Technical Assistance action to support tourism planning and policy for the promotion of sustainable tourism development in Greece

Component I: Tools for policy making

Activity I.1.2: Develop monitoring and reporting tools for Greek tourism: a system documenting and forecasting tourism development

Forecasting Tourism Development

Final Report

Table of Contents

Executive Summary

This report summarizes the main results of the Activity I.1.2: “Develop monitoring and reporting tools for Greek tourism: a system documenting and forecasting tourism development” of the Component 1 “Tools for strategic policy making” of the Technical Assistance Action. The Workplan stipulates as output of this Activity: “A concrete proposal on how to develop a system documenting and forecasting tourism development not only as a policy tool for the Ministry of Tourism but also as a campaigning tool for Greek National Tourism Organisation (GNTO)”. The main parts of the output of this Activity are (1) the report on the empirical analysis of tourism flow data and (2) the results from the investigation of forecasting methods applied to predict tourism flows including a proposal of a methodology which can be used routine-wise for forecasting the number of arrivals of visitors as well as the number of overnights.

Forecasts of tourism statistics are of crucial importance and interest for all institutions which are actors in the Greek tourism such as political authorities and tourism businesses. The interest in forecasting results concerns primary variables that describe the tourism flow like the number of visitors (arrivals, overnights), the duration of stay, and the expenditures of the visitors. Deeper analyses refer to details of the tourism flows like the inbound flows from certain countries of residence, flows according to purpose of travel, to regions of destination, and others. Deeper analyses may also refer to the generation of flows as a function of factors like disposable income of visitors, price levels in Greece and alternative destinations, travel costs, exchange rates, Greek marketing expenditure, events like political unrests, and others.

Forecasting methods for the extrapolation of time series like the monthly observations of tourism flows are based on rather simple models like exponential smoothing and

time-series models like AR, MA, ARMA, and ARIMA; the forecasts are typically only function of the past of the time-series. Forecasting methods which allow to make use of interactions between the variable to be predicted and factors which determine the data-generating process are more demanding both with respect to the data base and the models to be used such as Vector Autoregressive models, Error Correction models, Time Varying Parameter (TVP) models, etc.

It was decided that in a first stage of the project, the focus should be on tourism flows and time series models should be analysed in order to come to a proposal for a suitable forecasting tool. In a later stage, more sophisticated models shall be investigated, given that an appropriate data base will be available. Cooperation with academic researchers right from the beginning was considered to be a good way to involve high-level experts and arrange a long-term support also for the future routine-wise operation of the forecasting system.

The results of the forecasting project are reported in two parts:

1. Tourism flow data: Results of the empirical analysis
2. Forecasting methods: Characteristics and comparison

The first part gives a detailed survey of tourism flow data which are in the core of the project: the number of arrivals of visitors and the number of overnights. The presentation contains all relevant details of these time series like the trends and seasonality. Results are also shown for breakdowns for countries of origin of the visitors. Based on the experience of the forecasting project, recommendations to the owner of the data are provided that may help to improve the data base for the future forecasting system.

The second part presents the results from the analysis of forecasting methods. The data base were monthly numbers of arrivals and of overnights. The analysis was focused on two forecasting techniques, Triple Exponential Smoothing and Seasonal Autoregressive Integrated Moving-Average (SARIMA). The evaluation of the methods was done (1) by means of an ex-ante forecasting analysis whereby five different subsets of the data, 2000-2010, 2000-2011, …, and 2000-2014, were used to produce the monthly out-of-sample forecasts of the respective subsequent year, and (2) by calculating out-of-sample forecasts for 2016-2018. The comparison of the methods was based on the forecast errors. The evaluation of the forecast errors revealed that exponential smoothing outperforms SAR(I)MA in most analyzed cases.

The results of the study indicate that a forecasting system based on exponential smoothing is well suited for the implementation of routine-wise forecasting the tourism flows of Greek tourism. Forecasts of the numbers of arrivals and of overnights can be calculated, for inbound and for domestic visitors, and for breakdowns for countries of origin of the visitors.

For the future routine-wise operation of the proposed forecasting methods, an institutional arrangement has to be established. The institution has to deal with the development of an IT system which allows handling the data and estimate the forecasts, has to establish the data base for the forecasting system and care for updating and editing the data, has to run the forecasting procedures, and produce and disseminate the forecasting reports. Agreements with the owners of input data like ELSTAT and cooperation with academic research are recommended.

Future extensions shall focus on forecasts of regional tourism flows. Also, the use of more sophisticated models like Vector Autoregressive models, Error Correction models, Time Varying Parameter (TVP) models, etc. shall be envisaged, aiming at deeper analyses of Greek tourism, in particular the analysis of the economic background of the tourism key statistics.

Four appendices contain results from empirical data analyses and a comprehensive review of literature on tourism forecasting.

1. Introduction

Forecasts of tourism statistics are of crucial importance and interest for all institutions which are actors in the Greek tourism such as political authorities, tourism businesses, and agencies that are supporting tourism or representing actors in tourism like the Ministry of Tourism, GNTO, the Hellenic Chamber of Hotels, SETE, ITEP, etc., also research institutions including academia. The interest in forecasting results concerns primary variables that describe the tourism flow like the number of visitors (arrivals, overnights), the duration of stay, and the expenditures of the visitors. Deeper analyses refer to details of the tourism flow like the inbound flows from certain countries of residence, flows according to purpose of travel, to regions of destination, and others. Deeper analyses may also refer to the generation of flows as a function of factors like disposable income of visitors, price levels in Greece and alternative destinations, travel costs, exchange rates, Greek marketing expenditure, etc.

The aims of the project has to be in line with the availability of data. In a first stage, the focus of the project was on forecasting the tourism flows. For the variables of interest (number of arrivals, number of overnights, expenditures), monthly data as published by ELSTAT should be suitable both in scope and in quality. Modelling approaches involve rather complex methodological issues and shall be postponed at the time being to a later stage.

Among the statistical tools for documenting and forecasting tourism development, the forecasting methodology is the most demanding one. The forecaster is confronted with issues related both to the availability of data which can be used for trend extrapolation and model fitting and to the methods which must be suitable for the forecasting problem. Within the Technical Assistance Action, the Activity I.1.2 has the focus on the development of tools for forecasting the tourism development.

As a first step of the forecasting project, a literature survey was undertaken about methods that have been used for forecasting Greek tourism. The survey was extended to methods as published in the WTO Handbook on Tourism Forecasting Methodologies, in scientific journals, in particular in the Journal of Travel Research, in conference papers and books.

In meetings with representatives from academia, potentials for co-operation in the forecasting task have been investigated. Talks took place with representatives from the University of Piraeus and from the University of Patras. These talks revealed interest of the academics in co-operating in the forecasting task; e.g., research on related methodological issues would be suitable topic for a student or a post-doc research work.

A cooperation in the forecasting project has been arranged with Dr. Yiannis Smirlis from the University of Piraeus, and his colleague, Dr. Vangelis Tsioumas from The American College of Greece - DEREE. The cooperation was agreed to include the analysis of the available data and the investigation of suitable forecasting methodologies. The aim of the project was defined to investigate the use of time-series models for the extrapolation of time-series of tourism flow statistics, possibly also expenditures if such data are available. The focus was to investigate the suitability of various forecasting methods for tourism statistics, taking into account the time-series characteristics like trends, seasonality, and structural breaks.

Data basis are tourism statistics as published by ELSTAT but also by other data providers like Eurostat and SETE. ELSTAT publishes monthly tourism flow statistics as well as tourism expenditures that are based on various sources like the Frontier Survey of the Bank of Greece, on the Vacation Survey, the Household Budget Survey, and on the Survey in Hotels, Similar Establishments and Tourist Campsites, all three conducted by ELSTAT, and other data sources.

Forecasting methods: It was decided that forecasts of the numbers of arrivals and the numbers of overnights in hotels etc. would be subject of the first phase of the project. Monthly numbers of arrivals and numbers of overnights in hotels etc. are available. The data of at least 20 years should be used for fitting the models. Suitably disaggregated series with respect to national and regional tourism, in-bound and domestic tourism, in-bound tourism flows from certain countries of residence, and others should be used to estimate forecasts. The forecasting horizon should be up to 12 months. As forecasting methods, time-series methods like

- ARIMA and SARIMA
- Exponential smoothing

should be investigated and analysed with respect to forecasting accuracy and other quality criteria.

Methods that are based on more sophisticated models like Vector Autoregressive models, Cointegration and Error Correction models, Time Varying Parameter (TVP) models, etc. should be analysed in the second and advanced stage of the project. Such methods may allow for deeper analyses of Greek tourism, in particular of the economic background of the tourism flows, e.g., the economic determinants of inbound flows from certain countries of residence such as the effect of changes in the disposable income of the visitors, the price levels in Greece and alternative destinations, the travel costs, but also factors of the economic environment like the exchange rates, and factors like the Greek marketing expenditures, events like political unrests, and others.

Tourism forecasts for politics and business: For the future routine-wise operation of the then developed forecasting tool, an institutional arrangement has to be established, an IT system has to be developed which allows handling the data, running the forecasting procedures and producing the output that is to be published regularly.

2. The data set. Empirical Analysis and Results

2.1. Data collection, data base modelling

The initial data set was provided by the ELSTAT in Excel files. The data were organized in observations (records), each one of which corresponds to one month, starting from January 2000 and ending to December 2015. The total number of observations is 192.

The variables of the data set (record layout) appear in Figure 2.1-1

Name	Id	Count	Missi...	Type
Year	C1	192	0	N
Month_descr	C2	192	0	T
Month_no	C3	192	0	T
Month	C4	192	0	T
PeriodID	C5	192	0	T
Season	C6	192	0	N
Nights-Hotels-Residence	C7	192	0	N
Nights-Campsites-Residence	C8	192	0	N
Nights-Residence-Total	C9	192	0	N
Nights-Hotels-NonResidence	C10	192	0	N
Nights-Campsites-NonResidence	C11	192	0	N
Nights-NonResidence-Total	C12	192	0	N
Nights-Hotels-Total	C13	192	0	N
Nights-Campsites-Total	C14	192	0	N
Nights-Total	C15	192	0	N
Arrivals-Hotels-Residence	C16	192	0	N
Arrivals-Campsites-Residence	C17	192	0	N
Arrivals-Residence-Total	C18	192	0	N
Arrivals-Hotels-NonResidence	C19	192	0	N
Arrivals-Campsites-NonResidence	C20	192	0	N
Arrivals-NonResidence-Total	C21	192	0	N
Arrivals-Hotels-Total	C22	192	0	N
Arrivals-Campsites-Total	C23	192	0	N
Arrivals-Total	C24	192	0	N

Figure 2.1-1. The variables of the data set

The first five (C1-C5), i.e. Year, Month_descr, Month_no, month and PeriodID identify the month and the year of the observation and are used as auxiliary variables. Next variable C6 Season has been estimated to distinguish time observation in three clusters, depending on the amount of tourist arrivals and nights spent. This variable is discussed in detail in Chapter 2. The rest, C7-C24, describe the number of arrivals and nights spent and are include level of analysis for the type of accommodation (Hotels, Campsites) and origin of the tourists (Residents, Non-Residents). They appear in a hierarchical structure, with the extension "-Total" in the name of the variable to denote that the associated variable derives as sum of corresponding variables in the lower of the hierarchy. The hierarchical structure of the data model appears in Figure 2.1-2. Thus, for example the variable Nights-Hotel-Total, derives as the sum of Nights-Hotel-Residents and Nights-Hotel-Non-Residents, i.e. Nights-Hotel-Total = Nights-Hotel-Residents + Nights-Hotel-Non-Residents.

