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SARIMA intervention based forecast model for visitor arrivals to Chiang Mai, Thailand

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Abstract

The purpose of this research is to implement the forecast model for domestic and international visitor arrivals to Chiang Mai, Thailand using seasonal autoregressive integrated moving average (SARIMA) with intervention analysis. The ADF and extended HEGY tests for the unit root identify that the observed time series are regular and seasonal non-stationary. After differencing of log transformation to the series, the SARIMA model is formulated using monthly data 2000-2007 for the pre-intervention. The residuals obtained from the forecast and secondary data 2008-2013 are assessed with the prior knowledge of various significant crisis events to identify the intervention functions in the forecast model. From the analysis, the violent political turmoil is the major long-term adverse impact on the visitors, whereas the influx of Chinese visitors helps to increase the number of international visitors. The forecasting performance comparison evaluated in terms of the accuracy and reliability indicates that the proposed forecast model outperforms the other existing models for the out-of-sample forecasts. Furthermore, if the government intensifies for solving the internal politics while the provincial administrator can maintain the massive number of Chinese, Chiang Mai will welcome over 10 million visitors and will also generate tourism revenue of about USD 2,400 million in 2018 estimated from the proposed forecast model.

Keywords: SARIMA, SARIMA with Intervention, Visitor forecast.

1. Introduction

Due to the crucial of tourism that plays an important role of successful development in business and investment. The public sector as well as the private sector needs the accurate and reliable forecast model of visitor volume in order to make plan for tourism infrastructures and service industries achieved, effective and efficient forecasting is essential. This motivates the author to propose the accurate forecast model for domestic and international visitor arrivals to Chiang Mai (CM) where the tourism has exploded over the last decade. This 720-year-old city with a variety of charming nature and fascinating culture is the iconic destination for many visitors from all across the globe as well as from within the country. It is evident from the 1st runner up award for the World's Best City in 2010 and the third place for world's top 15 cities in Asia 2016-2017 by readers' survey of Travel and Leisure magazine. The number of visitor arrivals to this city grows rapidly about 10% in 2017 over 2016. During the period 2008-2016, the number of visitors and tourist receipts to CM have increased by 4.8 million from 5.2 million to 9 million (about 25% of total visitors in Thailand) and from THB 16 billion to 86 billion, respectively. In 2017, the revenue from tourism has contributed income to this city equal to 10% GDP. Many launched promotional activities are expected the targets of attracting over 10 million visitors by 2018 which may entail a number of investments in many aspects, the long-term planning is required.

However, the upward trend in the number of visitor arrivals to CM is deteriorated during 2008-2013 (Figure. 1) due to either positive or negative impact from various crisis events. It started from the protestors called "People's Alliance for Democracy (PAD)" in January, 2007 and followed by the closure of Bangkok's Suvarnabhumi and Don Muang airports in December, 2007. The political situation has turned increasingly violent from the dispersing of the protestors called "Cruel April" in April, 2009, resulting in many deaths and more injuries. In April, 2010, the other demonstration of the protestors called "United front of Democracy against Dictatorship (UDD)" began and continued over a year. During this political violence in the capital, the number of visitor arrivals to CM is clearly affected and dropped. For the natural disaster event, the major flooding of a large part of Thailand occurred during the period July (2011)-January (2012). Later, the demonstration was ongoing by the other protesters called "People's Democratic Reform Committee (PDRC)" into November, 2013 which ended by military coup on May, 2014. The other crisis events, including, Hamburger crisis (2008-2009), the influx of Chinese tourists (January, 2013), and the annual air pollution (on March-April) are affected the number of visitor arrivals to CM.

In order to improve the performance of the existing forecast models for the visitor arrivals to CM, in this work the SARIMA with intervention model is firstly introduced. The intervention analysis is used to estimate the effect of various crucial events that occurred during the period 2008-2013. The forecast results for the test data of 2013-2104 from the proposed model evaluated in terms of the accuracy with regards to the sum of squared error (SSE) and reliability through the Aikake's information criterion (AIC) is compared with the existing forecast models, including ARIMA, radial basis function neural network (RBFNN), two-types of hybrid model, i.e., *h*RBFNN-ARIMA and *h*ARIMA-RBFNN, and SARIMA. Furthermore, the out-of-sample forecasts for 2014-2018 using the proposed model are generated. The rest of the paper is organized into the following sections: literature review (Section 2), research methodology (Section 3), model formulations, including forecast results and discussions (Section 4) and conclusion (Section 5).

2. Literature review

In the field of forecasting tourism demand, the number of visitors depends on many factors, e.g., geography, tourism resources, security, infrastructures, facilities, advertising and public relation, image, political situation, and epidemic disease. Summing up all these factors to formulate the forecast model is an inconvenient task. Generally, the forecast model of visitor volume can be categorized into two types: time-series econometrics including the simple univariate specifications [1], exponential smoothing [2] to more advanced multivariate specifications [3] and artificial intelligence method ranging from artificial NNs [4] to genetic algorithm [5]. For the former category, the multivariate models may be expected to generate more accurate forecasts than the univariate models if the cross-correlation function exhibits meaningful and statistically significant correlation. However, in the absence of these conditions, univariate forecasting models may well outperform multivariate models [6]. Various econometric methods that use the historical data of the dependent variable to forecast the future values are popular in most researches. However, these linear models cannot effectively capture the nonlinear and complex patterns of data. Alternatively, the NN models can well reveal the correlation of nonlinear time series in a delay state space. Various studies, including reference [7] and our previous work [8], have emerged NN to the forecast in tourism researches. The performance comparison showed that the NN outperforms the others. However, the over-fitting and a local trapping parameters from back-propagation learning are the main drawback. To further improve the performance of forecasting model, the hybrid of ARIMA and NN has been proposed for various design aspects. In our previous work [8], the two different hybrid models including the *h*ARIMA-RBFNN and *h*RBFNN-ARIMA model applied to forecast the visitor of CM demonstrate that they outperform the single linear and nonlinear models. However, the accuracy and complexity from the hybrid model as well as the declining reliability need to be improved.

Besides, the SARIMA model for the time series with trends and seasonal patterns is widely used in many researches, including tourism. It is applied to visitor forecasting, for example, [9-13]. In the case of international visitor forecasting of Thailand during 2005-2010 using SARIMA model [9], the forecasting results are not satisfied due to the impacts of the Tsunami in 2004 and global spread of H5N1 in 2005. For the research in reference [14], the SARIMA model is used as the benchmark comparison with the structural time series model (STSM), it is proved that STSM outperforms the SARIMA with regards to the accuracy.

