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Forecasting of international tourists visiting Taiwan for the purpose of leisure

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Abstract

Forecasting is the basis of planning. Previous studies on international tourism forecasting have mostly examined international tourist arrivals. Few studies discuss international travelers for specific purposes. Tourists from Western countries are the main source of tourists for leisure purpose. Economic factors generally have a significant effect on the international tourist demand. Nevertheless in different settings, there will be different conclusions. Consequently, the study supposes the recurrent neural network with genetic algorithms and the ARIMAX model to forecast numbers of tourists to Taiwan from USA, U.K, Germany, and Australia for leisure, and analyzes economic factors. The findings can help the development of the Taiwan' tourism industry.

Subject Classification: *(2010) 62M10.*

Keywords: *Tourism demand, Forecasting, Taiwan, Neural networks, Genetic algorithms, ARIMAX.*

Introduction

International tourists have various purposes, covering business, leisure, conference, study, exhibition, medical treatment, and others. However, preceding studies focus on international tourist arrivals for tourism forecasting. Minority papers discuss international tourists for specific purpose. Accurately forecasting the number of tourists can enable governments and enterprises to effectively plan and implement tourism policies and obtain considerable profits. Economic factors often affect

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tourism demand [1][2][3]. Nevertheless, different situations will lead to different conclusions.

Neural network is an artificial intelligence method. Peng *et al*. (2014) [4] used RBF and SVM neural networks for forecasting UK tourism demand. Recurrent neural network (RNN) is suitable for predicting time series data. Saad *et al*. (1998) [5] used RNN for tremendously volatile stock trends prediction. The input data, network structure and learning parameters of the neural network model affect the outcome of neural network models. Genetic algorithms (GA) is a search algorithm that solves the problem of optimization. It was originally developed by drawing on some phenomena in evolutionary biology. GA can be applied in input data, network structure and learning parameters optimization on neural networks. Recently, Barman *et al*. (2020) [6] used GA in personalized query recommendation system. For popular deep learning topics, Jiang *et al*. (2017) [7] employed GA in the neural network model for outpatient departments demand forecasting.

Correspondingly, ARIMAX model is an extension of ARIMA model, and can analyze exogenous and endogenous factors, and impulse effects [8]. Tsui *et al*. (2014) [9] used the ARIMAX model to analyze several exogenous and endogenous factors for forecasting Hong Kong airport passenger demand.

In order to cope with the international political and economic changes and stabilize the economy and people's livelihood, Taiwan's President Tsai Ing-wen held a high-level national security meeting at the Presidential Palace on the morning of December 31, 2022. In response to the severe challenges of the global economy, Taiwan's overall economy, industrial difficulties and people's livelihood economy were discussed. And summarized the first wave of response measures, and made seven conclusions.

One of the seven conclusions is to accelerate the arrival of international tourists to Taiwan, with a target of 6 million person-times next year. With the goal of reaching 6 million inbound tourists in 2023 in advance, provide incentives and subsidies for the tourism industry to attract international tourists to Taiwan, foreign companies to encourage employees to travel to Taiwan, school trips, cruise ships and charter flights, etc. At the same time, for independent tourists coming to Taiwan, preferential plans are also provided to accelerate the recovery of the tourism market after the epidemic.

USA, U.K, European Union, and Australia have long been the main sources of tourists for leisure. Currently, Taiwan's tourism industry encounters significant difficulty related to conflict between China and Taiwan, and must compete with other countries in Asia. The Taiwan's government should focus on attracting travelers from Western countries. Otherwise, economic factors frequently affect tourist demand.

In summary, this work uses the ARIMAX model and RNN with GA for forecasting the tourism demand from western countries for the purpose of leisure, and conducts economic analysis. The findings can aid the Taiwan' tourism industry.

Literature review

Most quantitative tourism demand forecasting methods can be classified as time series methods, the econometric model, artificial intelligence approaches and big data methods.

Time series methods involve exponential smoothing, moving average (Sridevi *et al*., 2018) [10], SARIMA, ARFIMA, and ARAR methods. Goh and Law (2002) [11] employed SARIMA for forecasting Hong Kong travel demand. Chang and Liao (2010) [12] also utilized SARIMA for Taiwan demand forecasting.Chu (2008) [13] used ARFIMA for forecasting Singapore demand. Next year, Chu (2009) [14] further used ARAR, SARIMA, and ARFIMA for forecasting nine Asian Pacific countries demand.

