1^{(1)}(k-1) \quad (11)$$

$$\hat{x}_{1,J}^{(0)}(k) = -15.856\,x_2^{(1)}(k) - 0.06\,x_3^{(1)}(k) + 7474\,x_4^{(1)}(k) + 828618.17\,x_5^{(1)}(k) - 0.14x_1^{(1)}(k-1) \quad (12)$$

Equations (11) and (12) represent the FGM(1,5) forecasting models for the U.S.A. and Japan, respectively.

Song and Turner (2004) argued that it is very difficult to obtain a single model that consistently outperforms all other models in all situations. Hence, according to the GM(1,5) ranking results, we built FGM(1,5) for $TD = f(Pop, Y, FER, SP)$, FGM(1,4) for $TD = f(Pop, FER, SP)$, FGM(1,3) for $TD = f(FER, SP)$, and FGM(1,2) for $TD = f(SP)$ models for greater forecasting accuracy. The out-of-sample forecast performance is listed in Tables 4 and 5, respectively.

EMPIRICAL RESULTS OF BPNN

All neural networks were estimated (trained) and forecasted using PCNeuron (Yeh, 2001). The input layer comprises Y, Pop, FER, and SP, while the output layer is tourism demand (TD). The data include eight periods of discrete data for training and two periods of discrete data (1999-2001) for testing.

The value of the learning rate η and the momentum factor α will significantly affect the efficiency and the convergence of neural network learning algorithm. In addition to this, the number of neurons in the input layer also affects the performance of the neural network. To build a forecasting model, the parameter values were investigated by running the neural networks with different hidden nodes (from 3 to 10), number of epochs (from 300 to 2000 by 200), learning rates (from 0.1 to 2 by 0.2), and moment rates (from 0.1 to 0.8). A stopping criterion was established to determine when to terminate the training process to achieve optimum performance (minimize $RMSE$) to avoid overtraining. The best forecasting result and errors are listed in Tables 4 and 5, respectively.

EMPIRICAL RESULTS OF BENCHMARK STATISTICAL METHODS

Historically, the exponential smoothing model uses a smoothing average of past values, in which the weight reduces geometrically over time to suppress short term fluctuations in the data. The smoothing constant (α) ranges between 0.1 and 1, and was selected to be 0.98 with the smallest mean square error. Holt's method is a two parameter exponential model. At the end of time period t, Holt's method generates an estimate of the base level and the per period of the series. The two smoothing constants α and β are set to 0.9 and 0 for the USA example and 1 and 0 for the Japan example.

This study used Excel's data analysis tool for the linear regression analysis. The fitted equations are $TD_t^{USA} = 240067.2 + 35312.43\,t$ and $TD_t^{JP} = 612524.9 + 9981.147\,t$. The above mentioned empirical results are shown in Table 4 and 5.

Table 4
EMPIRICAL RESULTS OF FORECASTING TAIWANESE DEMAND FOR TRAVEL TO THE U.S.A.

Model	2002	2003	$RMSE$*	TIC*	$MAPE$*	Forecasting Power
Actual value	532,180.00	479,264.00				
Naïve	532,010.00	532,180.00	37,417.46	0.0360	5.54	Excellent
Exponential smoothing (0.98)	534, 357.73	532,223.55	37,479.70	0.0361	5.73	Excellent
Holt's (0.9,0)	543,065.17	533,268.52	38,954.94	0.0373	6.66	Excellent
LR	699,128.80	734,441.20	215,623.87	0.1762	42.31	Reasonable
MR (1,4)	537,546.83	524,194.93	31,996.80	0.0308	5.19	Excellent
BPNN	434,490.00	376,230.00	100,397.56	0.1100	19.93	Good
GM (1,1)	698,929.43	742,985.27	220,628.97	0.1797	43.18	Reasonable
FGM (1,5)	528,190.15	502,843.86	16,910.48	0.0165	2.84	Excellent

* $RMSE$ is the root mean square error, TIC is the Theil inequality coefficient and $MAPE$ is the mean absolute percentage error is.