In the upper level, the totals for Nights and Arrivals are estimated by the equations

Nights-Total= Nights-Hotel-Total + Nights-Campsites-Total =
= Nights-Residents-Total + Nights-Non-Residents -Total

Arrivals-Total= Arrivals -Hotel-Total + Arrivals -Campsites-Total

= Arrivals -Residents-Total + Arrivals -Non-Residents -Total

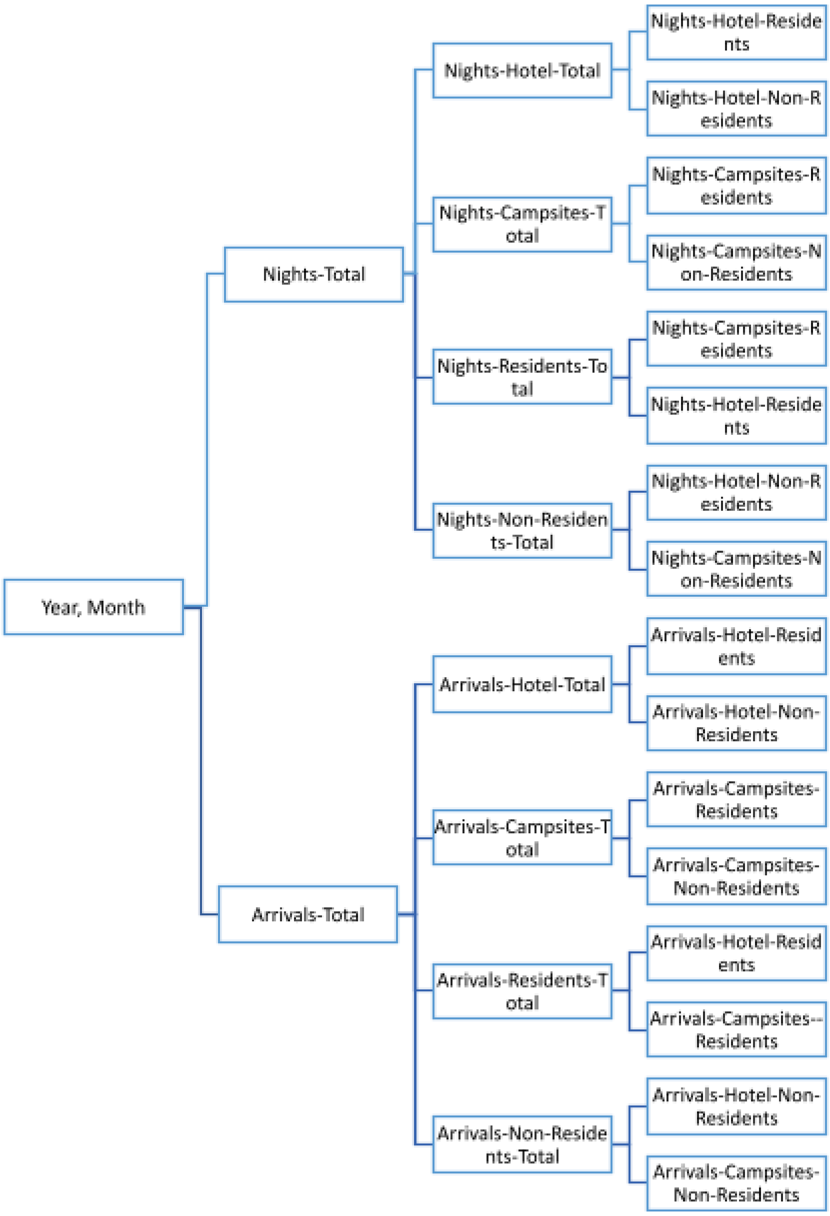


Figure 2.1-2. The hierarchical structure of the data

Next Figure 2.1-3 presents an indicative number of records in the data set.

	C1	C2-T	C3-T	C4-T	C5-T	C6	C7	C8	C9	C10	C11	C12
	Year	Month_descr	Month	Month	PeriodID	Season	Nights-Hotels	Nights-Ca	Nights-Resi	Nights-Hotels-	Nights-Camps	Nights-NonR
139	2011	July	07	07July	2011M07	1	2414620	316380	2731000	11265638	213576	11479214
140	2011	August	08	08August	2011M08	1	3242540	404347	3646887	11464267	290181	11754448
141	2011	September	09	09Septe>>	2011M09	1	1483151	69914	1553065	8805317	76304	8881621
142	2011	October	10	10October	2011M10	2	852015	4012	856027	3556947	8662	3565609
143	2011	November	11	11Novem>>	2011M11	3	636008	3296	639304	362260	1275	363535
144	2011	December	12	12Decem>>	2011M12	3	735819	3209	739028	269000	909	269909
145	2012	January	01	01January	2012M01	3	688531	724	689255	281701	423	282124
146	2012	February	02	02February	2012M02	3	641389	700	642089	284633	319	284952
147	2012	March	03	03March	2012M03	3	859683	935	860618	448096	486	448582
148	2012	April	04	04April	2012M04	2	878905	1240	880145	1381620	5527	1387147
149	2012	May	05	05May	2012M05	1	737586	30973	768559	5155845	30841	5186686
150	2012	June	06	06June	2012M06	1	1088378	80979	1169357	8677089	63962	8741051
151	2012	July	07	07July	2012M07	1	1835228	261386	2096614	10864627	167246	11031873
152	2012	August	08	08August	2012M08	1	2512235	341288	2853523	11183385	217620	11401005
153	2012	September	09	09Septe>>	2012M09	1	1181043	54448	1235491	8479970	59712	8539682
154	2012	October	10	10October	2012M10	2	748922	905	749827	3173351	7258	3180609
155	2012	November	11	11Novem>>	2012M11	3	619540	309	619849	349679	1235	350914
156	2012	December	12	12Decem>>	2012M12	3	723792	398	724190	259511	762	260273
157	2013	January	01	01January	2013M01	3	654100	422	654522	249686	747	250433
158	2013	February	02	02February	2013M02	3	644514	133	644647	260066	634	260700
159	2013	March	03	03March	2013M03	3	862193	265	862458	463954	968	464922
160	2013	April	04	04April	2013M04	2	847658	1076	848734	1220988	5837	1226825
161	2013	May	05	05May	2013M05	1	990564	21971	1012535	6227570	40738	6268308
162	2013	June	06	06June	2013M06	1	1191048	75931	1266979	10056022	88712	10144734
163	2013	July	07	07July	2013M07	1	1836230	241078	2077308	12127694	213209	12340903
164	2013	August	08	08August	2013M08	1	2567790	327615	2895405	12284130	243172	12527302
165	2013	September	09	09Septe>>	2013M09	1	1178014	45543	1223557	9601059	82498	9683557
166	2013	October	10	10October	2013M10	2	841333	1232	842565	3869414	8197	3877611
167	2013	November	11	11Novem>>	2013M11	3	656565	516	657081	407852	1705	409557
168	2013	December	12	12Decem>>	2013M12	3	737263	404	737667	289847	1032	290879
169	2014	January	01	01January	2014M01	3	704094	636	704730	306328	886	307214
170	2014	February	02	02February	2014M02	3	684774	194	684968	331814	535	332349
171	2014	March	03	03March	2014M03	3	876660	229	876889	509002	942	509944
172	2014	April	04	04April	2014M04	2	975792	1215	977007	1804915	7366	1812281

	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
	Nights-Hotels	Nights-Ca	Nights-Total	Arrivals-Hot	Arrivals-	Arrivals-Re	Arrivals-Hotel	Arrivals-	Arrivals-N	Arrivals-Hotels	Arrivals-Ca	Arrivals-Total
139	13680258	529956	14210214	817981	61675	879656	1876857	61995	1938652	2694638	123670	2818308
140	14706807	694528	15401335	908114	73266	981380	1858167	83911	1942078	2766281	157177	2923458
141	10288468	146218	10434686	593863	6026	599889	1532906	23408	1556314	2126769	29434	2156203
142	4408962	12674	4421636	403489	183	403672	672133	2685	674818	1075622	2868	1078490
143	998268	4571	1002839	328548	321	328869	137317	191	137508	465865	512	466377
144	1004819	4118	1008937	359115	40	359155	105866	82	105948	464981	122	465103
145	970232	1147	971379	345071	110	345181	107267	110	107377	452338	220	452558
146	926022	1019	927041	319821	30	319851	104444	62	104506	424265	92	424357
147	1307779	1421	1309200	412839	63	412902	168114	128	168242	580953	191	581144
148	2260525	6767	2267292	415488	257	415745	440537	2694	443231	856025	2951	858976
149	5893431	61814	5955245	370831	2718	373549	1057840	10660	1068500	1428671	13378	1442049
150	9765467	144941	9910408	506881	17163	524044	1486177	16930	1503107	1993058	34093	2027151
151	12699855	428632	13128487	645977	50698	696675	1758940	44590	1803530	2404917	95288	2500205
152	13695620	558908	14254528	740437	61193	801630	1820543	57203	1877746	2560980	118396	2679376
153	9661013	114160	9775173	492444	4579	497023	1451400	17087	1468487	1943844	21666	1965510
154	3922273	8163	3930436	358751	228	358979	612294	2282	614576	971045	2510	973555
155	969219	1544	970763	310151	218	310369	134759	217	134976	444910	435	445345
156	983303	1160	984463	338567	131	338698	101636	136	101772	440203	267	440470
157	903786	1169	904955	327639	111	327750	99705	73	99778	427344	184	427528
158	904580	767	905347	333591	18	333609	107389	55	107444	440980	73	441053
159	1326147	1233	1327380	426685	36	426721	193092	276	193368	619777	312	620089
160	2068646	6913	2075559	422833	270	423103	420402	2749	423151	843235	3019	846254
161	7218134	62709	7280843	452681	3504	456185	1254475	13891	1268366	1707156	17395	1724551
162	11247070	164643	11411713	536448	18605	555053	1728321	22878	1751199	2264769	41483	2306252
163	13963924	454287	14418211	638557	46222	684779	1950673	51646	2002319	2589230	97868	2687098
164	14851920	570787	15422707	777474	64673	842147	2040550	59473	2100023	2818024	124146	2942170
165	10779073	128041	10907114	500147	6103	506250	1673465	22097	1695562	2173612	28200	2201812
166	4710747	9429	4720176	410148	269	410417	740669	3068	743737	1150817	3337	1154154
167	1064417	2221	1066638	338712	237	338949	165375	260	165635	504087	497	504584
168	1027110	1436	1028546	353920	131	354051	115997	169	116166	469917	300	470217
169	1010422	1522	1011944	354400	165	354565	124781	138	124919	479181	303	479484
170	1016588	729	1017317	344931	72	345003	135763	92	135855	480694	164	480858
171	1385662	1171	1386833	432343	75	432418	214688	298	214986	647031	373	647404
172	2780707	8581	2789288	447848	339	448187	582616	3456	586072	1030464	3795	1034259

Figure 2.1-3. A sample of records in the data set

2.2. Descriptive Statistics

In the Figures included in Appendix I, a short statistical summary is presented for each one of the variables in the data set. This summary includes presentation of the basic statistical measures, the associated histogram, boxplot and 95% interval estimations for the mean and the median.