While the SARIMA with intervention model is another version of an extension of multivariate ARIMA (MARIMA) model used for capturing the effect of independent variables or exceptional external events [15]. This approach has been applied to the visitor forecasting, for example, [16-22]. On the basis of this model, the forecasts are derived for the post-intervention period. The risk metric volatility model a special case of a generalized autoregressive conditional heteroskedasticity (GARCH) is used to model an intervention function from the past values of the crisis events and residuals by mean regression method [23]. One strategy is to use the portion of residual series to model the interventions identifying the order of parameters using the autocorrelation function (ACF) and the partial ACF (PACF). The effect of the events are indicated by incorporating step and impulse function through regression and set as exogenous dummy variables. The results have proven that it enhances the robustness and outperforms the SARIMA. Alternatively, the residuals are modeled to formulate the interventional transfer function using least square (LS) method [21]. Besides, the model called interrupted neural networks (I-NN) as nonlinear to more those classical linear intervention models is proposed by Herrera, *et al.* [20], however the limited training data is the main problem. Unfortunately, there is no certain method to identify the best forecasting model among them. By the literature survey, it is acknowledged no related research on the visitor forecast that compares the performance between SARIMA with intervention and the other hybrid model.

Recently, data from the Google trend website with the appropriate searching queries keywords, such as "hotels in" and "flights to", for a particular destination country is employed through the autoregressive model to forecast the visitor arrivals [24]. In the study of Bangwayo-Skeete and Skeet [3], the sampling data obtained from this website through the mixed-data sampling (MIDAS) approach—a time series regression method that allows the explanatory and dependent variables to be sampled at different frequency, is utilized. However, the sampled data provides available spanning from January 2004 onwards which is limited. Further, some information cannot take from this website due to low search intensity, other languages searching instead of English, and using other platforms. Furthermore, Google is not the dominant search engine for example in the Russian market and is restricted in China. To overcome this problem, the study of Dergiades, Mavragani, and Pan [25] introduces an approach to correct for the language and the platform bias, improving the predictive power of the constructed index for Cyprus where English is not native language and their source markets do not use Google as the major search engine. Nowadays, there is no proof yet that the Google trend provides the entirely accurate in all cases. For this work, the searching by the native language, Thai, for domestic visitor and using other platforms of the big source market for international visitor for example China, the available data from Google trend seems inaccurate, and less reliable than the other official sources.

3. Research methodology

The procedure of the SARIMA and SARIMA with intervention based forecast model is as follows.

3.1 SARIMA model

SARIMA model is developed from the standard model of Box and Jenkins [15]. Generally, it integrates differently the process of time data series on the combination of the non-seasonal autoregressive (AR) and moving average (MA), and the seasonal effects with the periodicity (S). The SARIMA$(p,d,q)\times(P,D,Q)_S$ model can be expressed in multiplicative form as follows,

$$\Phi_P(\mathrm{B}^S)\phi(\mathrm{B}^p)\Delta_S^D\Delta^d Y_t = \delta + \Theta_Q(\mathrm{B}^S)\theta(\mathrm{B}^q)\xi_t\,, \tag{1}$$

where $\phi(\mathrm{B}^p)=1-\phi_1\mathrm{B}-\ldots-\phi_p\mathrm{B}^p$ and $\theta(\mathrm{B}^q)=1-\theta_1\mathrm{B}-\ldots-\theta_q\mathrm{B}^q$ are the non-seasonal AR polynomial of order p and MA polynomial order q, respectively, $\Phi_P(\mathrm{B}^S)=1-\Phi_1\mathrm{B}^S-\ldots-\Phi_P\mathrm{B}^{PS}$ and $\Theta_Q(\mathrm{B}^S)=1-\Theta_1\mathrm{B}^S-\ldots-\Theta_Q\mathrm{B}^{QS}$ are the seasonal AR (SAR) polynomial order P, and seasonal MA (SMA) polynomial order Q, respectively, Δ^d is the non-seasonal d^{th} differencing, $\Delta_S{}^D$ is the seasonal D^{th} differencing at the time span of S, B is the backward shift which $\mathrm{B}(Y_t)=Y_{t-1}$, and $\mathrm{B}^S(Y_t)=Y_{t-S}$, ξ_t is random error with ~IID$(0, \sigma^2)$, Y_t is the current value, t denotes time and δ is a constant. The unit root test is preliminarily used to examine the stationary of the time series. If it is non-stationary, i.e., containing a unit root, subsequently it has to be transformed into a stationary by removing the unit root(s) with a first difference of the original series. The Augmented Dickey-Fuller test (ADF test) is commonly used to test for hypothesis of a non-seasonal unit-root as follows,

$$\Delta Y_t = \rho Y_{t-1} + \mu_t\,, \mu_t \sim \mathrm{IID}(0, \sigma^2), \tag{2}$$

where $\Delta Y_t=Y_t-Y_{t-1}$, ρ is the estimated coefficient and μ_t is the error. The null hypothesis is H_0: $\rho = 0$ (existing unit root) and the alternative hypothesis is H_1: $\rho < 0$. Based on the t-stat of ρ, if all t-stat is smaller than the relevant critical value, then H_0 is rejected which is regarded as stationary. On the other hand, when H_0 cannot be rejected, the original series is non-stationary. In case of seasonality, a time series achieving stationary after taking d-non-seasonal and D-seasonal difference is denoted by $I(d, D)$. To further determine whether the seasonal component of each variable exhibits stochastic non-stationary, the monthly HEGY of seasonal unit root test [26] to the seasonality is applied in this work by the extension HEGY method [27] using the critical values proposed by Franses and Hobijin [28]. For the HEGY-test of the extent version for the monthly series, the corresponding tests for seasonal unit roots based on the regression model is as follows,

$$\begin{aligned}\Delta_{12}Y_t &= \pi_1 Y_{1,t-1} + \pi_2 Y_{2,t-1} + \pi_3 Y_{3,t-1} + \pi_4 Y_{3,t-2} + \pi_5 Y_{4,t-1} + \pi_6 Y_{4,t-2} + \pi_7 Y_{5,t-1} \\ &\quad + \pi_8 Y_{5,t-2} + \pi_9 Y_{6,t-1} + \pi_{10} Y_{6,t-2} + \pi_{11} Y_{7,t-1} + \pi_{12} Y_{7,t-2} + \varepsilon_t\end{aligned} \tag{3}$$

where $Y_{1,t}$=(1+B)(1+B^2)(1+B^4+B^8)Y_t, $Y_{2,t}$= –(1–B)(1+B^2)(1+B^4+B^8)Y_t, $Y_{3,t}$= –(1–B^2)(1+B^4+B^8)Y_t, $Y_{4,t}$= –(1– B^4)(1–√3B+B^2)(1+B^2+B^4)Y_t, $Y_{5,t}$= –(1–B^4)(1+√3B+B^2)(1+B^2+B^4)Y_t, $Y_{6,t}$ = –(1–B^4)(1–B^2+B^4)(1–B+B^2)Y_t, $Y_{7,t}$= –(1–B^4)(1–B^2+B^4)(1+B+B^2)Y_t, and π is the coefficient of the regression.