The economic model applies the relationship between economic variables and tourism demand to forecast tourism demand. Cho (2001) [15] employed the economic variables for Hong Kong demand forecasting.

The most commonly used artificial intelligence approaches are neural network-like methods. In 1999, there was research using a feedforward neural network model to predict the number of Japanese tourists in Hong Kong [16]. Recently, Peng *et al*. (2014) [4] employed SVR neural networks to forecast UK inbound demand. Zhang *et al*. (2017) [17] utilized integrated SVR neural network and bat algorithm to forecast tourism quantity.

Big data methods use internet data to predict tourism demand, including search engines, website traffic search engine, social media data, and other on-line economic data. It has recently become a research hotspot. Huang *et al*. (2017) [18] used the Baidu search engine data to forecast tourist demand.

Investigating diverse forecasting approaches in order to acquire the most correct forecast results is a new direction for future studies [19]. Nonetheless, although there are so many tourism demand forecasting methods, each method has its own advantages in specific circumstances [4]. No particular method is better than others in all cases.

The ARIMAX model (Harvey, 1990) [8] integrates moving averages, autoregression and explanatory factors components for time series prediction. In most cases, ARIMAX models outperform econometric causal and trend models in terms of their predictive power based on purifying economic and political factors. In the study of tourism demand forecasting, there are some explanatory factors that can be applied in demand forecasting. Tsui *et al*. (2014) [9] used some explanatory factors in the ARIMAX models for tourism demand forecasting.

Critical issues related to forecasting accurate tourism demand for Taiwan involved the study of possible effects of interventions or exogenous impacts during the analytical procedure. Notwithstanding, these problems can be carefully dealt with using the ARIMAX model, which considers both the real and possible influences of specific factors. This study selects income, consumer price index (CPI) and exchange rate factors in the proposed model.

For income, Sheldon (1993) [1] supposed that there are three main economic factors which include real per capita income, relative price and exchange rate in the tourism demand model. Additionally, Martins *et al*. (2017) [3] supposed that macroeconomic determinants of global tourism demand cover GDP per capita, domestic relative prices and exchange rates.

The CPI measures the price level which given payment to by the average consumer for a package of services and goods. Morley (1994) [20] supposed that the CPI can be regarded as a substitute for the tourism price index because the prices of non-fare tourist products have a close relationship with the CPI. Furthermore, from a traveler's perspective, in theory, relative CPI is better than CPI because it can estimate changes in consumer prices the country of destination relative to in the country of origin. Wu *et al*. (2017) [21] suggested that travel demand will be influenced by the destination travel prices level found on the relative CPI of destination prices and origin prices. Nevertheless, Martins *et al*. (2017) [3] indicated that tourism demand in low- and middle-income countries is more relevant to relative CPI.

Exchange rate is considered the value of one country's currency relative to another currency. Furthermore, like the relative CPI, from a traveler's perspective, in theory, relative exchange rate is better than exchange rate because it can estimate changes in exchange rate the country of destination relative to in the country of origin. Uysal and Crompton

(1984) [22] suggested that the number of international tourists in Turkey is affected by relative exchange rates, real per capita income, promotional expenses and transportation costs. Pham *et al*. (2017) [23] also has the same view. On the contrary, Sheldon (1993) [1] supposed that tourism demand will be affected by exchange rates, but tourism demand will not be affected by relative exchange rates.

Lately, Dogru *et al*. (2017) [2] suggested that country-specific research is needed to correctly identify the key factors affecting tourism demand in different countries. Therefore, further research on the factors affecting international tourism demand in Taiwan is needed.

Research Method

Tourists from USA, UK, European Union, and Australia are the main source of tourists for leisure purpose. This study chooses Germany as the representative, because the most tourists come to Taiwan among European Union.

First, this study uses the RNN with GA for forecasting international tourists for leisure. RNN is a type of neural network in which the connections between units create directed loops, which enables it to exhibit behaviour that changes over time.

The computation procedure of forward propagation of a typical RNN model is as follows.

$$A_j(t) = f(\Sigma_j^l x_i(t) d_{ji} + \Sigma_h^m A_h(t-1) c_{jh} + b_j),$$

Where t represent a certain time, $A_j(t)$ is the input of hidden layers, $\Sigma_j^l x_i(t) d_{ji}$ is the input of input layer, $\Sigma_h^m A_h(t-1) c_{jh}$ is the input of hidden layers.

During the training phase of an RNN, gradient descent is used to vary each weight in proportion to the error derivative associated with that weight for the aggregate error minimization.