However, due to the great variability of the data between distinct months of the year, in almost all of the cases, values for high season months (July, August etc.) appear as extreme outliers and affect the reliability of important measurement such as the mean. For this reason, greater attention has been given in times series trend analysis that follow in the next sections.

2.3 Analysis by month

In this section, we investigate the behaviour of the number of arrivals (variable Arrivals-Total) and nights spent (variable Nights-Total) by exploiting time-series graphs and statistics, associated with the months, from January to December. For every month, we provide three charts for the variable Arrivals-Total and three for Nights-Total (see Appendix III). The first chart in each group presents a time-series linear trend estimation for the variable under consideration. The second presents the basic statistics including statistical measures, histogram, boxplot and confidence intervals 95% for the mean and median. The third chart plots the time-series data for the components of the associated variable to explore their contribution.

At a first level of analysis, both numbers of arrivals and nights spent show great variation within each year, ranging between maximum values that correspond to summer months and minimum values in the winter months. Figure 2.3-1 and 2.3-2 show this variation for the Nights-Total and Arrivals-Total, respectively. The same graphs also indicate a positive (increasing) trend, especially from observation 95 (approx. year 2007) and afterwards.

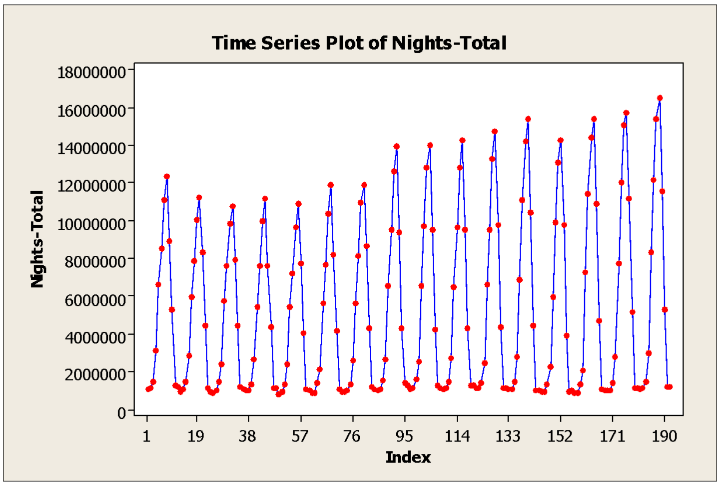


Figure 2.3-1 Time-series plot for Nights

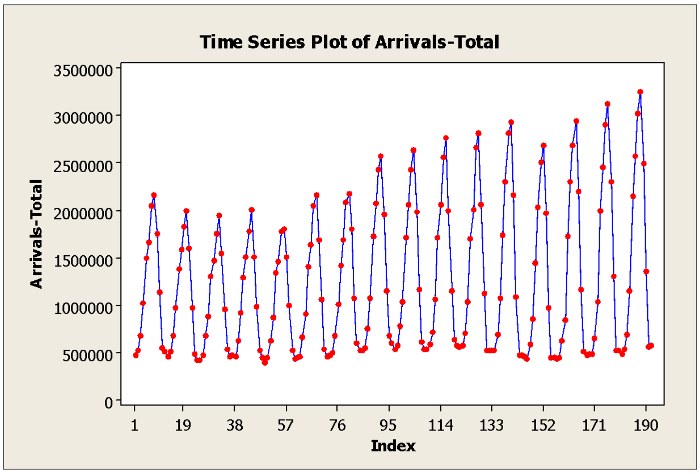


Figure 2.3-2 Time-series plot for Arrivals

The boxplots for the months of the year shown in Figures 2.3-3 and 2.3-4, present the same seasonal behaviour of months, as previously mentioned. For both variables, the maximum values and greater variation are observed in months between May-September. The pie charts next to the boxplots, also indicate that the summer months in high touristic season have obviously the greater contribution (percent) to the total number of tourist within the year.

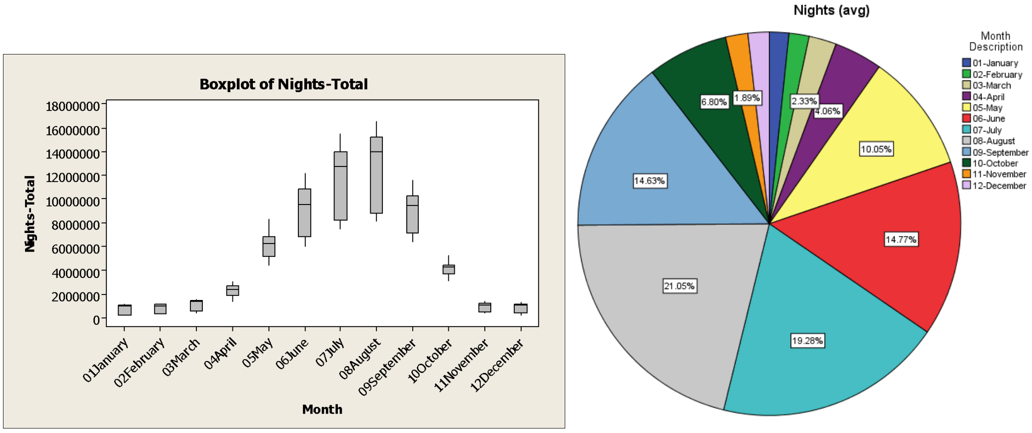


Figure 2.3-3 Box plot and pie chart for Nights-Total

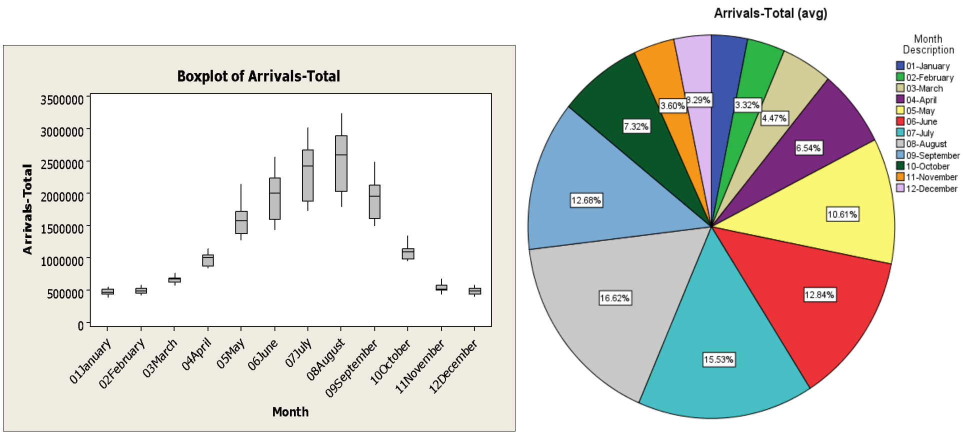


Figure 2.3-4 Box plot and pie chart for Arrivals-Total

In Appendix II, plots of the main data set variables are presented. From these it derives that:

1. Months December, January, February and March appear with great differences among the years. Particularly, in the period 2004-2010 there is a strong increase is observed of both arrivals and nights. For the next 2-3 years, there is strong decrease which after 2012-13 turns again to increase. In total, in most of the cases, graphs show a slight positive trend without any significant changes. The shape of the variation between the years diverges from linear trend.
2. The number of nights (variable Nights-Total), for months April, March and November, show a negative trend within the years. This behavior is an exception, as for all the rest of months the trend is slightly or strong positive.
3. During the first four months, January to April, and within the period 2003-2004, there is a significant decrease to the number of nights for

non-residents. In the opposite direction, the number of nights in Hotels show a significant growth, especially in February and March.

4. For the next months, May to September, the shapes of the time-series graphs change with approximately the same pattern, showing that these months should be considered as a cohesive time-period. The relative graphs for these months indicate a strong positive trend that approaches to linearity, as the reported relative small values for Mean Absolute Deviation, Mean Square Error and Mean Absolute Percentage Error show. The projection of the linear trend line in the future period 2017-2018 gives an indication about what is expected for those months. For example, from Figures II-38 and II-41 derive that the approximated values for July 2017 in Nights-Total will be approx. 16 million and in Arrivals-Total between 3-3,25 millions. In the same manner, for August 2017, Figures II-44 and II-47 give approximations of 17 millions for Nights-Total and of 3.2-3.6 millions for Arrivals-Total.
5. For October and November, the time-series pattern is similar to that of months March and April. Note that in year 2012, the smallest value for both nights and arrivals is observed. After that year follows a period with a strong increase.
6. Concerning the arrivals and nights spent in Campsites, their number is very small and remain constant, relative to that of hotels. Figures for Hotels show a significant positive trend in almost all years of the study period.
7. The figures for residents tourists for both nights and arrivals show a significant step decrease in 2003-2004 after which follows a period of non-significant variations. In an opposite direction, figures for non-residents show an increasing trend.

2.4. Analysis by Seasons

A basic conclusion extracted from the time-series analysis presented in the previous section was that months can be grouped in three similar clusters in terms of touristic activity, particularly by considering the variables Nights-Total and Arrivals-Total. The analysis of the previous chapter indicated that these three classes may be as follows :

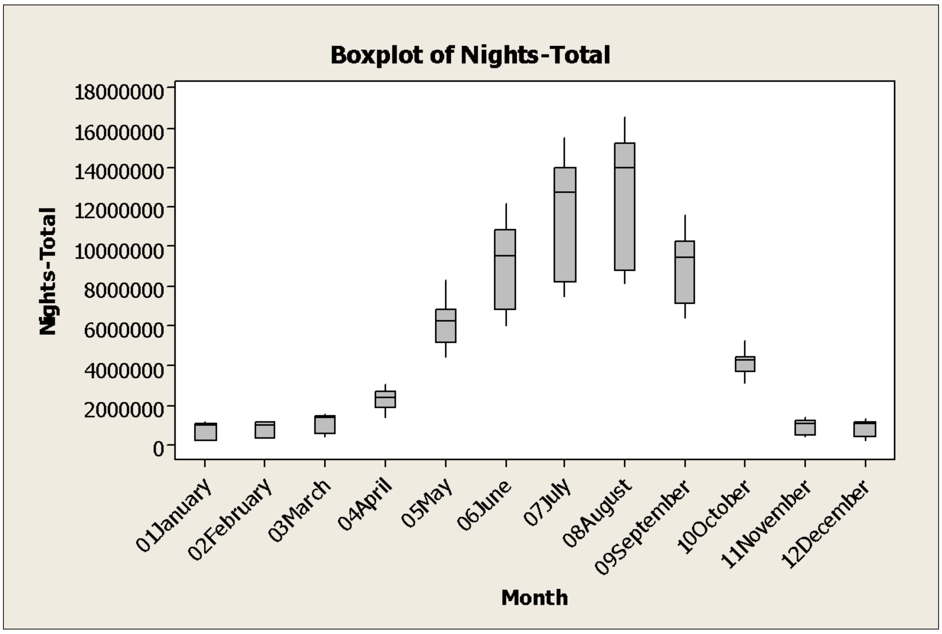
Class I – Low Season : November, December, January, February, March
Class II – Intermediate Season : October, April
Class III – High Season : May, June, July, August, September

In this chapter we provide further documentation to support such a month clustering and further investigate the distinct trends of these clusters.

