

Forecasting Chinese Tourism Demand for Thailand: Using Markov Switching Autoregressive Model

Sainatee Chernbumroong¹, Chonrada Nunti², and Kewalin Somboon³

¹Department of Management and Entrepreneurship, Faculty of Business Administration, Chiang Mai University, Chiang Mai, 50200, Thailand

² Faculty of Economics, Chiang Mai University, Chiang Mai, 50200, Thailand

³ Faculty of Economics, Maejo University, Chiang Mai, 50210, Thailand

*Corresponding author's e-mail: sainatee.c@gmail.com

Abstract. This study purposed to forecast the Chinese tourism demand for Thailand. The time series data of Chinese tourists arriving in Thailand were estimated by using MS-AR Model, the consumer price index of Thailand, and the Thai exchange rate (THB/RMP) based on a monthly basis ranged between 2014 and 2019 collected from Ministry of Tourism and Sports, Bank of Thailand, and Ministry of Commerce, respectively. The results showed that the consumer price index of Thailand and the Thai exchange rate had a significant effect on Chinese tourism demand for Thailand. The most crucial point of this study demonstrated that the CPI could stimulate the tourism industry during the low season, so that the government can utilize or put some policies in effect for stimulating the tourism industry by controlling the CPI. In addition, this study provides the most appropriate tools to forecast the demand of Chinese tourism in Thailand and the potential options for adaption in the tourism sector.

1. Introduction

The centre of the Southeast Asian region with the 22nd of the highest population country and the world's 50th largest country by area composing of 76 provinces belong to Thailand. The country's tourism infrastructure is relatively complete with various tourism attractions, which the islands are always the first choice of tourists from all over the world to visit. Moreover, the Buddhism culture is also another main factor to attract visitors, making Thailand become one of the world's most famous tourism countries with Bangkok as the capital city that was the city with the most visits in the world in 2019.

The MS-AR model, which was originally presented by [1], was chosen to explain the econometric time series for the AR models and a generalization of the HMM. It was a combination of different AR models for describing the process' evolution at the transformation and various timings between the AR models restricted as in HMM. Regarding the review of literature, other AR models have been shown regarding the meteorological time series ([2], and [3]). These models are used in accordance with dissimilar economy states and can be utilized for other applications as well ([4]). At first, the wind time series namely MS-AR models were presented in [5] and [6] before they were presented differently in the [7] and [8] contexts.

2. Methodology

Markov-Switching Autoregressive Model (MS-AR)

The MS-AR process is a discrete-time process which has two main components $\{S_t, Y_t\}$, in which $\{Y_t\}$ indicates the wind speed process with significant values in $(0, +\infty)$, and $S_t \in \{1, \dots, M\}$ demonstrates the type of weather at time t . Then, this mentioned process can be characterized by the two following conditional independent assumptions:

1. The conditional distribution of S_t generates the values of $\{S_{t'}\}_{t' < t}$ and $\{Y_{t'}\}_{t' < t}$ which depend on the value of S_{t-1} . It is assumed that the weather type $\{S_t\}$ is the first order of the Markov chain regardless of the past wind conditions.
2. The conditional distribution of Y_t generates the values of $\{Y_{t'}\}_{t' < t}$ and $\{S_{t'}\}_{t' < t}$ which depend on the values of S_t and Y_{t-1}, \dots, Y_{t-p} . By looking at particular application, it indicates that the wind speed process $\{Y_t\}$ is an autoregressive process of order $p \geq 0$ in which the weather type sequence evolves in time with the coefficients.

Generally, the hidden Markov chain $\{S_t\}$ in the HMM and MS-AR models applications is supposed to be homogeneous, and the time constant transition probabilities $P(S_t = s' | S_{t-1} = s)$, while the transition matrix $Q = (q_{s,s'})_{s,s' \in \{1, \dots, M\}}$ with $q_{s,s'} = P(S_t = s' | S_{t-1} = s)$ helps parametrize the evolution of $\{S_t\}$. In terms of HMM with non-homogeneous hidden Markov chain, it was proposed for meteorological applications; for example, it was used by [9] in order to indicate non-stationary components in time series of wind direction. In addition, [10] used the HMM with non-homogeneous hidden Markov chain to relate the local rainfall conditions to the large circulation. In the following sections, the non-homogeneous hidden Markov chain of the MS-R models have been proposed so as to describe seasonal and internal variations.