Table 5
EMPIRICAL RESULTS OF FORECASTING TAIWANESE DEMAND FOR TRAVEL TO JAPAN

Model	2002	2003	$RMSE$*	TIC*	$MAPE$*	Forecasting Power
Actual value	797,460.00	731,330.00				
Naïve	765,243.00	797,460.00	52,014.96	0.0336	6.54	Excellent
Exponential Smoothing (0.98)	766,133.25	796,833.46	51,342.32	0.0332	6.44	Excellent
Holt's (1,0)	765,247.00	797,460.00	52,013.72	0.0336	6.54	Excellent
LR	742,279.81	752,260.96	41,731.05	0.0276	4.89	Excellent
MR (1,3)	727,208.49	713,638.42	51,226.30	0.0345	5.61	Excellent
BPNN	639,570.00	639,150.00	129,279.55	0.0920	16.20	Good
GM 1,1)	739,520.43	749,099.90	42,853.02	0.0284	4.85	Excellent
FGM (1,2)	800,247.07	771,110.85	28,198.26	0.0182	2.90	Excellent

* $RMSE$ is the root mean square error, TIC is the Theil inequality coefficient and $MAPE$ is the mean absolute percentage error is.

COMPARING OF THE OUT-OF-SAMPLE FORECASTING RESULTS

Considering all of the empirical results for out-of-sample (see Table 4 and 5), based on the univariate model results, for case of travel to the USA case, naïve model had the smallest $MAPE$ (5.54%), $RMSE$ (37417.46) and TIC (0.03603). For the case of Japan, the LR and GM(1,1) model had low TIC value almost equal to zero. The GM(1,1) model had the smallest $MAPE$ (4.85%), had excellent forecasting power (Table 3).

Base on the multivariate model results, for the U.S.A. case, FGM(1,5) had the smallest $MAPE$ (2.84%), $RMSE$ (16910.48) and TIC (0.0165), for the Japan case, FMG(1,2) had the smallest $MAPE$ (2.90%), $RMSE$ (28198.26) and TIC (0.0182), that is to say, had highly accurate forecasting power (Table 3). Moreover, all of the Theil inequality coefficient value almost equal to zero. These results indicate that the forecasting performance of the model is relatively good. From the point of view of Witt and Witt (1992) or Law (2000), the smallest $MAPE$ had "highly" accurate forecasting. We may proceed from this to the conclusion that FGM(1,N) model may apply to the case of tourism demand forecasting.

Conclusions

This study presents a novel means of forecasting tourism demand, called FGM(1,N), which is based on grey theory. Due to the lack of large quantities of sample data, the grey model is very useful for establishing an accurate forecasting model. Consequently, this study assesses the impact of independent variables on tourism demand, and then forecasts future trends using the FGM(1,N) model.

The following conclusions are reached based on the empirical results. First, the FGM(1,N) outperformed the benchmark statistical methods during the out-of-sample period, while the training and learning results were poor for the BPNNs that lacked large amounts of data. Second, when important independent variables, including service price, foreign exchange rate, population, and per capita income are ranked and selected, the GM(1,N) model was improved and achieved viable performance. For the case of Taiwanese tourist arrival in America and Japan, this study shows that service price (SP) is the most important factor that affects the decisions of tourist to travel. The exchange rate (FER) is another important variable of demand determinant. Third, in terms of deciding which model to use, the general finding that can be drawn from this study appears to be that in situations involving little sampling data the grey model is superior to other traditional forecasting models.

The findings of this work have important managerial and practical implications. Tourism service providers should assess the costs and benefits of each model before choosing an appropriate forecasting tool. The ten models in this work differ in terms of the necessary amounts of historical data, personnel background, and software requirements. Since the BPNN model performs poorly overall due to the lack of large amounts of historical data to training and learning, thus BPNN requires special software and artificial intelligence expertise. The exponential models and multiple regression can be applied using existing software and do not require complicated statistical skills, but the sample data must satisfy the basic assumptions, such as normal distribution and homogeneous variants. Therefore, tourism managers must carefully assess the trade-off between forecasting accuracy and the above limitations of available methods.

References

Burger, CJSC, Dohnal, M., Kathrada, M., & Law, R. (2001). A practitioners guide to time-series methods for tourism demand forecasting - a case study of Durban, South Africa. *Tourism Management*, *22*, 403-409.

Crouch, G. I. (1994). The study of international tourism demand: a survey of practice. *Journal of Travel Research*, *32*(4), 41-57.

Deng, J. L., & Guo, H. (1996). *Grey pediction theory and application*. Taipei: Chun Hwa Press.