The null and alternative hypotheses to be tested are as follows: (1) H_0: $\pi_1 = 0$, H_1: $\pi_1 < 0$; (2) H_0: π_2=0, H_1: $\pi_2 < 0$; (3) H_0: π_i=π_{i+1}=0, H_1:$\pi_i \neq$0 and/or $\pi_{i+1} \neq 0$, for i = {3, 5, 7, 9, 11}; (4) H_0: π_1=π_2=…=π_{12}=0, H_1: $\pi_1 \neq 0$ and/or $\pi_2 \neq 0$ and/or … and/or $\pi_{12} \neq 0$; (5) H_0: π_2=…=π_{12}=0, H_1: :$\pi_2 \neq 0$ and/or $\pi_3 \neq 0$ and/or … and/or $\pi_{12} \neq 0$. The HEGY test involves the use of the t-test for the statistical significance of π_1 and π_2 for hypothesis 1) and 2) as mentioned above, and the F-test for the rest. The hypotheses 1) and 2) represent the time series with I(0,1) process. If the hypotheses 1) and 2) are rejected the rest are test by using an F statistic, denoted as $F_{1\text{-}12}$-stat, then the time series follows an I(1,0). If the hypnoses are rejected by using both statistics, the other $F_{2\text{-}12}$-stat is used, then the time series follows an I(0,0) process. In this work, the $I(d, D)$ of SARIMA model is determined by the results of the HEGY test.

A practical approach to construct SARIMA model includes three iterative steps, i.e., identification, parameter estimation, and diagnostic checking. For the model identification, the ACF and PACF of the sample data are as the basic tools to identify the order q and Q of the MA and order p and P of AR. In the identification step, the difference and data transformation are often required to make the time series data stationary. The set of system parameters are estimated after tentative model is identified and the overall measured error is minimized. This can be accomplished using a nonlinear optimization procedure. The residuals are examined in diagnostic checking by the several statistics assumptions such as Box-Pierce Chi-Square test or the correlation of the residual plot. The SARIMA model is not sufficient if there are still linear correlations remain in the residuals [29], then a new tentative or candidate model will be replaced and the three-step is repeated until a satisfactory model is finally selected.

3.2 SARIMA with intervention model

The intervention model is a stochastic transfer function model used to extend ARIMA or SARIMA set of time series model. The impact from the interventions may be instantaneous or spread over a period of time between the former and current equilibrium level which is examined and identified by interventional analysis. By simplicity, SARIMA with intervention model contains independent variables consisting of a SARIMA model and an intervention function to become a multivariate SARIMA model. The forecast model of Y_t is formulated through the pre-intervention SARIMA model (1) and post-intervention function, $f(I_t)$, as

$$Y_t = \frac{\Theta_Q(\mathrm{B}^S)\theta_q(\mathrm{B})\xi_t}{\Phi_P(\mathrm{B}^S)\phi_p(\mathrm{B})\Delta_S^D\Delta^d} + \sum_{i=1}^{k}\frac{\omega_i(\mathrm{B})}{\delta_i(\mathrm{B})}\mathrm{B}^{b_i}X_{i,t}^T, \tag{4}$$

where ω(B) and δ(B) with time lag c and d are the interventional polynomial function where $\omega(\mathrm{B}) = \omega_0 - \omega_1\mathrm{B} - \ldots - \omega_c\mathrm{B}^c$ and $\delta(\mathrm{B}) = \delta_0 - \delta_1\mathrm{B} - \ldots - \delta_d\mathrm{B}^d$ respectively, b is the time lag length covered the intervention effect and $X_{i,t}^T$ is the function of the individual intervention (dummy) variable i during the interval of T.

Since in the real world, the measured time series of the interventional variables is difficult and very expensive. In this work, the residuals of the post-intervention period obtained from original data and the corresponding SARIMA forecast of the same fitted on the pre-intervention data period are assumed to be auto-correlated. Then, the intervention functions are generated through the processing of these residuals instead. In order to determine the parameter b, c, and d, cross-correlation between intervention variable and the dependent variable cannot be used since the intervention variable is not continuous over the time series.

Generally, there are two types of functions described the intervention effect, i.e., the step function (U_t) and pulse function (P_t). The step function is typically modeled an event which is expected to result in a permanent effect. It is normally established for a long period of event crisis, such as political violent conflict and natural disaster. Whereas the pulse function is typically modeled an event which is expected to have a temporary change, such as pollution. In the case of multiple events that are close together in time, the overall intervention is the sum of the individual event components. To identify the intervention model, the frequently used functions of immediately change, constant temporally change, and gradually decreasing/ increasing eventually levels off are as (δ_0/1−w_1B)P_t, δ_0(1−B^b)U_t, and (δ_0/1−w_1B)U_t, respectively, where δ_0 is the magnitude of intervention at the initially occurrence time, w_1 is the geometrical ratio of decreasing/ increasing, P_t and U_t are defined as 1, for $t = T$, and as 0, for t=$T \leq t \leq T$+d, respectively.

4. Results and discussion

Throughout this work, the monthly data of the domestic visitor (*YT*) and international visitor (*YF*) arrivals to CM from January, 2000 to December, 2014 provided from the Tourism Authority of Thailand (TAT) and CM airport immigration is employed to formulate the forecast models. There are two-stage approaches: in the first stage the sampled data during 2000-2008 are employed to formulate the SARIMA model, and in the second stage the residuals from the in-sample forecasting for 2009-2014 are used to capture the intervention functions for formulating the SARIMA with intervention model. The test data during the period 2013-2014 are used to evaluate the performance of the proposed forecast models and other existing models. Some missing data is replaced by interpolated data. All statistical tests and parameters estimation are processed using the Eviews 7, whereas the forecasting computations were performed by Matlab program.

4.1 The forecasts by SARIMA model

Considering {*YT*} and {*YF*} time series (Figure.1), it is observed that monthly movements of the series show a risen amount during the period September-December, sharply fell from January to July, and slightly increase in August. The trends tends to slightly increase from 2003-2006 and rapidly rise in 2007. They exhibit strong seasonal fluctuation with trend during 2000-2007 until they are affected by the various crisis events started in 2008 which sharply destroy their seasonal trends. The significant variation is clearly seen especially in 2009 with the chaos. During the post intervention (2008-2014), the trend is unpredictable.