By concerning about the autoregressive models, the most standard MSAR model could be obtained with the use of standard AR(p) models with Gaussian innovations. If $S_t = s_t$, the equation is assumed to be:

$$Y_t = a_0^{(s_t)} + a_1^{(s_t)} Y_{t-1} + \dots + a_p^{(s_t)} Y_{t-p} + \sigma^{s_t} \varepsilon_t \quad (1)$$

where $a_0^{(s)}, a_1^{(s)}, \dots, a_p^{(s)}, \sigma^{(s)} \in \mathbb{R}^{p+1} \times (0, +\infty)$ reveals the unknown parameters of the AR(p) model that imply the observed process' evolution in the regime $s \in \{1, \dots, M\}$, and $\{\varepsilon_t\}$ is a sequence of identically distributed and independent Gaussian variables with the mean value equaling to zero and unit variance independent of the Markov chain $\{S_t\}$. It can also be assumed that the conditional distribution $P(Y_t | Y_{t-1} = y_{t-1}, \dots, Y_{t-p} = y_{t-p}, S_t = s_t)$ is a Gaussian distribution with conditional mean given by the following equation:

$$E(Y_t | Y_{t-1} = y_{t-1}, \dots, Y_{t-p} = y_{t-p}, S_t = s_t) = a_0^{(s_t)} + a_1^{(s_t)} y_{t-1} + \dots + a_p^{(s_t)} y_{t-p} \quad (2)$$

3. Data description

The time series data used in this study were obtained from the Ministry of Tourism and Sports, Bank of Thailand, and Ministry of Commerce based on a monthly basis ranging between 2014 and 2019. Let the number of Chinese tourists arrived in Thailand (Y_t) be the dependent variable while the explanatory variables indicated by the consumer price index (CPI) of Thailand, and the Thai exchange rate (THB/RMP) (Ex_t).

4. Empirical results

4.1 Time Unit root test.

The use of Levin, Lin & Chu t (LLC) test, Augmented Dickey-Fuller (ADF) test, Im, Pesaran, and PP-Fisher test were employed for checking unit root test according to the procedure. The stationary in all variables with logarithm transformation were provided as the results.

4.2 Lag Selections

To identify the most appropriate model, the Akaike information criterion (AIC) was adopted since these criteria could help measure the deviation of the fitted model from the actual one. The MS-AR(2) was chosen with the minimum value of AIC as shown in Table 1.

Table 1. The lag selection from Akaike information criterion (AIC)

Lag-Selection	AIC
MS-AR(1)	-64.352
MS-AR(2)	-77.180
MS-AR(3)	-67.925
MS-AR(4)	-69.949

4.3 The Transition Probability

The transition probabilities of high season (regime I) and low season (regime II) as shown in **Table 2** are 0.88 and 0.76, respectively. According to the mentioned values, the first regime is the persistence state due to the higher transition probability of the growth regime than the recession regime. Moreover, the computed transition probability occurred from the low season (Regime II) to the high season (Regime I) and the high season (Regime I) to the low season (Regime II) are 0.47 and 0.24, respectively.

Table 2. The estimated parameters of Markov Switching Autoregressive

	High Season (Regime I)	Low Season (Regime II)
High Season (Regime I)	0.88	0.24
Low Season (Regime II)	0.47	0.76

4.4 The estimated results of Markov Switching Autoregressive Model

The results demonstrate the high season in regime I as shown in **Table 3**, resulted by CPI of Thailand, Thai exchange rate (THB/RMP), the number of tourists in year t-1 and t-2 with the parameters of -14.844, 1.087, 0.586, and 0.1681, respectively. It implies that the demand of Chinese tourists visiting Thailand will increase to 14.844% if the CPI of Thailand decreases at 1% and will increase by 1.087% when Thai exchange rate (THB/RMP) increases by 1%. The numbers of Chinese tourists in year t-1 and t-2 have a positive impact on the number of current tourists. Meanwhile, the low season in regime I also shows that the CPI of Thailand results in a grammatical boost in the number of tourists. Chinese tourists will increase to 22.666% if the CPI of Thailand decreases by 1%, while the exchange rate has no effect in the decision of Chinese tourists for traveling to Thailand.

