Forecasting Monthly Tourist Arrivals from ASEAN+3 Countries to the Philippines for 2015-2016 Using SARIMA Noise Modeling

Cesar C. Rufino
School of Economics, DLSU-Manila
Email: cesar.rufino@dlsu.edu.ph

Abstract. This study is an attempt to develop and operationalize empirical time series forecasting models for the monthly number of short-haul tourists coming from each of the countries comprising the ASEAN+3 region. The central goal is to formulate two-years-ahead arrival scenarios from the most active source region of the Philippines international tourism. Employing a framework that takes into account possible influential events that may impact on the level and direction of arrival series, together with a reliable procedure of modeling seasonal background noise, the study aims to establish for each source country a-theoretic (non-structural) forecasting models that will pass all conventional econometric model selection criteria and immune to the "Lucas Critique". The first model (ex-post model) will be used in out-of-sample performance assessment, and the other (ex-ante model) is to be used in predicting monthly arrival scenarios (most likely, worst case and best case) for the next two years – for each of the ASEAN+3 countries and the spatially aggregated regional forecasts. An estimation procedure to determine the Philippines aggregate demand for international tourism will also be presented. Using the Best-case scenario forecast of the study, the Philippines is expected to attract 6.5 million visitors in 2015, and 8.4 million in 2016. The encouraging results of the out-of-sample performance assessment of the ex-post models for the individual countries amply demonstrated the efficacy of the non-structural approach in inbound tourism demand forecasting for use in crafting operational, tactical and strategic plans by stakeholders of the country's travel and tourism industry.

Keywords: Tourism demand forecasting, Lucas Critique, ASEAN+3 region, A-theoretic method, SARIMA Noise

1. INTRODUCTION

The ASEAN Travel and Tourism industry has been at the forefront of pursuing socio-economic and cultural goals consistent with the avowed objectives of the ASEAN Integration, which has been fully operational since the end of 2015. This milestone offers a "*unique window of opportunity to launch an entirely new era of tourism development that will allow ASEAN travel & tourism to reclaim its erstwhile leadership role as the only industry capable of driving growth in an economically-productive way.*" (UNTWO Technical Paper 2010). With most of the transportation and allied infrastructures, agreements and protocols now in place, ensuring easier and efficient intra-regional movements of people, goods and services, the industry is once again a high-profile industry, true to its potential of becoming a veritable engine of growth (Egan & Nield 2003, Sinclair 1998) to most countries in the region. In light of the great impact of the ASEAN integration on tourism, plans are to be crafted, anchored on reliable demand forecasts of each country's international tourism sources, especially those coming from countries within the region and the traditional high valued short-haul sources like the three East Asian Economic giants (China, Japan and South Korea), which together form the expanded region called ASEAN+3.

Most of the tourism demand forecasting models presented in the literature are classified as structural or theoretic (see e.g. the review articles: Witt & Witt 1995, Lim 1997, Song & Witt 2000, and Li, et. al 2005). Unlike non-structural models however, these models are subject to the so-called "Lucas Critique", which states that parameters of structural models are not policy invariant, such that when policy changes, these models will not be able to capture this change resulting in less accurate forecasts (Lucas 1976) or a form of Meese-Rogoff paradox where econometric models are often out-performed by even the simple non-structural random walk models in producing ex-ante forecasts (Meese & Rogoff 1983). Furthermore, when used in forecasting, structural models (particularly the static ones) will require policy values or forecasts of explanatory variables, which at times can only be extrapolated with substantial error. Their comparative advantage though lies in estimating parameters useful in policy formulation, counterfactual simulations and stylized facts analysis (e.g. elasticities, multipliers, marginal propensities, etc.). The tourism literature also point out that econometric regression models are almost always out-performed by time-series models (e.g., Witt & Witt 1995).