Dritsakis, N. (2004). Cointegration analysis of German and British tourism demand for Greece. *Tourism Management*, *25*, 111-119.

Gaynor, P. E. & Kirkpatrick, R. C. (1994). *Introduction to time-series modeling and forecasting in business and economics*. New York: McGraw-Hill.

Gonzalez, P., & Moral, P. (1995). An analysis of the international tourism demand in Spain. *International Journal of Forecasting*, *11*, 233-251.

Hsu, C. I., & Wen, Y. H. (1998). Improved grey prediction models for the trans-pacific air passenger market. *Transportation Planning and Technology*, *22*, 87-107.

Hsu, L. C. (2003). Applying the grey prediction model to the global integrated circuit industry. *Technological Forecasting and Social Change*, *70*, 563-574.

Hsu, L. C., & Wang, C. H. (2002). Grey forecasting the financial ratios. *The Journal of Grey System*, *4*(14), 399-408.

Kon, S. C., & Turner, L. W. (2005). Neural network forecasting of tourism demand. *Tourism Economics*, *11*(3), 301-328.

Law, R. (2000). Back-propagation learning in improving the accuracy of neural network-based tourism demand forecasting. *Tourism Management*, *21*(4), 331-340.

Law, R., & Au, N. (1999). A neural network model to forecast Japanese demand for travel to Hong Kong. *Tourism Management*, *20*(1), 89-97.

Lee, C. K., Var, T., & Blaine, T. W. (1996). Determinants of inbound tourism expenditures. *Annals of Tourism Research*, *23*(3), 527-542.

Lewis, C. (1982). *Industrial and business forecasting methods*. London: Butterworth Scientific.

Li, G., Song, H. & Witt, S. F. (2005). Recent developments in econometric modeling and forecasting. *Journal of Travel Research*, *44*, 82-99.

Lim, C. (1997). An econometric classification and review of international tourism demand models. *Tourism Economics*, *3*(1), 69-81.

Lim, C. & Wang, Y. (2005). Forecasting Japanese outbound tourism using seasonal time series models. Journal of Hospitality & Tourism, *3*(2), 37-53.

Morley, C. L. (1997). An evaluation of the use of ordinary least squares for estimating tourism demand models. *Journal of Travel Research*, *35*(4), 69-73.

Morley, C. L. (1999), Estimating Integrated time series and other problems in modeling tourism demand. *RMIT Business Working Paper Series*, WP 1999/3.

Ong, C. (1995). Tourism demand models: a critique. *Mathematics and Computers in Simulation*, *39*, 367-372.

Preez, J. D., & Witt, S. F. (2003). Univariate versus multivariate time series forecasting: an application to international tourism demand. *International Journal of Forecasting*, *19*, 435-451.

Song, H., Romilly, P., & Liu, X. (2000). An empirical study of outbound tourism demand in the U.K. *Applied Economics*, *32*, 611-624.

Song, H., & Turner, L. (2004). Tourism demand forecasting. *La Trobe University School of Business seminar program 2004 May 14*, 1-34.

Song, H., & Witt, S. F. (2003). Tourism forecasting: the general-to specific approach. *Journal of Travel Research*, *42*, 65-74.

Song, H., Wong, K. F., & Chon, K. S. (2003). Modeling and forecasting the demand for Hong Kong tourism. *Hospitality Management*, *22*, 435-451.

Turner, L. W., & Witt, S. F. (2001). Forecasting tourism using univariate and multivariate structural time series models. *Tourism Economics*, *7*(2), 135-147.

Vangegas, M., & Croes, R. (2000). Evaluation of demand: US tourists to Aruba. *Annals of Tourism Research*, *27*(4), 946-963.

Wang, C. H. (2004). Predicting the tourism demand using fuzzy time series and hybird grey theory. *Tourism Management*, *25*(3), 367-374.

Witt, S. F., & Witt, C. A. (1992). *Modeling and forecasting demand in tourism*. London: Academic Press.

Witt, S. F., & Witt, C. A. (1995). Forecasting tourism demand: a review of empirical research. *International Journal of forecasting*, *11*, 447-475.

Yeh, I. C. (2001). *PC-based neural network package professional version 4.0* [online]. Retrieved from: http://www.axin.com.tw.

Yu, G., & Schwartz. Z. (2006). Forecasting short time-series tourism demand with artificial intelligence models. *Journal of Travel Research, 45*(2), 194-203.

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