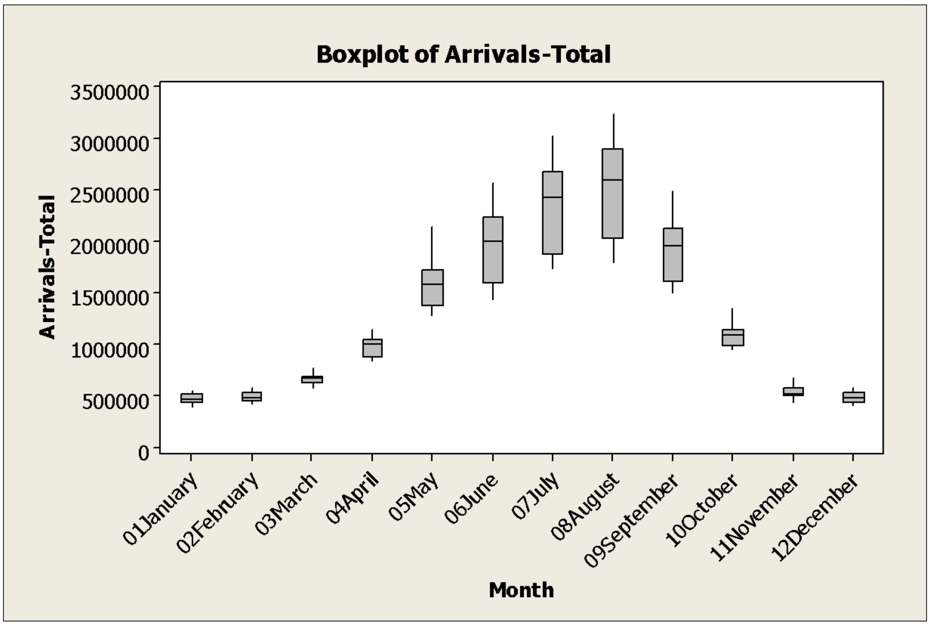
2.4.1. Definition of Seasons

In order to explore the above defined grouping of months, a new variable Season has been introduced in the data set. This variable accepts values 1, 2 and 3, depending on which season the particular time observation belongs.

Based on these values, the mean and Anova tests presented at Appendix III, show statistically significant difference of the mean values in the three seasons of the variables Nights-Total and Arrivals-Total and thus confirms the distinction between them. The boxplot graphs in the following Figures 2.4-1, 2.4-2 provide a further indication about the differences between the three seasons.



Figures 2.4-1 Boxplot of Nights-Total by Month



Figures 2.4-2 Boxplot of Arrivals-Total by Month

2.4.2. Analysis of Seasons

Table 2.4-1 presents simple descriptive statistics for Arrivals-Total and Nights-Total when the classification based on the variable Season is considered. The range and the distribution of values within the classes is also presented graphically in the boxplots and histograms in Figures 2.4-3 - 2.4-6.

The obtained classification of the months applies to the rest of the variables of the data set. In Figures 2.4-7, 2.4-8, 2.4-9 and 2.4-10 interval graphs present a clear distinction of values when the seasons 1, 2 and 3 are related to the variables Nights-Residents-Total, Nights-Non-Residents-Total, Nights-Campsites-Total, Nights-Hotel-Total and Arrivals-Residents-Total, Arrivals-Non-Residents-Total, Arrivals-Campsites-Total, Arrivals-Hotel-Total.

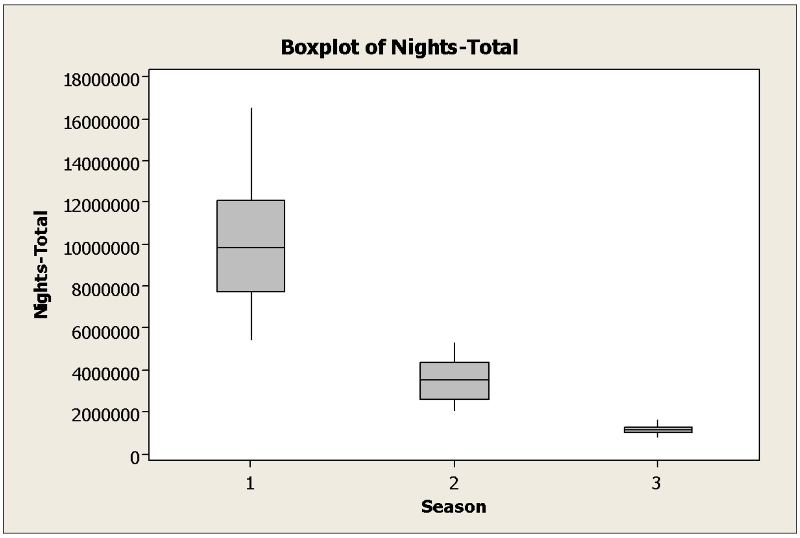
Concerning the time-series trend when classes are considered, Figures 2.4-11 and 2.4-12 present composite trend lines for Nights-Total and Arrivals-Total. In Figures 2.4-11 for Nights-Total , classes 2 and 3 show a constant trend within the years but class 1 (high season) appears with a slight increasing trend especially after observation number 57 which corresponds to year 2004. This trend is evident in Figures 2.4-12 which plots Arrivals-Total.

Next, follow the Tables and Figures mentioned in this section.

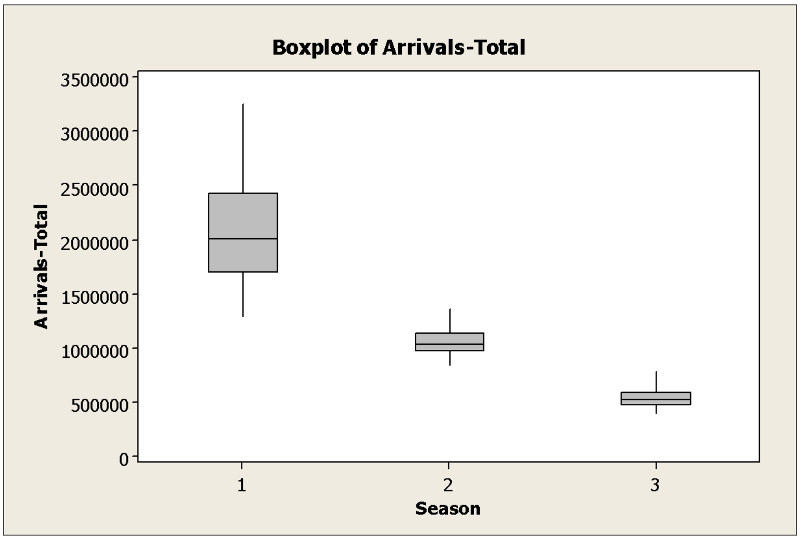
Table 2.4-1. Simple descriptive statistics of Arrivals-Total and Nights-Total by Season

Variable	Season	Mean	StDev	Minimum	Maximum
Arrivals-Total	1	2050593	485580	1285523	3247472
	2	1040318	118331	846254	1351422

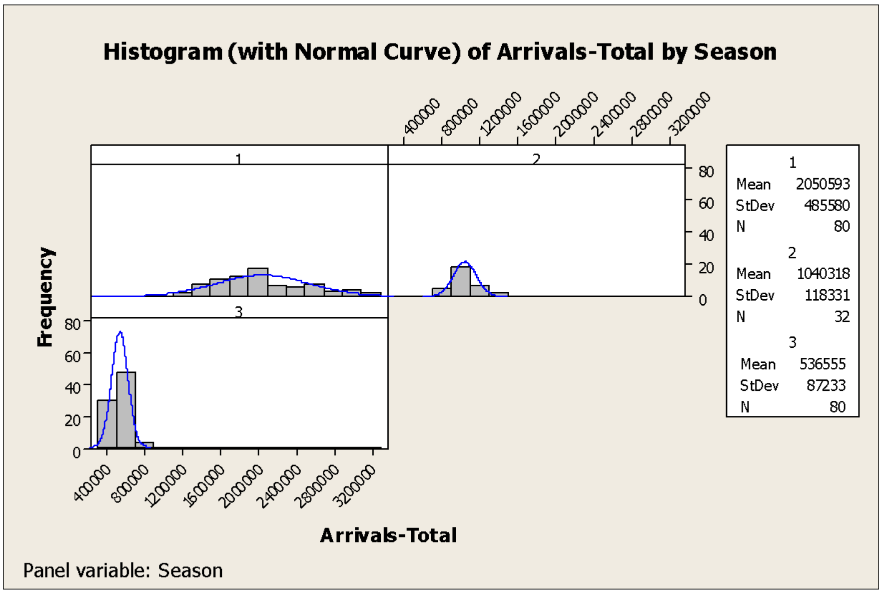
	3	536555	87233	395040	770093
Nights-Total	1	10158424	2912383	5418574	16527563
	2	3538000	1024726	2075559	5288263
	3	1142992	179382	828899	1575610



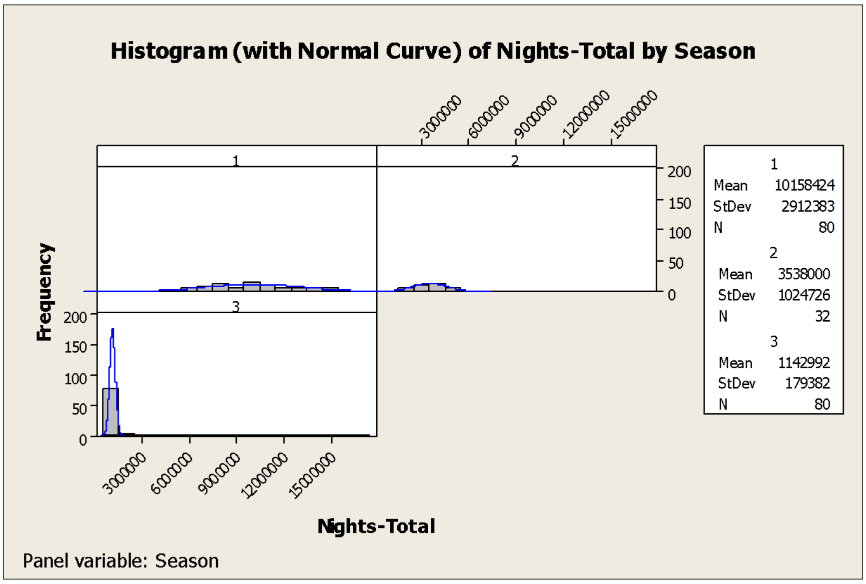
Figures 2.4-3 Boxplot of Nights-Total by Season



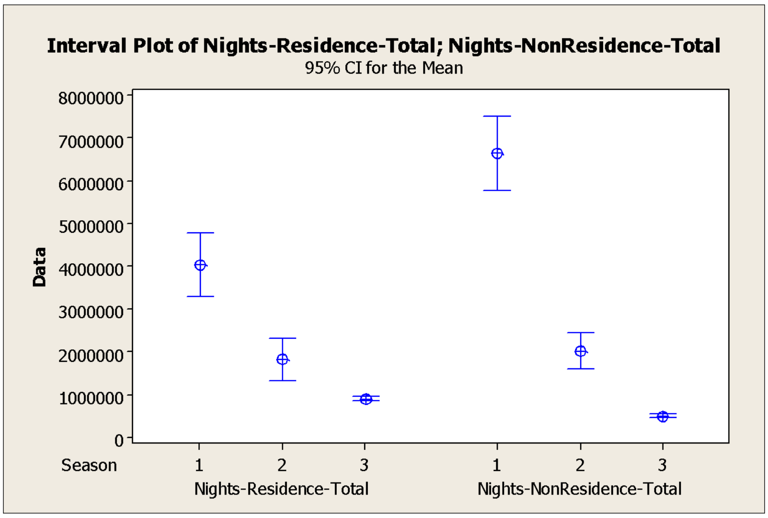
Figures 2.4-4 Boxplot of Arrivals-Total by season.