2. METHODOLOGY

The a-theoretic modeling approach adopted in the study is the so-called ARIMA Model-Based (AMB) Methodology. Under the AMB approach, each of the 12 monthly visitor arrival time series, one for each ASEAN+3 country will be depicted as being generated by a stochastic process driven by different deterministic factors and a non-stationary stochastic seasonal noise element. These exogenous factors are classified into two categories, namely - The Calendar Effects (**Trading Day (TD) Effects** – caused by the distribution of weekdays indifferent months, captured by the number of trading days in a month; and **Easter Effect (EE)** which captures the moving date of Easter in different years.) and Outliers – Dummy variables representing the date of occurrences of influential events which are further classified into: **Additive Outliers (AO)** – events that cause one time spikes in the series, **Transitory Change (TC)** outliers – events that create fleeting or transitory changes, and **Level Shift (LS)** outliers – are shocks with permanent effects.

Symbolically, if y_{it} represents the number of tourists arriving to the Philippines from source ASEAN+3 country i during month t and D_{sjit} is a dummy variable that indicates the position of the s^{th} event of category j outlier (i.e., *AO, TC and LS* for the i^{th} source country during time t and TD_t is the number of trading days in month t and $D_{EEt} = 1$ if Easter occurs during month *t*, zero otherwise) , we can formulate a regression model that would explain the arrival process as:

$$y_{it} = \varphi_i + \psi_{TDt} TD_t + \psi_{EEt} D_{EEt} + \sum_{j=AO}^{LS} \sum_{s=1}^{n_j} \psi_{sjit} D_{sjit} + x_{it} \quad (1)$$

The parameter ψ_{sjit} is the effect of the s^{th} event of the j^{th} outlier type on the series during time t and x_{it} is a non-stationary stochastic noise element (random error) that follows a seasonal $ARIMA(p,d,q)(P,D,Q)$ process for i^{th} country over time. Algebraically, the noise element x_{it} can be represented in *Lag Polynomial* form as:

$$\phi_p(L)\Phi_P(L)\delta(L)x_{it} = \theta_q(L)\Theta_Q(L)\varepsilon_{it} \quad (2)$$

The two finite lag polynomials at left side of (2) contain respectively the p stationary regular Auto regresssive (AR) roots and the P seasonal AR roots of the noise element x_{it} while the two finite lag polynomials at the right side contain respectively the q invertible regular Moving Average (MA) roots and Q invertible seasonal MA roots of x_{it}. The lag polynomial $\delta(L) = (1-L)^d(1-L^s)^D = \nabla^d \nabla_s^D$ contains the d non-seasonal and D seasonal unit roots of x_{it}. This lag polynomial, when applied to x_{it} will convert it into stationary stochastic process.

2.1 The Modified Box-Jenkins Procedure

The ARIMA Model Based (AMB) approach is implemented by the modified Box-Jenkins procedure (Figure 1) for.-identification, estimation, diagnostics, and forecasting beyond the sample horizon of the observed time series. The iterative component of the procedure lies in the diagnostics stage where the assumed model is tested for adequacy using a number of criteria. Aside from testing the statistical adequacy of the parameters, the following ***diagnostic procedures*** are implemented:

- **Ljung-Box (LB)** test for residual autocorrelation
- **Jarque-Bera (JB)** test for normality of residuals
- **SK t-test** for residual skewness
- **Kur t-test** for residual kurtosis of
- **Box Pierce (QS)** test of residual seasonality
- **McLeod and Li (Q2)** test of residual linearity
- **Runs** t-test for residuals randomness
- **Correlogram Analysis** – for alternative models selection

2.2 Data and Time-Line in Forecasting

Actual data available for the study range from January 2000 to December 2014 for use in developing forecasting models that will be used in establishing ex-ante monthly visitor arrival To check the out-of-sample forecasting performance of the AMB approach, part of the historical sample is set aside (January 2013 to December 2014), with the rest of the available data to be used in estimating ex-post models to produce the out-of-sample forecasts.