This study uses GA optimize technology. The computation procedure is as follows. The quantity of neurons in the hidden layer and DBD learning rule parameters were indicated by the chromosomes. Initially, the chromosome population is randomized. The training cycle is nested within the evolution cycle of the population. During the cycle, the fitness of the network is evaluated using the roots of the MSE, thereby progressing as the network optimization evolves.

The analytical steps are demonstrated as following:
Stage 1: Constructing the RNN with GA model.
Stage 2: Forecasting international tourists for leisure.

Next, the work uses the ARIMAX model for forecasting using the same data

This study uses GNI per capital data to represent income. Regarding the CPI and exchange rate, this study assumes that the demand for international tourists to travel to Taiwan will be affected by relative CPI and relative exchange rate, as tourists try to use the relative ratio between the source country and Taiwan to compensate for travel expenses. This study adopts the CPI of USA, UK, Germany, and Australia against Taiwan to represent relative CPI. The exchange rates of USA, UK, Germany, Australia, Taiwan against USA represent the exchange rate. The relative exchange rate uses the exchange rate between the United States, the United Kingdom, Germany, and Australia against Taiwan.

The formula of the ARIMAX model is expressed as follows:

$$y_t = \mu + \sum_{i=1}^{3} \frac{\Theta_i(B)}{\Phi_i(B)} B^{l_i} x_{it} + \varepsilon_t$$

$$\varepsilon_t = \frac{\Theta(B)}{\Phi(B)} a_t$$

Where Φ and Θ represent autoregression and moving averages components, x_{it} represents relative CPI, relative exchange rate and income, at time t.

This study employs the MAPE (mean absolute percentage error) forecast error evaluation measures to evaluate the method performance, because it can be used to standardize the errors to ameliorate comparisons among distinct scale variables (Cao *et al*., 2005) [24]. Table 1 shows the abbreviations.

Table 1

Abbreviation

Abbreviation	
AR	Autregressive
MA	moving average
ARMA	autregressive moving average
ARIMA	autregressive integrated moving average

Contd...

ARIMAX	autregressive integrated moving average cause effect
ARFIMA	autoregressive fractionally integrated moving average
SARIMA	seasonal ARIMA
RNN	recurrent neural network
GA	genetic algorithms
RNN with GA	recurrent neural network with GA
SVR	support vector regression
CPI	consumer price index

Results

Tourism demand comes from the Taiwan Tourism Bureau's tourism statistics database. The number of tourists to Taiwan for leisure purpose every month from USA, UK, Germany, and Australia is defined as the tourism demand data. The downturn in 2003, attributed to the SARS disease outbreak created unsatisfied demand that was met by extraordinarily rapid growth in subsequent periods. This study conducted the experiment because of a proper treatment of the SARS disease crisis period in 2003. For the experiment, the data from January 2004 to July 2016 is classified into training data set and test data set. The training data set uses data from January 2004 to December 2014 for 11 years, and the test

Table 2

The MAPE of RNN with GA

USA	
	MAPE
recurrent neural network with GA	0.15775689
UK	
	MAPE
recurrent neural network with GA	0.11968128
Germany	
	MAPE
recurrent neural network with GA	0.23382555
Australia	
	MAPE
recurrent neural network with GA	0.27250134

Table 3

ADF test Phillips and Perron test for the monthly tourists

	Ln(the number of tourists)	
Origins	**Intercept only**	**Trend and Intercept**
	ADF unit root test	Phillips and Perron unit root test
USA	-0.359143	-10.40286***
	ADF unit root test	ADF unit root test
UK	-1.901582	-14.72035***
	ADF unit root test	Phillips and Perron unit root test
Germany	0.498912	-9.550731***
	ADF unit root test	Phillips and Perron unit root test
Australia	-1.352944	-7.589247***

Remarks: The values indicate the statistics for ADF and Phillips and Perron tests. *, **, and *** represent significant at the 0.10, 0.05, and 0.01 level.

data set uses data from January 2015 to July 2016 for one year and seven months. This collection of tourism data ends in July 2016 because the research was funded by Taiwan's Ministry of Science and Technology and ended in 2016.

This study uses the RNN with GA approach according to the analytical steps. Table 2 demonstrates the forecasting results.

This study also constructs the ARIMAX model for analyzing and forecasting. The analytical steps are expressed as follows:

First, convert tourism demand, the relative CPI, relative exchange rate and income using logarithms of raw data. For the monthly tourists, unit root test adopts the ADF and Phillips and Perron tests, for which the results are shown in Table 3. The transformed time series for the trend and intercept were stationary.