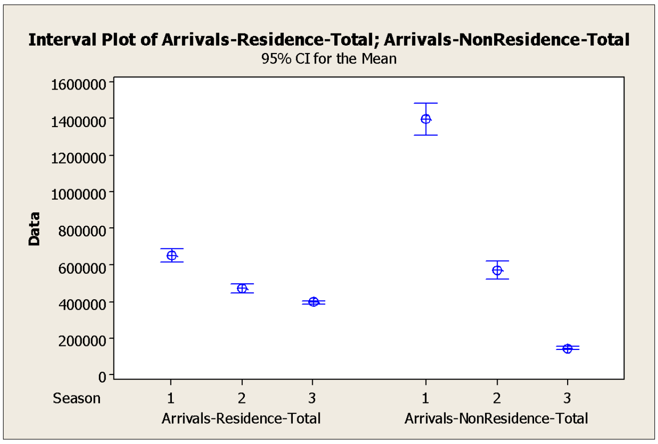
Figures 2.4-5 Histograms for Arrivals-Total by Season.



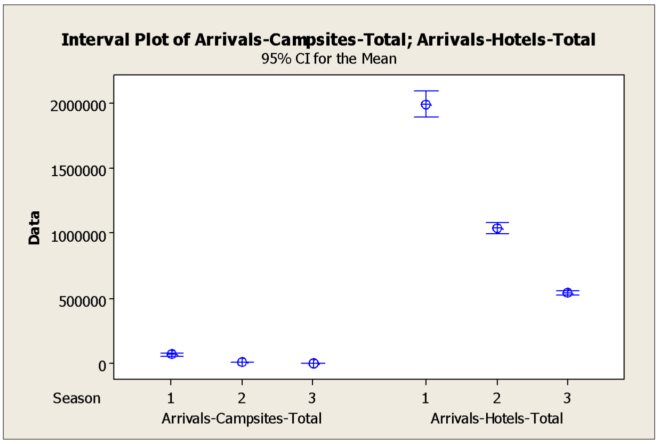
Figures 2.4-6 Histograms for Nights-Total by Season.



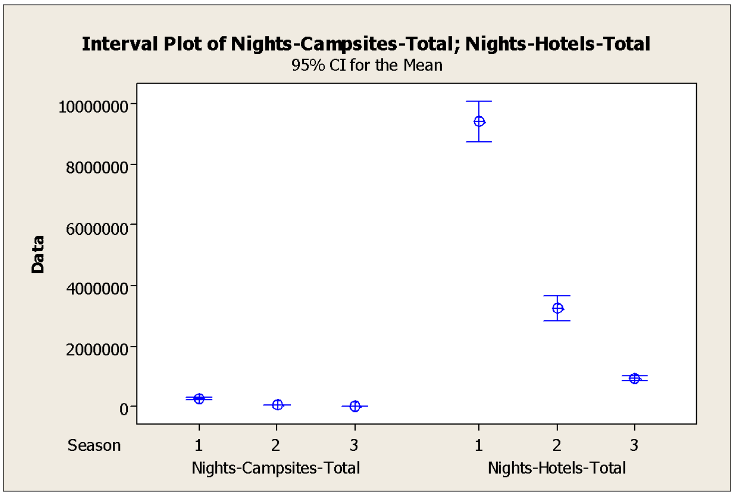
Figures 2.4-7 Interval plot for Nights-Residents-Total and Nights-Non-Residents-Total by Season.



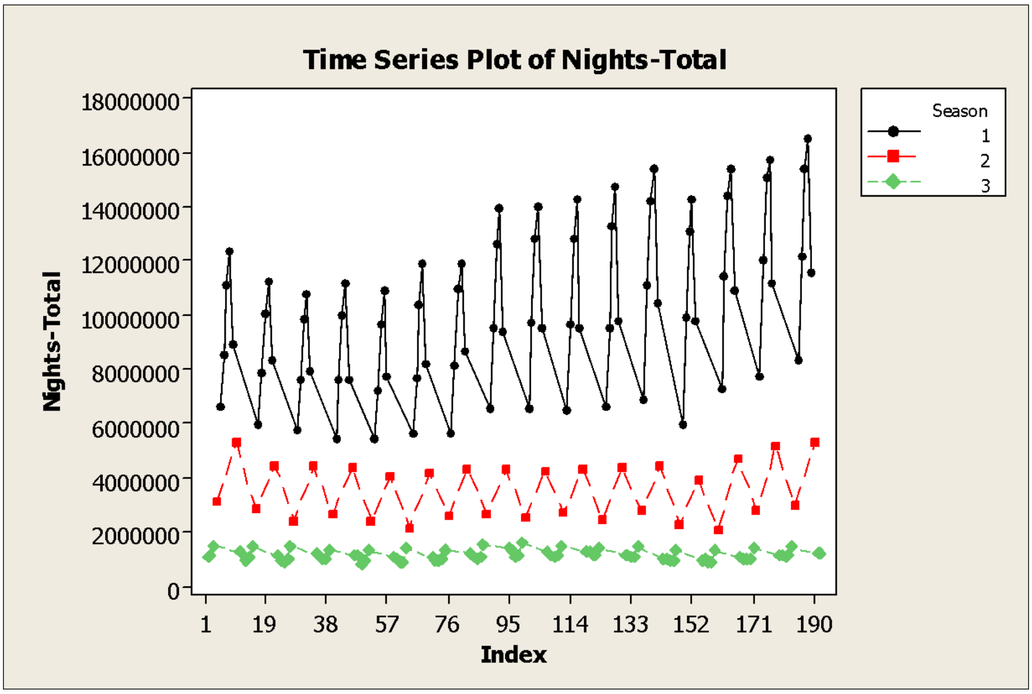
Figures 2.4-8 Interval plot for Arrivals-Residents-Total and Arrivals-Non-Residents-Total by Season.



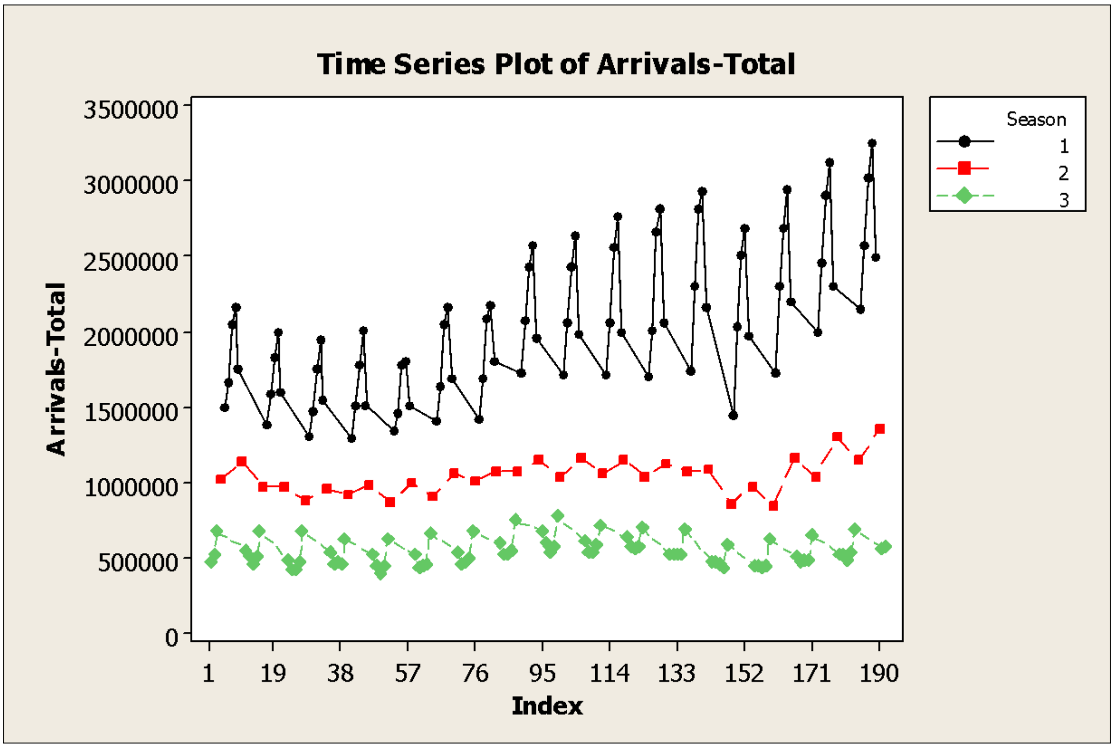
Figures 2.4-9 Interval plot for Arrivals-Campsites-Total and Arrivals-Hotels-Total by Season.



Figures 2.4-10 Interval plot for Nights-Campsites-Total and Nights-Hotels-Total by Season.



Figures 2.4-11 Time-series composite graph for Nights-Total by Seasons



Figures 2.4-12 Time-series composite graph for Arrivals-Total by Seasons

2.5. Correlations

This section investigates possible correlations between nights spend and number of arrivals. From the analysis, the following results and comments derive.

1. The variable Nights-Total, considered as dependent variable, is linearly correlated to Arrivals-Total with a high significant degree (R^2=98%). Figure 2.5-1 and the following regression analysis document this observation.
2. However, this strong relation between total values for arrivals and nights spent is not applied to other breakdown factors such as Campsites, Resident and NonResident. Scatterplot graphs presented in Figures 2.5-2, 2.5-3 and 2.5-4 indicate this independent relation.
2. When examine the relation between Nights-Hotels-Total and Arrivals-Hotels-Total, the same strong correlation with the corresponding total values is observed (Figure 2.5-5). This is due to the fact that Campsites-Total, being the second factor, has very small values relative to those of Hotels-Total.