In order to assess the out-of-sample forecasting performance of the ex-post models, graphs of the Forecasts against the Actual arrivals for three scenarios (most likely, worst case and best case) will be constructed to pictorially show how the models' predictions follow accurately, both the levels and directions of actual realizations during the hold out period January 2013 to December 2014. To quantify the forecasting performance of the models, the MAPE or *Mean Absolute Percentage Error* and the RMSE or *Root Mean Square Error* criteria will be used.

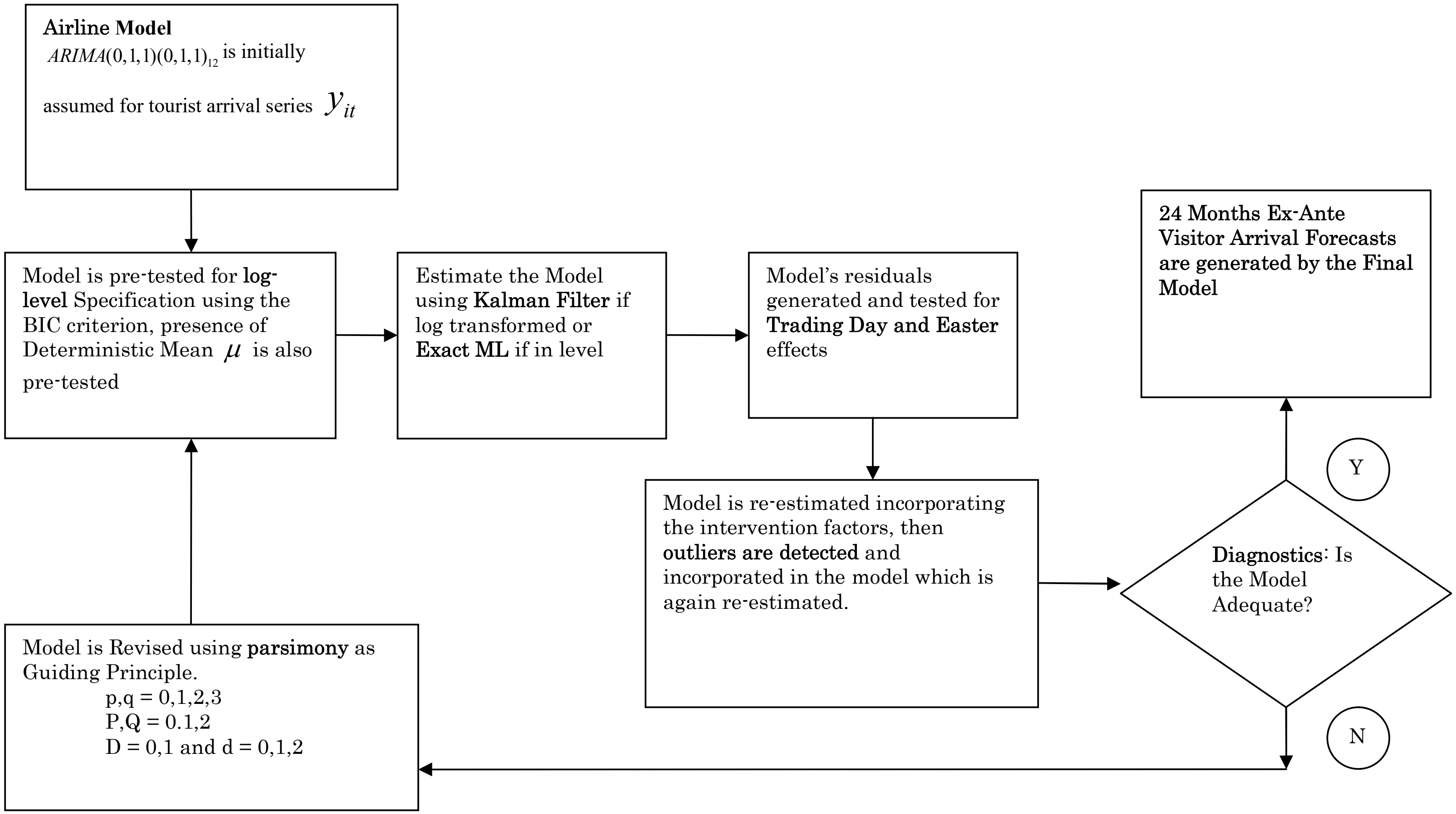

Figure 1. The Modified Box-Jenkins Procedure in Forecasting Tourist Arrivals from ASEAN+3 Countries to the Philippines

3. RESULTS AND DISCUSSIONS

3.1 Ex-Post and Ex-Ante Forecasting Models

Successive runs of the expert system called TRAMO which implements the AMB procedure through the TSW (TRAMO-SEATS for Windows) software in AMI (Automatic Model Identification) mode produce Tables 1 and 2. Table 1 summarizes the outcomes of implementing the Modified Box-Jenkins methodology in determining the best *Ex-Post models*, while Table 2 is the summary for *Ex-Ante models*. As seen in Table 1, all Ex-Post noise models which will be used in out-of-sample forecast assessment passed all conventional diagnostics criteria of adequacy, hence can be safely used in tracking down actual monthly arrivals from ASEAN+3. The importance of examining the capability of the models to accurately predict the levels and directions of the hold-out sample observations is to gain confidence in using the AMB methodology. If the models can consistently anticipate even the turning points in the observed series, further employment of this forecasting approach to anticipate arrivals beyond the sample horizon can be adequately justified. The Ex-Ante models presented in Table 2, which also manifest highly desirable statistical properties, will be employed in generating the different scenarios that would meet the central goal of the study.

3.2 Results of the Assessment of Out-of-sample Forecasting Performance of Ex-Post Models