Next, aim at the relative CPI, relative exchange rate and income, the unit root test was conducted, for which the results are shown in Table 4. Making the transformed time series stationary using the first difference.

Table 4

Unit root test for the economic variables

	Ln(relative CPI)	**Δ Ln(relative CPI)**
	Intercept only	Intercept only
Origins	ADF unit root test	ADF unit root test

Contd...

USA	-1.520370	-12.52988***
UK	-0.901392	-8.374405***
Germany	-1.486462	-9.817005***
Australia	-2.308490	-8.038778***
	Ln(relative exchange rate)	Δ Ln(relative exchange rate)
	Intercept only	Intercept only
Origins	ADF unit root test	ADF unit root test
USA	-2.221230	-8.214218***
UK	-1.143589	-13.04915***
Germany	-3.526750***	-13.78308***
Australia	-0.922890	-13.81966***
	Ln(income)	Δ Ln(income)
	Intercept only	Intercept only
Origins	ADF unit root test	ADF unit root test
USA	-2.494952	-8.147333***
UK	-1.895435	-11.02333***
Germany	-1.988449	-12.16436***
Australia	-1.806134	-12.22794***

Remarks: The values are the statistics for ADF unit root test. *, **, and *** represent significant at the 0.10, 0.05, and 0.01 level.

Estimate the AR and MA parts, and add the economic factors in the model. Table 5 demonstrates the results. The tourists from USA, UK, Germany, and Australia are affected by trends, autoregression, moving averages and seasonality, and tourists from USA, UK, Germany, and Australia are influenced by a seasonal cycle of 12 months. Otherwise, tourists from USA and UK are influenced by relative exchange price (Δ Ln(relative exchange rate)).

Table 5

Proposed model

	Ln(the number of tourists) for the purpose of leisure			
	USA	**UK**	**Germany**	**Australia**
Constant	8.509729 (43.74039***)	6.169078 (8.618909***)	5.156531 (24.85415***)	6.288067 (19.29465***)

Contd...

Trend	0.004618 (4.344809***)	0.007976 (2.868849***)	0.011850 (10.21294***)	0.010776 (5.794613***)
Δ Ln(relative CPI)	0.006203 (0.316595)	-0.345386 (-0.268752)	0.720852 (0.713028)	0.519621 (0.791479)
Δ Ln(relative exchange rate)	-3.072428 (-2.672073***)	-7.117510 (-2.513481**)	-3.006103 (-0.948722)	-1.921896 (-1.059337)
Δ Ln(income)	-1.049607 (-1.259214)	0.128511 (0.064546)	0.669675 (0.188915)	-0.978527 (-0.460533)
Δ Ln(relative CPI)* Δ Ln(relative exchange rate)	1.622757 (0.399633)	-217.4801 (-1.670749)	-12.50736 (-0.121692)	29.34084 (0.590935)
Δ Ln(relative CPI)* Δ Ln(income)	0.876783 (0.390123)	-48.92902 (-0.673285)	1.406629 (0.006685)	4.720596 (0.015106)
Δ Ln(relative exchange rate)* Δ Ln(income)	-91.16482 (-1.323823)	-23.17535 (-0.033717)	-691.4958 (-0.601574)	124.2031 (0.739342)
Δ Ln(relative CPI)* Δ Ln(relative exchange rate) * Δ Ln(income)	-326.7689 (-0.971170)	4644.504 (0.168860)	-29275.91 (-0.440921)	1787.344 (0.075475)
AR(1)	0.904180 (12.41860***)	0.926557 (20.95439***)	0.907586 (7.663208***)	0.868773 (9.230172***)
SAR(12)	0.989698 (94.47067***)	1.000000 (4728.125***)	0.999999 (37766.22***)	0.971645 (45.64131***)
MA(1)	-0.677530 (-5.062107***)	-0.597491 (-6.415073***)	-0.814246 (-5.518227***)	-0.630300 (-4.109668***)
SMA(12)	-0.672757 (-5.291754***)	-0.999875 (-5299.539***)	-0.998767 (-1669.138)	-0.545895 (-4.785785***)
Adjusted R-squared	0.874665	0.740020	0.831574	0.903051
AIC	-1.533906	0.144609	0.237236	-0.485734
SIC	-1.226633	0.451882	0.544509	-0.178461
Forecasts				
MAE (mean absolute error)	926.6676115	237.4692014	399.0754688	225.0680713
RMSE (root mean square error)	1215.715453	351.3023498	559.3604838	288.9298922
MAPE	0.073693124	0.151778706	0.157109495	0.150295614

This study adopts numerous exponential smoothing methods for comparison. Table 6 demonstrates the results. It is confirmed that the ARIMAX model is superior to many exponential smoothing methods.