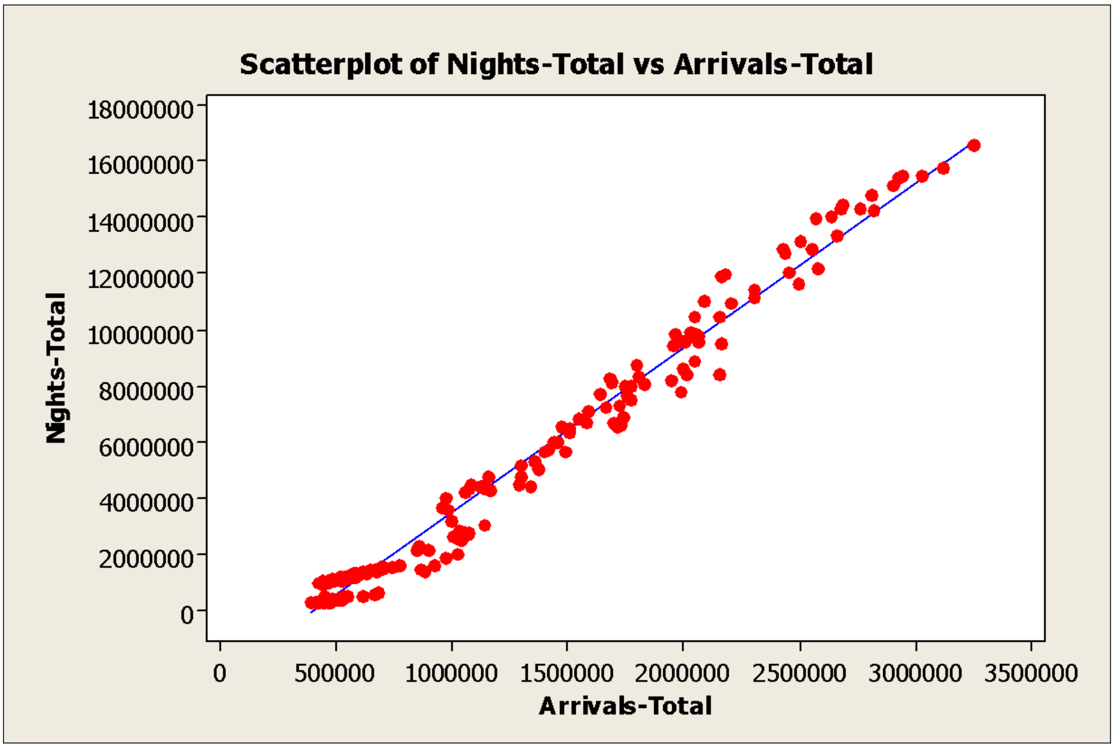


Figure 2.5-1 Scatterplot for Nights-Total vs Arrivals-Total

Regression Analysis: Nights-Total versus Arrivals-Total

The regression equation is Nights-Total = - 2446610 + 5,90 Arrivals-Total

Predictor Coef SE Coef T P

Constant -2446610 88111 -27,77 0,000
Arrivals-Total 5,89679 0,06002 98,24 0,000
S = 638250 R-Sq = 98,1% R-Sq(adj) = 98,1%
PRESS = 7,897867E+13 R-Sq(pred) = 98,03%

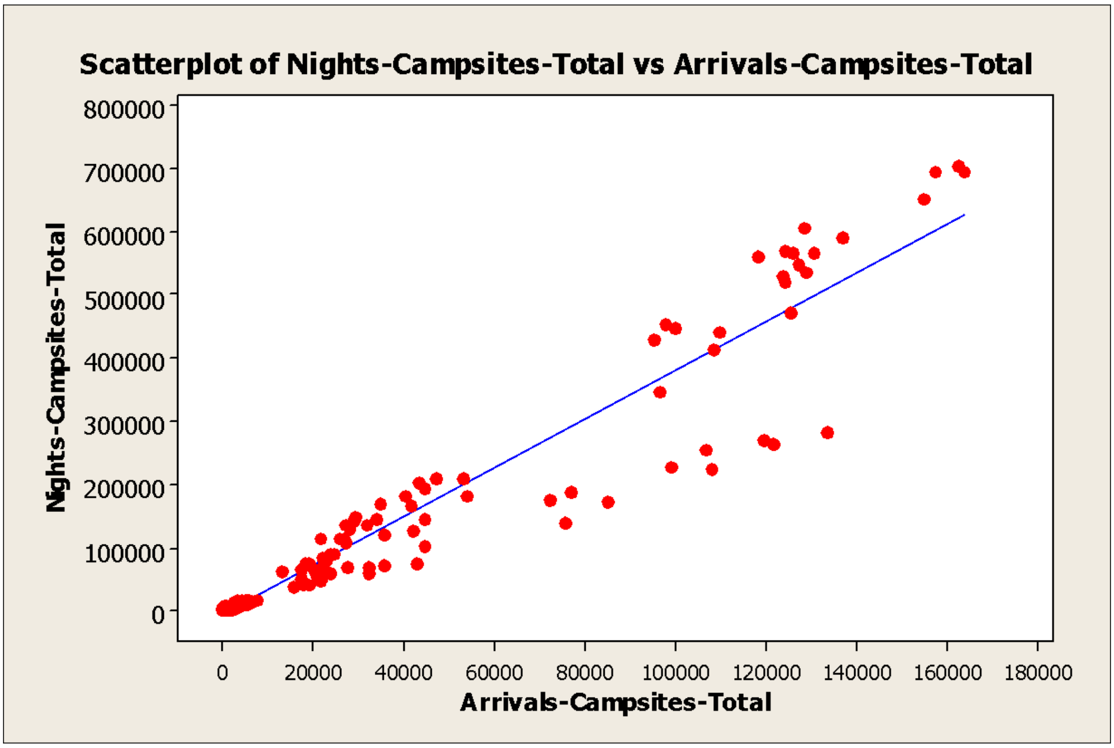


Figure 2.5-2 Scatterplot for Nights-Campsites-Total vs Arrivals-Campsites-Total

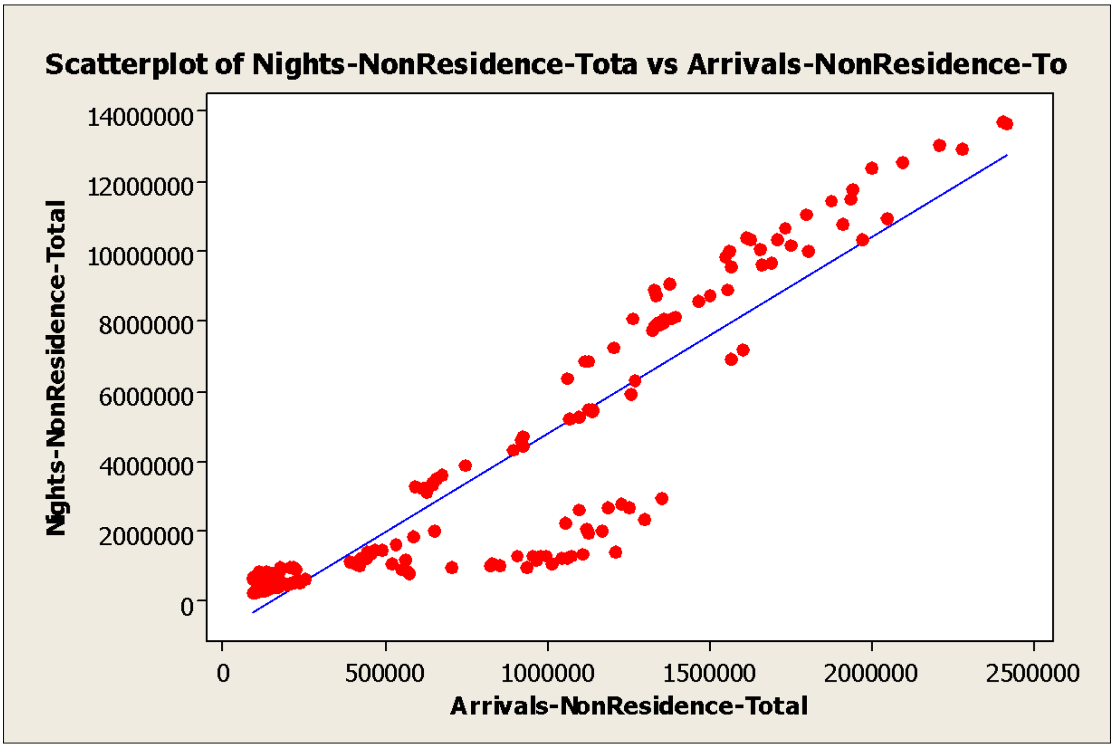


Figure 2.5-3 Scatterplot for Nights-Non-Residents-Total vs Arrivals-Non-Residents-Total