Using the two forecast evaluation criteria of Root Mean Squares Error (RMSE) and Mean Absolute Percentage Error (MAPE), the out-of-sample forecasting performance of the Ex-post models are analyzed. Estimating the models using sample period January 2000 to December 2012, simulated tourist arrivals during the hold-out period January 2013 to December 2014 are generated and compared with actual arrival data, with summarized results exhibited in Table 3.

Empirical evidence can be gleaned from Table 3 revealing that a particular scenario forecast for each country produced extraordinarily small RMSE and MAPE, suggesting remarkable out-of-sample accuracy of the ex-post models. Interestingly, for major international markets of Philippine tourism like South Korea and Japan, the most likely scenario forecasts closely anticipate actual arrivals, while major Philippine competitors in the region like Malaysia and Singapore, the worst case forecast scenarios prevail. For emerging Philippine tourism markets Brunei and Myanmar, the best case forecast scenarios produce smaller forecast errors. The rest of the countries produce mixed signals, especially the fourth biggest inbound tourism market of the Philippines, China which turned in the noisiest signals as it registered very wide confidence bands.

3.2 Two-year Ahead Ex-Ante Monthly Arrival Forecasts

The very encouraging results of the out-of-sample forecast evaluation of the Ex-Post models provide the needed impetus to use the Ex-Ante forecasting models whose ARIMA noise models are shown in Table 2, in order to establish the different arrival scenarios for the next two years (January 2015 to December 2016) beyond the sample period. The following three tables present the results of the forecast generation. Best case and the Worst case arrival scenarios are mathematically represented by the Upper and Lower 95% confidence interval forecasts. The spatially aggregated arrival forecasts from the entire ASEAN+3 Region are just the sum of the individual country's forecasts for each assumed scenario. Ultimately, from these aggregated figures, the annualized forecasts for total visitor arrivals for the Philippines for the next two years will be extrapolated.