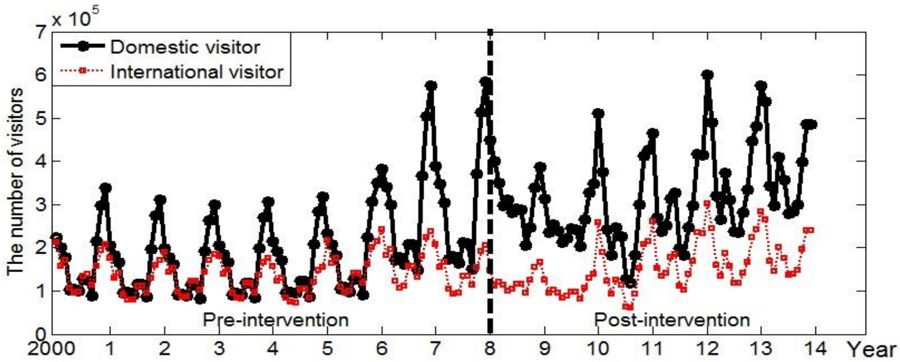
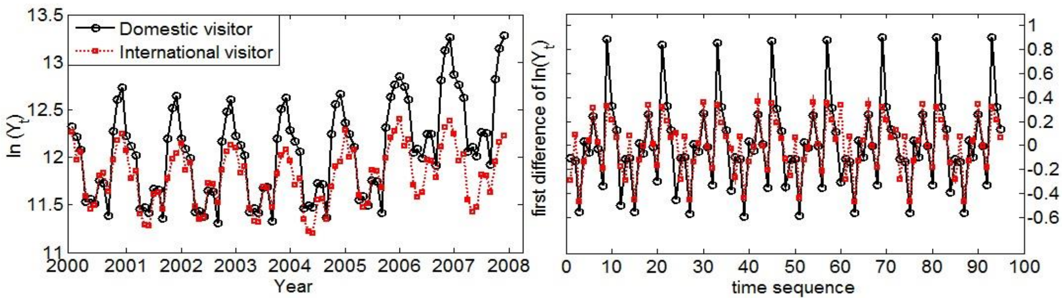


Figure 1 The monthly data in the period of 2000-2014 for the visitor arrivals to Chiang Mai.

Firstly, the variance of both {*YT*} and {*YF*} is reduced by applying the natural logarithm which is depicted in Figure. 2(a). Then, the ADF test is used to test the null hypothesis of a non-seasonal unit root. As reported in Table 1, the absolute of t-statistics of ADF test for both series at level, $d=0$ is lower than MacKinnom critical value at 5% significance level. Therefore, the null hypothesis is not rejected. Alternatively, through the first difference, $d=1$, is applied to $\ln(YT_t)$ and $\ln(YF_t)$, Figure. 2(b), the statistical results are opposite then the null hypothesis is rejected, and the transformed data is stationary.



(a) (b)

Figure 2 Data transformation for the visitor time series by (a) logarithm and (b) first difference of logarithm.

Table 1 Non-seasonal and seasonal unit root test for the domestic and international visitor time series at d=0 and d =1 level, and D = 0 and D = 1 level, respectively.

Non-seasonal unit root test				Seasonal unit root test			
Visitor	Series	ADF-stat	Critical value	Visitor	Series	ADF-stat	Critical value
Domestic	$\ln(YT_t)$ $\Delta\ln(YT_t)$	0.910 -12.846	-2.895	Domestic	$\Delta\ln(YT_t)$ $\Delta_S\Delta\ln(YT_t)$	-1.374 -15.620	-3.463
International	$\ln(YF_t)$ $\Delta\ln(YF_t)$	-1.212 -10.447	-2.895	International	$\Delta\ln(YF_t)$ $\Delta_S\Delta\ln(YF_t)$	-2.046 -10.677	-3.463

Seasonality of CM tourism depends on various aspects including weather, festival and calendar which differently affects to $\{YT\}$ and $\{YF\}$. The ADF test is repeatedly used to test the null hypothesis of a seasonal unit-root. For ADF test of $\Delta\ln(YT_t)$ and $\Delta\ln(YF_t)$. As reported in Table 1, it can be concluded that both time series are seasonal non-stationary at level. It is clearly seen in Figure. 3 (a) and (b) that the seasonality affects the series of S=12 corresponding to the repeated 12-time-lag-length. To apply the first order difference for seasonality of $\Delta_S\Delta\ln(YT_t)$ and $\Delta_S\Delta\ln(YF_t)$, the ACF died off rapidly after 12-time-lag, Figure. 3(c) and (d), which indicates that the seasonal unit root is eliminated. In Table 1 with ADF test of $\Delta_S\Delta\ln(Y_t)$ for both series, the absolute of t-stat at d=1 is higher than the MacKinnom critical value at 5% significance level, then the null hypothesis is rejected, and the transformation time series are stationary.

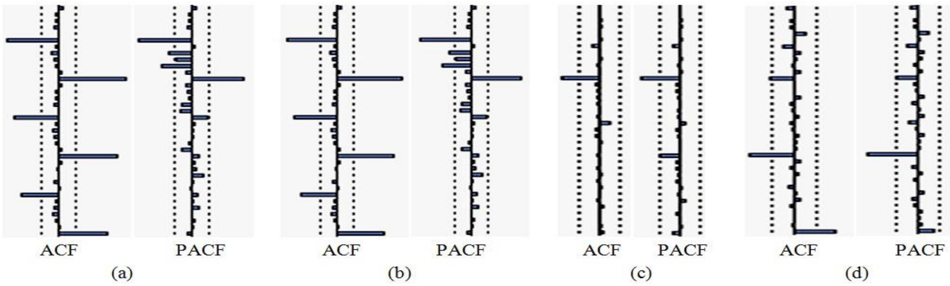


Figure 3 ACF and PACF plot of (a) $\Delta\ln(YT_t)$, (b) $\Delta\ln(YF_t)$ (c) $\Delta_S\Delta\ln(YT_t)$, and (d) $\Delta_S\Delta\ln(YF_t)$.

To further apply the HEGY test for $\ln Y_t$, the statistic values are compared with 5% critical values obtained from Franses and Hobijin [26] using the observed data of 2000-2008 (Table 2). The null hypotheses at annual and semi-annual frequencies is accepted at $t(\pi_1)$ and $t(\pi_2)$. However, the F-stats indicate the null hypotheses of unit root at quarterly and all other higher frequencies are rejected. These results imply the non-stationary of the series at annual and quarterly level but not at the monthly (higher frequency level), $I(0,1)$. However, in case of the logarithm transformation, the less fluctuation around the mean can cause the stationary at level for high frequency data. To test the robustness of the results, the null hypotheses of the series is seasonally integrated of order one, i.e., $I(1,1)$. The null hypotheses to be tested are as follows: (1) H_0: $\pi_1 = 0$ (called t_1); (2) H_0: π_i=0, i=2,3,…,12; using t-stat and corresponding to the joint hypotheses (3) H_0: $\pi_i=\pi_{i+1}=0$, for i = {3, 5, 7, 9, 11} using F-stat following Beaulier and Miron [25]. From the results, the null hypotheses of the presence of unit root at all seasonal frequencies are rejected for both series. This confirms our previous finding for non-seasonal unit roots identified by the ADF-test, we agree that the series have both non-seasonal and annual seasonal unit roots based on the HEGY test.