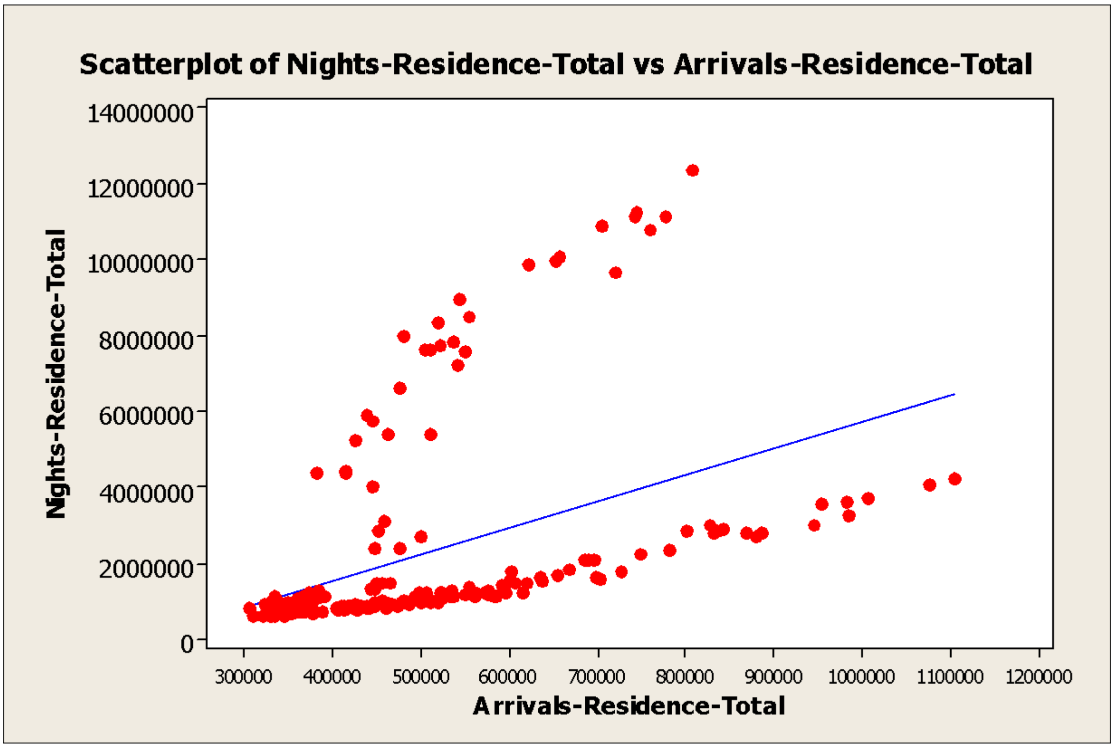


Figure 2.5-4 Scatterplot for Nights-Residents-Total vs Arrivals-Residents-Total

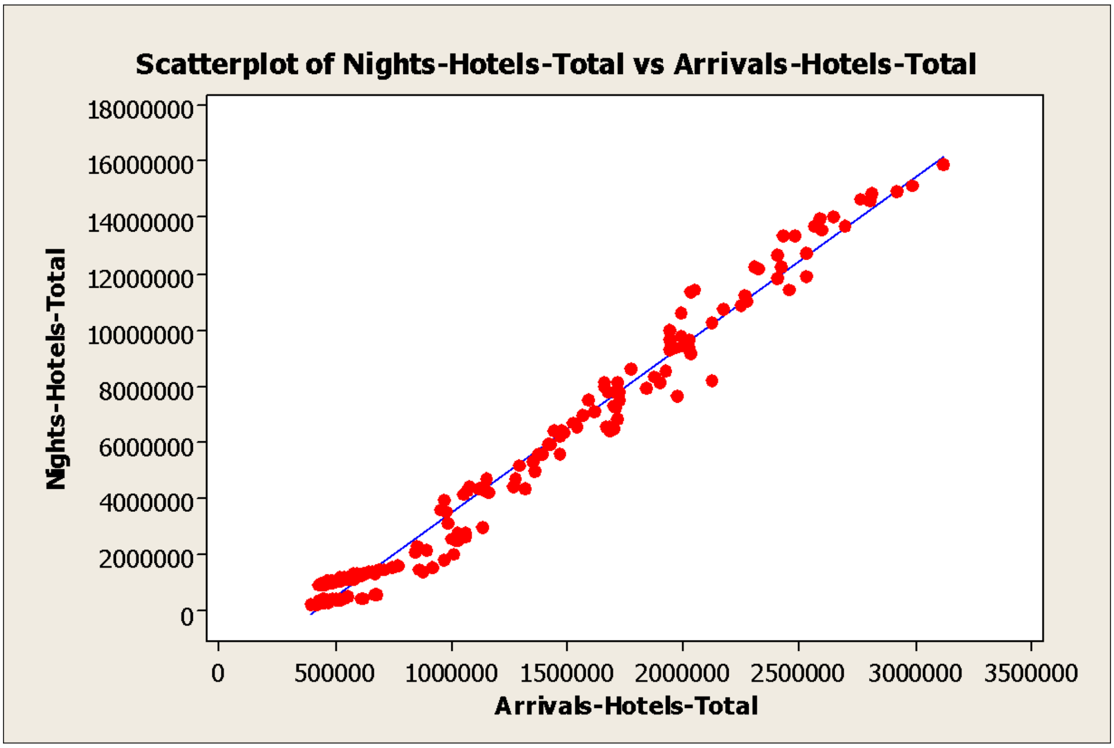


Figure 2.5-5 Scatterplot for Nights-Hotels-Total vs Arrivals-Hotel-Total

The regression equation is

Nights-Hotels-Total = - 2482278 + 5,978 Arrivals-Hotels-Total
R-Sq(pred) = 97,9%

2.6. Analysis of Arrivals by country of origin

This section presents descriptive statistics and time-series trend analysis on data measuring the tourist arrivals by country of origin. The data have been retrieved from the ELSTAT web site (www.elstat.gr) and refer to years 2007-2015. They were published in the form of MS-Excel files named "A2001_STO04_TB_QQ_00_<year>_01_F_GR and were structured in summary tables. Data for other factors such as nights spent, types of accommodation etc. were not available on the ELSTAT website.

The structure of this report is as follows: Section 2.6.1 presents the collected data set and the basic descriptive statistics measurements. Section 2.6.2 focuses on the most important countries in terms of their number of arrivals and examines the total number in years 2007-2015. Section 2.6.3 presents plots the monthly time-series for each country and estimates its trend.

2.6.1. The data set

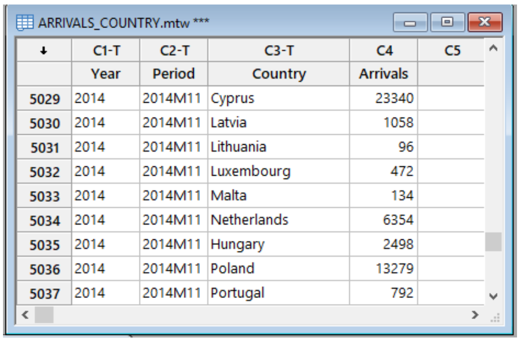
The data is organized in observations (records), each one of which corresponds to one month, starting from January 2007 and ending on December 2015. The total number of countries mentioned is 48 and the total number of observations is 5015.

Note that in the published tables there was a reference for "Rest Asian, African… countries". The associated data were not included in this analysis. Moreover, Serbia was reported sometimes as Serbia and others as Serbia-Montenegro and for simplicity reasons the two cases were joined in one.

The data set has the following structure:

YEAR = year of the observation
PERIOD = in the form <YEAR>M<Month>. E.g., 2014M11 is for November 2011
COUNTRY = Name of the country of origin
ARRIVALS = Number of arrivals recorded

A sample of few records is presented in the following figure.



↓	C1-T	C2-T	C3-T	C4	C5
	Year	Period	Country	Arrivals	
5029	2014	2014M11	Cyprus	23340	
5030	2014	2014M11	Latvia	1058	
5031	2014	2014M11	Lithuania	96	
5032	2014	2014M11	Luxembourg	472	
5033	2014	2014M11	Malta	134	
5034	2014	2014M11	Netherlands	6354	
5035	2014	2014M11	Hungary	2498	
5036	2014	2014M11	Poland	13279	
5037	2014	2014M11	Portugal	792	

The associated table for the basic descriptive statistics are presented in the following Table 2.6-1.

Table 2.6-1. Descriptive statistics of arrivals by country of origin

Country	Mean	St.Dev	Q1	Median	Q3	Min	Max	Range	N
Albania	29663	13561	17439,5	30009	39409	541	64513	63972	108
Argentina	1981	2453	457,5	1562	2687	0	16459	16459	108
Austria	26094	27435	3286,8	12210	51471	1172	91081	89909	108
Belgium	32401	32954	4729,5	19104	58279	641	119338	118697	108
Brazil	3123	2896	888,3	2344	4494	0	13519	13519	108
Bulgaria	74621	51057	44191,0	56748	75982	16885	290083	273198	108
Canada	12484	10507	3135,5	11091	19023	0	51407	51407	108
China	1807	1826	404,0	1203	2791	0	7725	7725	108
Croatian	1345	1634	0,0	607	2477	0	5350	5350	34
Cyprus	38005	15851	27038,8	35950	46821	0	83130	83130	108
Czech republic	25662	32834	1298,5	4213	52882	0	127742	127742	108
Denmark	19898	21441	1433,5	13162	35887	0	79932	79932	108
Egypt - Sudan	1018	1189	0,0	732	1411	0	6382	6382	108
Estonia	1541	1969	0,0	688	2518	0	8383	8383	108
Finland	13653	13279	895,8	11387	25078	0	54459	54459	108
France	92557	90459	13396,8	66750	154266	5439	388076	382637	108
FYROM	251922	254650	69897,0	108666	480637	63853	725789	661936	12
Germany	198801	166347	41863,5	127985	336953	19094	558146	539052	108
Hungary	9524	12122	1578,3	4057	13797	195	59776	59581	108
Iceland	245	601	0,0	0	297	0	4700	4700	108
Iran	478	945	0,0	0	536	0	5857	5857	108
Ireland	5424	6138	816,8	2099	9659	0	24510	24510	108
Israel	12880	13811	2629,0	6912	18673	0	67847	67847	108
Italy	86612	107673	19893,0	34597	119968	9890	500396	490506	108
Japan	2388	9495	353,3	897	1535	0	73666	73666	108
Latvia	2220	4137	0,0	882	3049	0	29314	29314	108
Lebanon - Syria	1473	1738	284,8	1047	2090	0	10384	10384	108
Lithuania	2687	3475	187,0	1215	4045	0	19909	19909	108
Luxembourg	1770	2362	191,0	879	2217	0	13608	13608	108
Malta	613	1592	0,0	0	601	0	11735	11735	108
Mexico	1011	1033	0,0	754	1691	0	5072	5072	108
Netherlands	51646	50354	6351,0	35562	93574	0	191506	191506	108
Norway	21113	22633	1117,3	8762	35597	0	75382	75382	108
Poland	32715	43465	3346,3	9326	50147	458	184920	184462	108
Portugal	1682	2001	405,0	958	2193	0	12488	12488	108
Romania	27902	22579	12213,3	20805	35445	149	118643	118494	108
Russia	55134	76962	4033,8	13997	78700	0	320577	320577	108

Serbia - Montenegro	57845	75751	9175,5	25557	85002	1702	339655	337953	108
Slovakia	5065	7687	280,5	990	8435	0	32608	32608	108
Slovenia	3063	5182	272,3	867	3696	0	33247	33247	108
South African Union	2024	2322	472,8	1143	2853	0	12711	12711	108
South Korea	731	871	15,0	444	1207	0	5870	5870	108
Spain	12543	12030	4505,8	7813	16600	1246	55705	54459	108
Sweden	28152	27173	2656,8	21489	51104	0	93756	93756	108
Switzerland	29045	25686	5332,0	20573	50409	1782	92493	90711	108
Turkey	47690	44380	16421,0	39432	66093	0	251973	251973	108
United Kingdom	173268	160740	26697,0	120160	327008	11475	538093	526618	108
USA.	45396	31111	18150,3	40085	66942	753	135079	134326	108

From Table 2.6-1 derives that Croatia and FYROM have limited number of observations (34 and 12 respectively), as the last column (labeled N) indicates. Moreover, the minimum number of arrivals in many cases is zero, denoting no touristic activity. This happens in winter and low season months.

2.6.2. Most significant countries

To identify the most significant countries, the total number of arrivals per year has been calculated and based on that the share (percentage) of each, relative to the total arrivals for all countries has been extracted.

Table 2.6-2 presents the figures of the total number of arrivals in years 2005-2017 for the 48 countries included in the analysis. The two last columns present the total number of arrivals in years 2005-2017 and the percentage relative to the grand total.

Note that FYROM appears to have reported values for only 2015 and the total number is high enough to result in a percentage of 2,11%. However, due to the limited data, FYROM has not been included in the analysis.