Table 3. The estimated parameters of Markov Switching Autoregressive

Regime	Variables	The estimated parameters MS-AR(2)
Regime I	Constant	-62.380 (0.000)****
	ln(CPI _t)	-14.844 (0.000) ****
	ln(Ex _t)	1.087 (0.000) ****
	ln(Y _{t-1})	0.586 (0.000) ****
	ln(Y _{t-2})	0.1681 (0.043) ***
	Adjust R ²	0.82
Regime II	Constant	-96.696 (0.000) ****
	ln(CPI _t)	-22.666 (0.003) ****
	ln(Ex _t)	0.667 (0.113)
	ln(Y _{t-1})	1.144 (0.257)
	ln(Y _{t-2})	0.821 (0.125)
	Adjust R ²	0.93

Note that: 1. *, **, ***, **** denote the weak, evidence, strong evidence, and very strong evidence, respectively
2. (...) are Minimum Bayes factor criteria

4.5 The forecast of Chinese Tourism Demand

Table 4 represents the forecast of Chinese Tourism Demand in 2020. There is a rising trend in Chinese tourism demand for Thailand, but the effects of the COVID-19 pandemic did not play an important role.

Table 4. The forecasting of Chinese Tourism Demand in 2020 Exclude Covid-19 effects

Month	Jan	Feb	Mar	Apr	May	Jun
Number of Chinese tourists	995,209	1,137,360	1,277,858	1,416,721	1,553,968	1,689,619
Month	Jul	Aug	Sep	Oct	Nov	Dec
Number of Chinese tourists	1,823,692	1,956,205	2,087,177	2,216,625	2,344,568	2,471,022

Note: unit is people

5. Conclusion

This paper aimed to forecast the Chinese tourism demand for Thailand by using MS-AR (2) to estimate the time series data of Chinese tourists arriving in Thailand. The results showed that the number of Chinese tourists in the high season is more than in the low season. The most significant demand variable belongs to the CPI of Thailand which adheres to the law of demand. In addition, the number of Chinese tourists will increase if Thai currency depreciates. Nonetheless, regarding the low season, only the CPI of Thailand affects Chinese tourism demand. Hence, the consumer price index of Thailand or the general product prices have a great influence in stimulating Chinese tourism demand for Thailand.

Acknowledgement

It is our pleasure to acknowledge the roles of several individuals who were instrumental for completion of this study. We are very thankful to Department of Management and Entrepreneurship, Faculty of Business Administration, Chiang Mai University for providing us with the publication scholarship. This acknowledgement would not be complete without mentioning our family for their encourages and helps are every aspect throughout this paper working.

References

- [1] Hamilton, J.D., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica* 57, 357 - 384.
- [2] Zwiers, F., von Storch, H., 1990. Regime-dependent autoregressive time series modelling of the southern oscillation. *Journal of Climate* 3 (12), 1347 - 363.
- [3] Parlange, M.B., Katz, R.W., 2000. An extended version of the Richardson model for simulating daily weather variables. *Journal of Applied Meteorology* 39, 610 - 622.
- [4] Ephraim, Y., Merhav, N., 2002. Hidden Markov processes. *IEEE Transactions on Information Theory* 48, 1518 - 1569.
- [5] Monbet, V., Ailliot, P., Prevosto, M., 2007. Survey of stochastic models for wind and sea-state time series. *Probabilistic Engineering Mechanics* 22 (2), 113 - 126.
- [6] Ailliot, P., 2004. Modèles autorégressifs à changements de régimes Markoviens. Applications aux séries temporelles de vent. PhD thesis, Université de Rennes 1.
- [7] Ailliot, P., Monbet, V., Prevosto, M., 2006a. An autoregressive model with time varying coefficients for wind fields. *Environmetrics* 17 (2), 107 - 117.
- [8] Pinson, P., Christensen, L.E.A., Madsen, H., Sorensen, P.E., Donovan, M.H., Jensen, L.E., 2008. Regime-switching modelling of the fluctuations of offshore wind generation. *Journal of Wind Engineering and Industrial Aerodynamics* 96 (12), 2327 - 2347.
- [9] Zucchini, W., McDonald, I.L., 2009. Hidden Markov Models for Time Series: An Introduction Using R. Chapman & Hall/CRC, London.
- [10] Hughes, J.P., Guttorp, P., 1994. A class of stochastic models for relating synoptic atmospheric patterns to local hydrologic phenomenon. *Water Resources Research* 30, 1535 - 1546.