Table 2 Test statistic under HEGY unit root test for domestic and international visitor series.

Series	Lags	$t(\pi_1)$	$t(\pi_1)$	$F(\pi_3,\pi_4)$	$F(\pi_5,\pi_6)$	$F(\pi_7,\pi_8)$	$F(\pi_9,\pi_{10})$	$F(\pi_{11},\pi_{12})$	$F(\pi_2\ldots\pi_{12})$	$F(\pi_1\ldots\pi_{12})$
$\ln(YT_t)$	0	1.23	1.19	5.35*	20.83*	10.21*	10.08*	12.02*	15.35*	18.21*
$\ln(YF_t)$	0	2.12	2.67	10.31*	8.89*	7.72*	12.33*	14.31*	23.23*	43.88*
Critical value		-2.81	-2.81	6.35	6.48	6.33	6.41	6.47	4.37	4.44

* denotes reject the null hypothesis at 5% level.

After determining the order of integrate $I(1,1)$ based on the HEGY test, the values of p, q, P and Q are estimated from the ACF and PACF plot. It is seen from the graph of Figure. 3(c)-(d) that the ACF and PACF rapidly died off after the 12th and 12th lag for $\Delta_S\Delta\ln(YT_t)$, and 12th and 24th lag for $\Delta_S\Delta\ln(YF_t)$, respectively. Then, the tentative SARIMA models are introduced as SARIMA(0,1,0)×(12,1,12) and SARIMA(0,1,0)× ([12,24],1,[12,24])$_{12}$. However, after diagnostic checking and model selection by the criteria including adjust R^2, AIC, and Schwarz's Bayesian Information Criterion (SBC), it is shown that these models are proved as suitable models which have greater adjusted R^2 value and smaller AIC and SBC value than those of the other candidate models. At 99%

statistic test of confidence interval level as shown in Table 3, the standard errors are less twice than the coefficient of parameters and all *p*-value are less than 0.01. It can be concluded that the selected coefficients of the parameters have the statistical significance.

Table 3 Statistical test of the coefficient of parameters for the SARIMA models.

SARIMA model	Variable	Coefficient	Standard error	t-stat	Prob.
Domestic visitor	SAR(12)	-0.262	0.089	-2.935	0.0045
	SMA(12)	-0.970	0.041	-23.615	0.0000
International visitor	SAR(12)	-0.807	0.0767	-10.518	0.000
	SAR(24)	-1.031	0.0790	-13.053	0.000
	SMA(12)	1.048	0.1045	10.033	0.000
	SMA(24)	0.9412	0.0252	37.304	0.000

Now, the residuals from two selected models are tested the serial correlation using Ljung-Box test. The Q-stat of 6.15 with df = 21-2 and of 34.60 with df = 21-4 at 95% confident interval is less than the critical value of 12.34 and 37. 56 for *YT* and *YF*, respectively, implying that the residual has no correlation. Then, the SARIMA(0,1,0)×(12,1,12) and the SARIMA(0,1,0)×([12,24],1,[12,24])$_{12}$ are finally accepted and expressed by (5) and (6), respectively,

$$\ln YT_t = \ln YT_{t-1} + \frac{(1-0.970\mathrm{B}^{12})}{(1-\mathrm{B})(1-\mathrm{B}^{12})(1-0.262\mathrm{B}^{12})}\varepsilon_t, \tag{5}$$

$$\ln YF_t = \ln YF_{t-1} + \frac{(1-0.807\mathrm{B}^{12}-1.031\mathrm{B}^{24})}{(1-\mathrm{B})(1-\mathrm{B}^{12})(1+1.05\mathrm{B}^{12}+0.94\mathrm{B}^{24})}\varepsilon_t. \tag{6}$$

The forecast results by SARIMA model of (5) and (6) are shown in Figure. 4 (a)-(b), respectively.

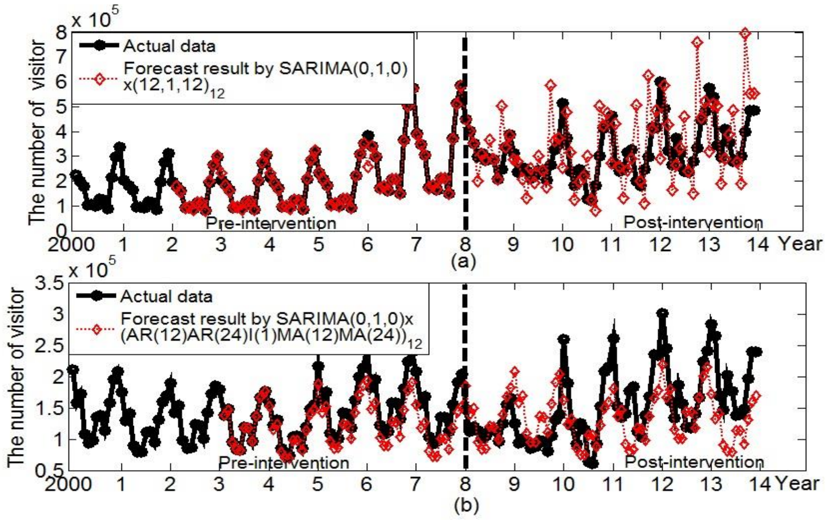


Figure 4 The forecasting results of SARIMA model for (a) domestic and (b) international visitor arrivals to Chiang Mai during pre- and post-intervention.

During the in-sample forecasts, the SARIMA model of domestic and international visitor have the RMSE and MAE of 0.141 and 0.125; and 0.174 and 0.142, respectively, whereas during the post-intervention period, their RMSE and MAE are increased of 0.382 and 0.328; and 0.367 and 0.304, respectively. The SARIMA models lack of an efficient forecast by generating higher and lower forecast value than the actual data approximately 60% and 50% for domestic and international visitor, respectively.

4.2 Interventions in the structural break

To improve any unusual forecasts from the SARIMA model, an intervention analysis is alternatively undertaken to assess the impact of the crisis events on the time series. For the domestic visitor, the portions of residual illustrated on the time line diagram (Figure. 5) from the SARIMA model (5) of the post-intervention are considered simultaneously with the prior knowledge of the crisis events and used to formulate the intervention functions.