3.3 Procedure in Estimating Arrivals from All Sources

One of the main concerns of this study is to estimate the ex-ante overall arrival figures for the Philippine for the same two-year period 2015-2016, with the spatially aggregated ASEAN+3 forecasts as major input together with the historical over-all arrivals from all sources during the sample period 2000 to 2014. It is assume here that the market share of ASEAN+3 region for the Philippine international tourism is a time varying process that can be modeled by an appropriate regular ARIMA model. When the classical Box-Jenkins methodology (Box & Jenkins 1970) is applied on the historical share of ASEAN+3 region on Philippine inward tourism traffic, the resulting ex-ante model can be used to forecast this ratio, which will then applied to extrapolate total arrivals ex-ante. If $\varpi_t = \frac{\omega_t}{z_t}$ = ASEAN+3 Arrivals during month t / Arrivals from all sources during month t

$$\phi_p(L)\delta(L)\varpi_t = \theta_q(L)\varepsilon_t$$

with $\delta(L) = (1-L)^d$ if ϖ_t is non-stationary with d unit roots, (5) is the $ARIMA(p,d,q)$ model of ASEAN+3 market share, which when estimated and evaluated for goodness-of-fit will be employed in predicting future overall arrivals.

Table 1. Summary of the Diagnostic Results of the Final Ex-Post Models

Country	Fitted SARIMA Noise Model	Level Log (1/0)	With Mean =1	Box-Ljung Q	Jarque Bera N	Skew-ness t-test	Kur-tosis t-test	Mc-Cleod Li Q2	RUNS Test	LEVEL /LOG	Model Fit
Brunei	ARIMA(0,1,1)(0,1,1)	0	1	34.02	12.90	0.261	3.58	11.15	-0.16	1.44	Mildly Poor
Cambodia	ARIMA(0,1,1)(0,1,1)	0	0	20.14	4.51	1.31	1.67	30.93	0.94	0.95	Acceptable
Indonesia	ARIMA(0,1,1)(0,1,1)	0	0	17.82	0.80	0.679	0.59	15.85	-1.56	0.99	Good
Laos	ARIMA(0,1,1)(1,0,0)	0	0	16.26	6.61	1.84	1.79	15.90	0.31	1.12	Good
Malaysia	ARIMA(0,1,1)(0,1,1)	0	1	27.13	7.13	0.53	2.62	25.27	0.63	1.41	Good
Myanmar	ARIMA(0,1,1)(0,1,1)	0	0	24.39	0.50	0.7	0.11	22.76	1.25	1.40	Good
Singapore	ARIMA(0,1,1)(0,1,1)	1	0	19.44	6.60	1.63	1.98	30.20	-0.31	0.57	Good
Thailand	ARIMA(0,1,1)(0,1,1)	0	0	16.75	0.39	-0.62	0.08	24.20	-0.32	1.06	Good
Vietnam	ARIMA(0,1,3)(0,0,0)	0	1	23.89	2.47	1.57	-0.04	16.33	-0.31	1.35	Good
China	ARIMA(0,1,1)(0,0,0)	0	0	21.25	2.29	0.983	1.15	30.90	-1.11	4.99	Good
Japan	ARIMA(0,1,1)(0,1,1)	1	0	16.86	1.53	1.09	0.58	23.87	0.00	0.82	Good
Korea	ARIMA(0,1,1)(0,1,1)	0	0	37.41	3.75	0.64	1.83	22.73	0.00	1.20	Good
Table 2. Summary of the Diagnostic Results of the Final Ex-Ante Models											
Brunei	ARIMA(2,0,0)(0,1,1)	0	0	25.14	1.17	-0.94	0.54	28.62	0.34	1.32	Good
Cambodia	ARIMA(0,1,1)(0,1,1)	0	0	25.07	4.15	1.89	0.77	31.12	2.53	1.07	Good
Indonesia	ARIMA(0,1,1)(0,1,1)	0	0	22.72	0.65	0.59	0.55	17.27	-1.18	0.97	Good
Laos	ARIMA(0,1,1)(0,1,1)	0	1	25.88	4.45	-0.08	2.11	12.77	-0.49	1.19	Good
Malaysia	ARIMA(0,1,1)(0,1,1)	0	1	33.93	9.44	1.44	2.71	22.88	0.17	1.02	Good
Myanmar	ARIMA(0,1,1)(0,1,1)	0	0	24.70	1.04	0.93	0.42	18.44	0.00	1.43	Good
Singapore	ARIMA(0,1,1)(0,1,1)	1	0	15.78	3.47	-0.32	1.84	12.99	-0.51	0.59	Good
Thailand	ARIMA(0,1,1)(0,1,1)	0	0	23.10	0.39	-0.41	0.47	31.07	-1.03	1.00	Good
Vietnam	ARIMA(0,1,3)(0,0,0)	0	1	18.52	1.30	1.07	-0.41	15.84	0.00	1.22	Good
China	ARIMA(0,1,1)(0,1,1)	0	1	17.02	8.28	2.58	1.28	28.85	-0.16	4.09	Mildly Poor
Japan	ARIMA(0,1,1)(0,1,1)	1	0	14.26	1.08	0.99	0.33	22.51	-0.17	0.83	Acceptable
Korea	ARIMA(0,1,1)(0,1,1)	0	0	31.04	2.49	0.96	1.25	25.68	0.00	1.18	Good
Brunei	ARIMA(2,0,0)(0,1,1)	0	0	25.14	1.17	-0.94	0.54	28.62	0.34	1.32	Good