Table 6

The proposed model contrasts to numerous exponential smoothing methods

USA		
Approach	**MAPE**	**Improvement**
ARIMAX	0.07369312	
Single exponential smoothing	0.17187667	57.12%
Double exponential smoothing	0.16360658	54.96%
holt-winter exponential smoothing	0.16510554	55.37%
holt-winters additive exponential smoothing	0.16633733	55.70%
holt-winters multiplicative exponential smoothing	0.16734772	55.96%
UK		
Approach	**MAPE**	**Improvement**
ARIMAX	0.15029561	
Single exponential smoothing	0.15089876	0.40%
Double exponential smoothing	0.15679280	4.14%
holt-winter exponential smoothing	0.17787996	15.51%
holt-winters additive exponential smoothing	0.19179664	21.64%
holt-winters multiplicative exponential smoothing	0.19259301	21.96%
Germany		
Approach	**MAPE**	**Improvement**
ARIMAX	0.15177871	
Single exponential smoothing	0.27865639	45.53%
Double exponential smoothing	0.27805069	45.41%
holt-winter exponential smoothing	0.29944876	49.31%
holt-winters additive exponential smoothing	0.29746080	48.98%
holt-winters multiplicative exponential smoothing	0.30114965	49.60%
Australia		
Approach	**MAPE**	**Improvement**
ARIMAX	0.15710950	
Single exponential smoothing	0.34708065	54.73%
Double exponential smoothing	0.42132479	62.71%
holt-winter exponential smoothing	0.38924543	59.64%
holt-winters additive exponential smoothing	0.36792746	57.30%
holt-winters multiplicative exponential smoothing	0.37178218	57.74%

Remarks: Improvement refers to the ARIMAX model decreases the percentage in the MAPE prediction accuracy measures compared to numerous exponential smoothing methods.

Finally, this study contrasts the results of the RNN with GA with the results of the ARIMAX model. Table 7 shows the results. In USA, Germany and Australia, the proposed ARIMAX model performed better than the RNN with GA, but not in the UK.

Table 7

The comparison results for ARIMAX vs RNN with GA

USA		
	MAPE	**Improvement**
recurrent neural network with GA	0.15775689	53.29%
UK		
	MAPE	**Improvement**
recurrent neural network with GA	0.11968128	-25.58%
Germany		
	MAPE	**Improvement**
recurrent neural network with GA	0.23382555	35.09%
Australia		
	MAPE	**Improvement**
recurrent neural network with GA	0.27250134	42.35%

Remarks: Improvement refers to the ARIMAX model decreases the percentage in the MAPE prediction accuracy measures compared to numerous exponential smoothing methods.

Conclusions and Implications

This work is the pioneer study for exploring international tourists to Taiwan for the leisure purpose. In addition, most studies in Taiwan only discuss individual economic factors, such as Lu *et al*. (2018) [25]. Lu *et al*. (2018) [25] explore only income variable. However, this research explores the three variables of income, CPI and exchange rate simultaneously.

This research demonstrates that the RNN with GA outperforms the ARIMAX models in the UK, but not in the US, Germany and Australia. The advantage of RNN over GA is that it does not require additional assumptions and restrictions due to its non-parametric characteristics. However, the proposed ARIMAX model can provide more data characteristics than the RNN with GA. The results indicate that that the tourists from USA, UK, Germany, and Australia are affected by trends, autoregression, moving averages and seasonality. Otherwise, the tourists from USA and UK are influenced by differences in relative exchange price.

This study selects high income countries, covering USA, UK, Germany, and Australia, for analysis. For economic factors, international tourists to Taiwan for leisure are mainly influenced by relative exchange rates, like USA and UK. For European Union and Oceania, this study suggested that Taiwan may not be a famous tourist destination. Taiwan should invest more resources for promotion activities.

This work only discusses the high income countries. Future studies can investigate other countries which could potentially contribute to the development of international tourism to Taiwan for leisure.

Future research can also use other AI technologies or analyze other economic factors and the effect of specific events including the global financial crisis and disease influencing tourism demand.

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