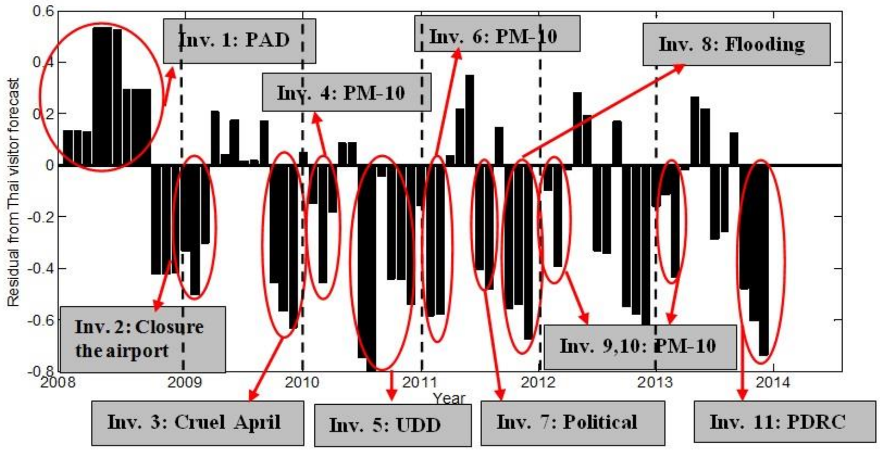


Figure 5 Time line of the crisis events corresponding to residuals obtained from SARIMA model for domestic visitor arrivals to Chiang Mai during 2008-2014.

The interventions comprised of 7 major crisis events, including 1) the demonstration by PAD in January, 2007, 2) the closure of airports by PAD in December, 2007, 3) Cruel April in April, 2009, 4) the demonstration by UDD in April, 2010, 5) the severe flooding in July, 2011, 6) PM-10 (January, 2012) and 7) the demonstration of PDRC in November, 2013. It is visually obvious from Figure. 5 that the residuals as the results from the intervention take place not only one time period but affect more than two time periods. They are normally remained in effect thereafter except for the PM-10 event which effect in a short range. Therefore, most crisis events are captured in the model by step function. The interventions are considered to select either the corresponding step or impulse transfer function through a range of possible effects. The residuals are employed to identify and determine the intervention functions through the regression method. The intervention functions can be expressed as,

$$f_T(I_t)=\frac{0.136\,U_{T,1}}{0.371-0.524\text{B}+0.305\text{B}^2}+\frac{-0.421\,U_{T,2}}{1-0.701\text{B}}+\frac{0.457\,U_{T,3}}{0.624+0.214\text{B}}-0.262U_{T,4}+\frac{-0.747\,U_{T,5}}{-0.433+0.237\text{B}+0.495\text{B}^2} \quad (7)$$
$$-0.582P_{T,1}+0.283U_{T,6}+\frac{0.554\,U_{T,7}}{0.61+0.079\text{B}}-0.58P_{T,2}-0.274P_{T,3}+\frac{0.479\,U_{T,8}}{0.732+0.304\text{B}},$$

where $U_{T,1}=U(t-t_{1,2008})-U(t-t_{9,2008})$, $U_{T,2}=U(t-t_{12,2008})-U(t-t_{3,2009})$, $U_{T,3}=U(t-t_{10,2009})-U(t-t_{12,2009})$, $U_{T,4}=U(t-t_{1,2010})-U(t-t_{3,2010})$, $U_{T,5}=U(t-t_{6,2010})-U(t-t_{2,2011})$, $P_{T,1}=P(t-t_{1,2011})+P(t-t_{2,2011})$, $U_{T,6}=U(t-t_{7,2011})-U(t-t_{8,2011})$, $U_{T,7}=U(t-t_{9,2011})-U(t-t_{11,2011})$, $P_{T,2}=P(t-t_{1,2012})-P(t-t_{2,2012})$, and $U_{T,8}=U(t-t_{10,2013})-U(t-t_{12,2013})$.

The estimated parameters of SARIMA with interventions are tested by t-value and p-value (Table 4) for individual intervention function. Almost all standard errors and p-value are less twice than the parameter values and less than 0.05, respectively. Then, the estimated parameters have statistical significance.

Table 4 Maximum likelihood estimated of fitted SARIMA with interventions model.

Variable	Parameter	Value	Standard error	*t*-value	*p*-value	Lag
SAR(12)	Φ_{12}	-0.428	0.0689	-6.20	<0.001	12
SMA(12)	Θ_{12}	0.967	0.0309	31.29	<0.001	12
Intervention 1	$\omega_{1,0}$	0.136	-	-	-	0
	$\delta_{1,0}$	0.371	0.083	4.46	0.036	1
	$\delta_{1,2}$	-0.524	0.436	1.20	0.049	1
	$\delta_{1,3}$	0.305	0.414	-0.73	0.053	1
Intervention 2	$\omega_{2,0}$	-0.421	-	-	-	0
	$\delta_{2,1}$	-0.701	0.32	2.19	0.078	1
Intervention 3	$\omega_{3,0}$	0.457	-	-	-	0
	$\delta_{3,1}$	0.624	0.0304	-20.4	<0.00001	0
	$\delta_{3,2}$	0.214	0.051	4.19	<0.00001	1
Intervention 4	$\omega_{4,0}$	-0.262	-	-	-	0
Intervention 5	$\omega_{5,0}$	-0.747	-	-	-	0
	$\delta_{5,0}$	-0.433	0.048	-8.91	0.037	0
	$\delta_{5,1}$	0.234	0.241	0.97	0.074	1
	$\delta_{5,2}$	0.495	0.214	-2.31	0.035	1
Intervention 6	$\omega_{6,0}$	-0.582	-	-	-	0
Intervention 7	$\omega_{7,0}$	0.283	-	-	-	0
Intervention 8	$\omega_{8,0}$	0.554	-	-	-	0
	$\delta_{8,1}$	0.610	0.030	-20.0	<0.0001	0
	$\delta_{8,2}$	0.079	0.061	1.28	0.0038	1
Intervention 9	$\omega_{9,0}$	-0.580	-	-	-	0
Intervention 10	$\omega_{10,0}$	-0.274	-	-	-	0
Intervention 11	$\omega_{11,0}$	0.479	-	-	-	0
	$\delta_{11,0}$	0.732	0.091	-7.98	<0.0001	0
	$\delta_{11,1}$	0.304	0.122	2.49	<0.0001	1

The interventions corresponding to the residuals obtained from the SARIMA model (6) of the international visitor are illustrated through the time line (Figure. 6) which comprised of 5 major crisis events, including 1) Hamburger crisis (2008), 2) the demonstration of PAD, 3) Cruel April, 4) the demonstration of UDD and 5) the influx of Chinese visitor started in January, 2013. It is seen from Figure. 6 that the number of international visitor arrivals to CM has been not affected by severe flooding even some roads and railways are closed since the visitors can access by the air. Besides, the massive influx of Chinese tourists have spiked drastically due to the famous film's 2012 of "Lost in Thailand" which was mostly shot in CM. It is increased from 0.6 to 2 million (from 2012 to 2013) or 235% which is the great positive impact.