Table 3. Out-of-sample Forecasting Performance of Ex-Post Models for the Monthly Visitor Arrivals for the Period Jan. 2013-Dec. 2014

Source Country	Forecast Scenario					
	Most Likely		Worst Case		Best Case	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Brunei	186	20.06%	410	50.57%	143	16.49%
Cambodia	48	14.32%	227	79.96%	289	92.79%
Indonesia	593	13.53%	1,413	35.48%	561	12.69%
Laos	27	32.11%	60	57.69%	80	102.48%
Malaysia	5,775	52.10%	2,071	14.06%	12,921	111.79%
Myanmar	195	30.71%	344	63.22%	97	15.77%
Singapore	2,523	21.18%	800	5.18%	4,795	39.64%
Thailand	410	8.27%	1,014	23.96%	842	19.12%
Vietnam	395	12.65%	894	34.62%	502	19.23%
China	16,143	38.04%	23,579	61.36%	12,202	31.96%
Japan	2,520	6.31%	5,628	12.54%	8,310	21.76%
Korea	15,380	13.60%	28,714	26.77%	52,437	48.61%
ASEAN+3 Aggregate	**21,055**	**8.87%**	**60,326**	**28.42**	**80,449**	**34.66%**

Summing-up the ex-ante monthly forecasts for arrivals from ASEAN+3 and from all other sources will give the spatially aggregated figures for the country. It can be seen that forecasts from ASEAN + 3 countries and from all sources in 2015, using the most likely and best case scenarios far outstrip respective actual arrival figures in 2014. However, worst case forecasts show significant declines. Same observation can be made for the forecasts in 2016 versus actual arrivals in 2014. For the year 2015, over-all target tourist arrivals is set by the Department of Tourism (DOT) at 6.5 Million visitors, which many think to be too optimistic since the actual figure is only 4.8 Million in 2014. All promotional efforts are geared in achieving this target, which incidentally coincide with the best case scenario forecast generated by our ex-ante models..

Whether our forecasts can accurately track down what will actually happen, only time will tell. However, since statistics are already available for the first four months of 2015, we can undertake a partial assessment of the forecasting accuracy of the ex-ante models. It appears that the ***best case scenario***, with MAPE of 7.8% is the most reliable, implying that planning under the most optimistic demand assumptions may prove to be the most judicious strategy.

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