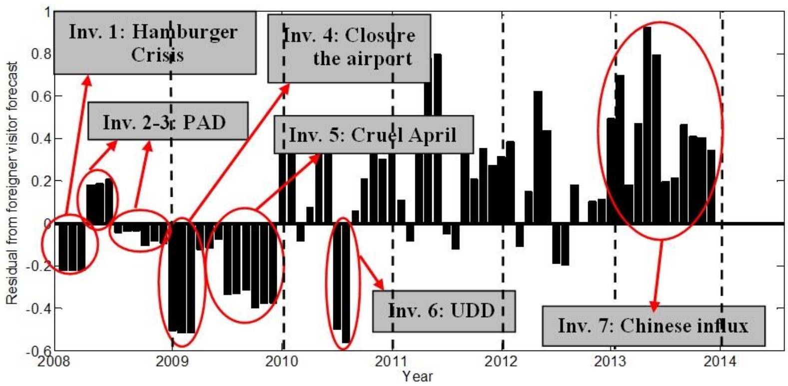


Figure 6 Time line of crisis events corresponding to residuals obtained from SARIMA model for international visitor arrivals to Chiang Mai during 2008-2014.

The intervention functions of the crisis events through the regression method are expressed as,

$$f_F(I_t) = -0.222U_{F,1} + 0.193U_{F,2} + \frac{-0.044}{-0.073 - 0.117B}U_{F,3} + -0.512U_{F,4} + \frac{-0.116}{-0.352 - 0.66B}U_{F,5} - 0.530U_{F,6} + \frac{0.494}{0.46 - 0.36B + 0.67B^2 - 0.24B^3}U_{F,7}, \quad (8)$$

where $U_{F,1}=U(t-t_{1,2008})-U(t-t_{3,2008})$, $U_{F,2}=U(t-t_{4,2008})-U(t-t_{6,2008})$, $U_{F,3}=U(t-t_{7,2008})-U(t-t_{12,2008})$, $U_{F,4}=U(t-t_{1,2009})-U(t-t_{3,2009})$, $U_{F,5}=U(t-t_{5,2009})-U(t-t_{12,2009})$, $U_{F,6}=U(t-t_{7,2010})-U(t-t_{8,2010})$ and $U_{F,7}=U(t-t_{1,2013})-U(t-t_{12,2013})$.

The estimated parameters of SARIMA with interventions are tested by t-value and p-value (Table 5). Almost all standard errors and all p-value are less twice than the value of parameters and less than 0.05, respectively. Then the estimated coefficients have statistical significance.

Table 5 Maximum likelihood estimated of fitted SARIMA with interventions model.

Variable	Parameter	Value	Standard error	t-value	p-value	Lag
SAR(12)	Φ_{12}	1.059	0.0075	13.976	0.00001	12
SAR(24)	Φ_{24}	-0.395	0.084	-4.652	0.00001	24
SMA(12)	Θ_{12}	-1.801	0.0252	-71.488	0.00001	12
SMA(24)	Θ_{24}	0.845	0.0219	38.576	0.00001	24
Intervention 1	$\omega_{1,0}$	-0.222	-	-	-	0
Intervention 2	$\omega_{2,0}$	0.193	-	-	-	0
Intervention 3	$\omega_{3,0}$	-0.044	-	-	-	0
	$\delta_{3,0}$	-0.073	0.0165	-4.415	0.001	0
	$\delta_{3,1}$	-0.117	0.123	0.95	0.054	1
Intervention 4	$\omega_{4,0}$	-0.512	-	-	-	0
Intervention 5	$\omega_{5,0}$	-0.116	-	-	-	0
	$\delta_{5,0}$	-0.352	0.125	-2.806	0.001	0
	$\delta_{5,1}$	-0.660	0.276	2.386	0.001	0
Intervention 6	$\omega_{6,0}$	-0.530	-	-	-	0
Intervention 7	$\omega_{7,0}$	0.494	-	-	-	0
	$\delta_{7,0}$	0.46	0.056	8.10	0.0053	1
	$\delta_{7,1}$	0.36	0.272	1.32	0.0030	1
	$\delta_{7,2}$	-0.67	0.256	-2.61	0.0032	1
	$\delta_{7,3}$	0.24	0.237	1.01	0.049	1

4.2 The forecasts by SARIMA with intervention model

For the domestic and international visitor forecast using the SARIMA model (5) with intervention functions (7), $\Delta\ln(YT_t)=$ SARIMA$(0,1,0)\times(12,1,12)_{12}+f_T(I_t)$, and the SARIMA model (6) with intervention function (8), $\Delta\ln(YT_t)$ =SARIMA$(0,1,0)\times(AR(12),(24),1,MA(12),(24))_{12}+f_F(I_t)$, the forecast results and residuals during 2008-2014 are shown in Figure. 7. The diagnosis checking for the residuals is tested through the serial correlation by using Ljung-Box test. For the residual of domestic and international visitor, the Q-stats are equal to 22.11and 33.91 with df =42-26 and df=42-19 at 95% confident interval which are less than the critical value of 26.29 and 34.77, respectively. Therefore the residuals have no correlation and these SARIMA with intervention models are suitable

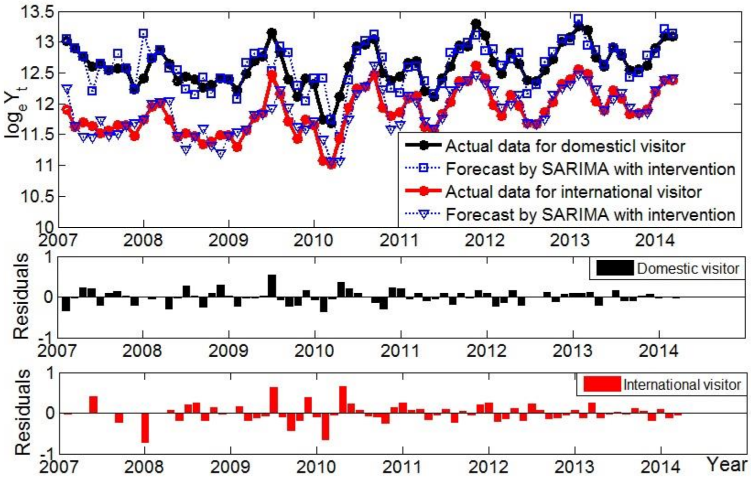


Figure 7 The forecast results of the domestic and international arrivals to Chiang Mai and the residuals by SARIMA with intervention models.

4.3 Comparisons of the forecasts

The performance comparison between the forecast models based on SARIMA with intervention model and existing forecast models [8] in terms of SSE, AIC, the number of system parameters (K) through the test data during 2013-2014 is tabulated in Table 6. From the SSE, it is found that the proposed model performs the best among others. For the forecast model assessment, AIC that seeks a model that has a good fit but few parameters, is adopted to be a criterion to measure the quality of the forecast models and defined as

$$AIC = n\log\left(\frac{\sum_n e_i^2}{n}\right) + 2K, \quad (9)$$

where e_i are the residual, n is the number of test data, and K is the total number of parameters in the model. The preferred model is the one with the minimum AIC.

For domestic visitor forecast, the number of parameters of ARIMA(2,1,1) model is 3 (2-AR- and 1-MA-coefficient), RBFNN(7,10,1) model is 97 (80-weight and 17-bias), the hybrid ARIMA(2,1,1)-RBFNN([5,5],5,1) model is 73 (3 from ARIMA, 55-weight, and 15-bias), hybrid RBFNN(7,10,1)-ARIMA(4,0,8) model is 109 (97 from RBFNN, 4-AR- and 8-MA-coefficient), SARIMA$(0,1,0)\times(12,1,12)_{12}$ model is 2 (1-SAR- and 1-SMA-coefficient) and SARIMA$(0,1,0)\times(12,1,12)_{12}$ with 7 interventions is 28 (2 from SARIMA and 26-parameter from intervention functions). For international visitor forecast, the number of parameters of ARIMA(2,1,1) model is 3 (2-AR- and 1-MA-coefficient), RBFNN(7,9,1) model is 88 (72-weight and 16-bias), the hybrid ARIMA(2,1,1)-RBFNN([1,5],5,1) model is 49 (3 from ARIMA, 35-weight and 11-bias), hybrid RBFNN(7,9,1) - ARIMA(9,0,9) model is 106 (88 from RBFNN, 9-AR- and 9-MA-coefficient), SARIMA$(0,1,0)\times(AR(12),AR(24),1,MA(12),MA(24))_{12}$ model is 4 (2-SAR- and 2-SMA-coefficient) and SARIMA$(0,1,0)\times(AR(12),AR(24),1,MA(12),MA(24))_{12}$ with 5 interventions is 19 (4 from SARIMA and 15-parameter from intervention functions). From Table 6, it is found that SARIMA with intervention is the optimal model while SARIMA are the sub-optimal regards to the AIC.

Table 6 Comparison of performances of the forecast models.

Model	Model representation		Sum of square error (SSE) ($\times10^5$)		The number of parameters (K)		AIC	
	Domestic visitor (DV)	International visitor (IV)	DV	IV	DV	IV	DV	IV
ARIMA	(2,1,1)	(2,1,1)	6.19	2.36	3	3	111	101
RBFNN	(7,10,1)	(7,9,1)	4.50	1.68	97	88	296	268
*h*ARIMA-RBFNN	(2,1,1)-([5,5],5,1)	(2,1,1)-([1,5],5,1)	3.52	1.57	73	49	245	189
*h*RBFNN-ARIMA	(7,10,1)-(4,0,8)	(7,9,1)-(9,0,9)	0.027	0.0093	109	106	267	250
SARIMA	$(0,1,0)\times(12,1,12)_{12}$	$(0,1,0)\times(AR(12),AR(24),1,MA(12),MA(24))_{12}$	2.93	1.19	2	4	102	96
SARIMA with intervention	$(0,1,0)\times(12,1,12)_{12}+f_T(I_t)$	$(0,1,0)\times(AR(12),AR(24),1,MA(12),MA(24))_{12}+f_F(I_t)$	0.010	0.0068	28	19	**95**	**73**

The out-of-sample forecasts of Chiang Mai's visitor during 2014-2018 through the SARIMA with intervention models are shown in Figure.8. The trend appears to be increasing while the rate is declining for both series especially for international visitors. The numerical forecast results are shown in Table 5.

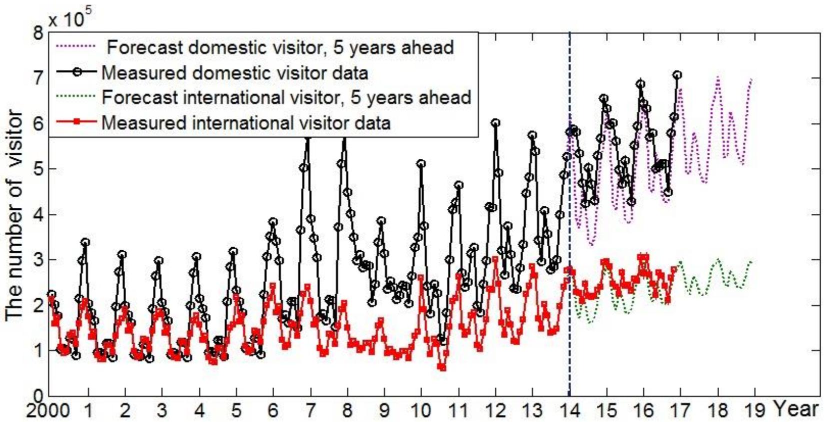


Figure 8 Out-of-sample forecasts in the period 2014-2018 for domestic and international visitor arrivals to Chiang Mai by the proposed SARIMA with intervention.

Table 7 Numerical results of out-of-sample forecast for domestic and international visitor arrivals to Chiang Mai in the period of 2014-2018 by SARIMA with intervention model.

Year	Domestic visitor			International visitor		
	Measured	Forecast	Error	Measured	Forecast	Error
2014	5,331,527	5,356,604	25,077	2,552,837	2,565,039	12,202
2015	5,757,303	5,770,823	13,520	2,724,077	2,731,316	7,239
2016	6,207,945	6,221,768	5,823	2,887,989	2,889,897	1,908
2017	6,680,785	-	-	3,042,694	-	-
2018	7,173,544	-	-	3,187,054	-	-

From the forecast results, the number of domestic and international visitor arrivals to CM increases with a declining rate of 20.3% and 65.44%, respectively, implies that the effect of crisis events affected to the international visitor than the domestic visitor.

5. Conclusion

In this work, the SARIMA with intervention based forecast model for domestic and international visitor arrivals to Chiang Mai, Thailand is proposed. The political conflict and the influx of Chinese tourist are the main sensitive and effective events among various events. The forecasting performance of the proposed model evaluated in terms of the trade-off between accuracy with respect to the SSE and reliability through AIC clearly outperforms the other existing models. From the forecasts, if the government is to intensify efforts to solve the internal politics, and the provincial administrator can maintain the massive amount of Chinese visitor by establishing a trade and business information centre for them, Chiang Mai will welcome over 10 million visitors and can generate around USD 2,400 million of revenue at the end of 2018. For the future work, the multivariate SARIMA model using other related series such as the visitor arrivals to Bangkok (the capital city) series, the number of tourist and per capita income of the origin country series for example China the big market for Chiang Mai.

6. Acknowledgments

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7. Conflict of Interest

No conflict of interest declared.

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