In order to further examine the behavior of each country, the most significant of them have been identified. To distinguish them, an empirical rule has been applied: The countries that exceeded the threshold of 2% were identified as the most significant countries. The countries that have such level of arrivals are: Germany, United Kingdom, France, Italy, Bulgaria, Serbia – Montenegro, Russia, Netherlands, Turkey, USA, Cyprus, Poland, Belgium, Albania, Switzerland, Sweden, FYROM, and Romania. Their total share reaches 85,3% of the total arrivals in Greece for the period 2005-2017. These countries are listed in Table 2.6-3. Figure 2.6-1 presents graphically the total number of arrivals and the percentage of each country.

Germany appears to be the most significant country with a percentage of 15,01%. It is followed by United Kingdom with 13,09%, France with 6,99% and Italy with 6,54%.

Table 2.6-2. Total arrivals by Country of Origin in years 2007-2015

Country	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total	Percent
Albania	213725	242999	234276	242083	411245	469215	456391	442325	491380	3203639	2,24%
Argentina	9390	14299	13878	17772	13834	20207	41947	47923	34662	213912	0,15%
Austria	377341	354747	352223	338367	310357	236417	236475	285131	327121	2818179	1,97%
Belgium	408655	420747	334240	339836	432625	326938	344554	409199	482524	3499318	2,45%
Brazil	23534	27487	24540	34015	52119	31125	26673	52220	65589	337302	0,24%
Bulgaria	701666	623476	657130	664389	686208	599109	691873	1534565	1900643	8059059	5,64%
Canada	158795	158447	134983	113358	142287	102694	198543	156892	182299	1348298	0,94%
China	5331	5941	7793	13620	15838	12203	29335	49943	55098	195102	0,14%
Croatian							3686	21891	20137	45714	0,03%
Cyprus	492473	474942	434746	574764	439757	424827	373875	419029	470092	4104505	2,87%
Czech republic	269774	267597	267833	294936	309061	289036	287801	348704	436704	2771446	1,94%
Denmark	267650	245948	264040	240563	244986	205194	202476	240418	237656	2148931	1,50%
Egypt - Sudan	14645	13558	12610	15925	4675	4724	5558	12137	26077	109909	0,08%
Estonia	28732	26018	21242	13842	9862	4757	8093	30552	23323	166421	0,12%
Finland	174202	147746	170341	205282	167633	154134	139685	165601	149893	1474517	1,03%
France	991118	910021	962435	868346	1149389	977375	1152217	1463159	1522100	9996160	6,99%
FYROM									3023058	3023058	2,11%
Germany	2711663	2469151	2364486	2038871	2240480	2108787	2267545	2459228	2810349	21470560	15,01%
Hungary	201703	180914	70894	109160	69756	69790	83496	96505	146379	1028597	0,72%
Iceland	8236	4475	3340	0	0	2059	1995	4697	1705	26507	0,02%
Iran	641	847	1647	9189	8748	13631	5491	879	10599	51672	0,04%
Ireland	77451	93536	73167	65623	58939	32358	42577	69532	72653	585836	0,41%
Israel	73283	84221	82443	197159	226111	207711	209824	194395	115868	1391015	0,97%

Italy	1251779	1099983	935011	843613	938231	848073	964314	1117711	1355329	9354044	6,54%
Japan	28780	10927	6765	10021	10124	8841	86559	85860	9982	257859	0,18%
Latvia	11862	31010	12027	21948	7846	15301	45665	60399	33709	239767	0,17%
Lebanon - Syria	14010	11458	14753	4639	4916	12844	36195	30002	30257	159074	0,11%
Lithuania	16399	34537	37501	16295	13666	21600	32195	57892	60143	290228	0,20%
Luxembourg	20146	25136	22792	18593	28475	15193	20372	18449	22038	191194	0,13%
Malta	21745	11701	4367	9651	1368	2206	1619	3702	9867	66226	0,05%
Mexico	12010	8878	8909	10470	5531	8067	19791	19627	15900	109183	0,08%
Netherlands	737771	756939	651440	528157	560723	478482	577658	647509	639107	5577786	3,90%
Norway	213350	277304	315595	187319	226627	294113	271019	250039	244859	2280225	1,59%
Poland	227363	270039	203487	402170	450617	254683	382821	587620	754401	3533201	2,47%
Portugal	17947	24678	13300	19497	34642	20484	16267	16972	17821	181608	0,13%
Romania	350723	327261	307596	257939	223699	230396	263639	511860	540289	3013402	2,11%
Russia	199591	309072	276021	451239	738926	874787	1348077	1243926	512789	5954428	4,16%
Serbia - Montenegro	553500	686996	498356	706635	692059	620450	774887	986524	727831	6247238	4,37%
Slovakia	68643	63095	48549	49406	41788	44783	61478	94043	75187	546972	0,38%
Slovenia	33038	75186	45924	40082	31130	35720	18691	26700	24379	330850	0,23%
South African Union	34243	35688	20539	19985	21982	19686	17084	23278	26055	218540	0,15%
South Korea	9677	4391	5123	7623	1846	6100	8585	15526	20081	78952	0,06%
Spain	182644	219917	164461	155302	154773	155722	91988	136230	93623	1354660	0,95%
Sweden	311358	382922	356154	281069	333906	319756	367288	336383	351573	3040409	2,13%
Switzerland	310295	339809	352514	274418	361405	299620	388853	418733	391247	3136894	2,19%
Turkey	182490	207609	200348	561198	552091	602305	770512	920962	1153046	5150561	3,60%
United Kingdom	2508651	2278015	2112149	1802203	1758092	1920794	1846332	2089529	2397169	18712934	13,09%
USA.	617478	612826	531276	498301	484707	373832	454071	580031	750251	4902773	3,43%

Table 2.6-3. Countries with total arrivals over 2% of the total in years 2007-2015

	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total	Percent	CV
Germany	2711663	2469151	2364486	2038871	2240480	2108787	2267545	2459228	2810349	21470560	15,01%	0,11
United Kingdom	2508651	2278015	2112149	1802203	1758092	1920794	1846332	2089529	2397169	18712934	13,09%	0,13
France	991118	910021	962435	868346	1149389	977375	1152217	1463159	1522100	9996160	6,99%	0,21
Italy	1251779	1099983	935011	843613	938231	848073	964314	1117711	1355329	9354044	6,54%	0,17
Bulgaria	701666	623476	657130	664389	686208	599109	691873	1534565	1900643	8059059	5,64%	0,53
Serbia - Montenegro	553500	686996	498356	706635	692059	620450	774887	986524	727831	6247238	4,37%	0,20
Russia	199591	309072	276021	451239	738926	874787	1348077	1243926	512789	5954428	4,16%	0,64
Netherlands	737771	756939	651440	528157	560723	478482	577658	647509	639107	5577786	3,90%	0,15
Turkey	182490	207609	200348	561198	552091	602305	770512	920962	1153046	5150561	3,60%	0,59
USA.	617478	612826	531276	498301	484707	373832	454071	580031	750251	4902773	3,43%	0,20
Cyprus	492473	474942	434746	574764	439757	424827	373875	419029	470092	4104505	2,87%	0,12
Poland	227363	270039	203487	402170	450617	254683	382821	587620	754401	3533201	2,47%	0,47
Belgium	408655	420747	334240	339836	432625	326938	344554	409199	482524	3499318	2,45%	0,14
Albania	213725	242999	234276	242083	411245	469215	456391	442325	491380	3203639	2,24%	0,33
Switzerland	310295	339809	352514	274418	361405	299620	388853	418733	391247	3136894	2,19%	0,14
Sweden	311358	382922	356154	281069	333906	319756	367288	336383	351573	3040409	2,13%	0,09
FYROM									3023058	3023058	2,11%	
Romania	350723	327261	307596	257939	223699	230396	263639	511860	540289	3013402	2,11%	0,35
										TOTAL	**85,30%**	

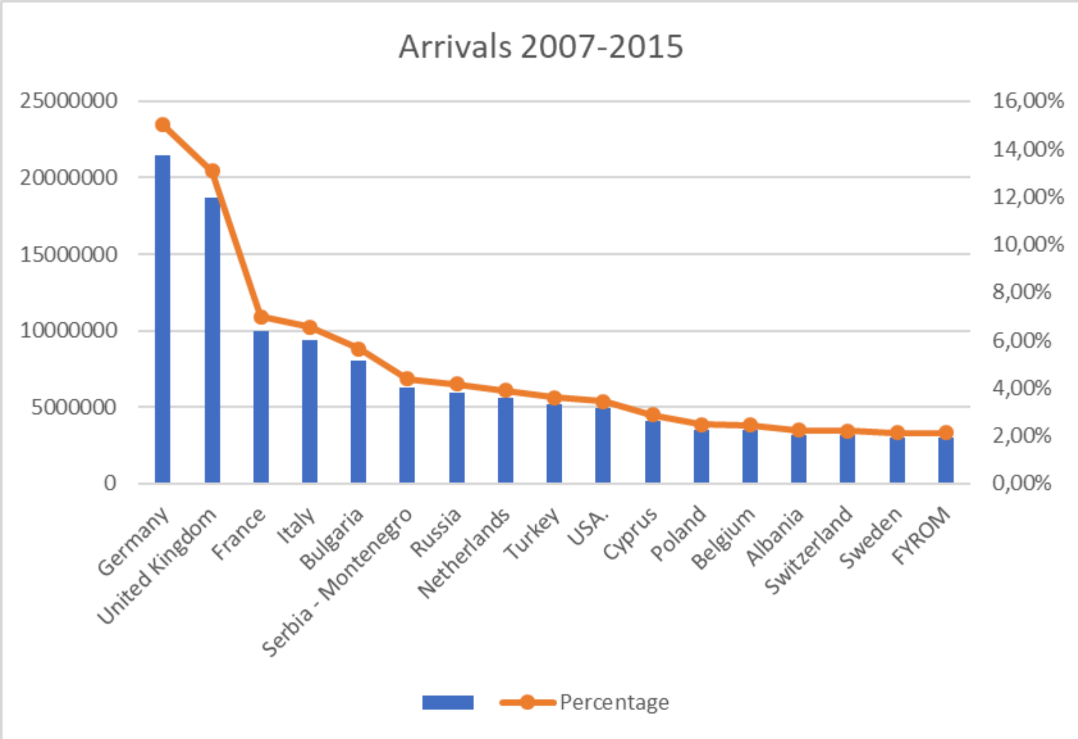


Figure 2.6-1. Total arrivals and percentage of the most significant countries.

In order to further examine how significant are the changes of arrivals within the years of reference in the countries of Table 2.6-3, the coefficient of variation (CV) for each country is estimated and reported in the last column of Table 2.6-3. From this derives that a number of countries have low variation, relatively constant arrival activity and others appear with significantly higher-lower values during the period of the analysis. In the first case (Group 1) there are those countries with CV $\leq 0{,}25$ and in the second case those that have CV $\geq 0{,}25$ (Group 2). Figures 2 and 3 present graphically the variation of total arrivals in years 2005-2017 for group 1 and 2 as previously defined.

It is interesting to note that the majority of EU countries, such as Germany, UK, France, Italy, Sweden, Switzerland, Netherlands, Belgium, and additionally Cyprus, Serbia-Montenegro and USA belong to the first group. These countries have a relatively constant flow of arrivals and this fact indicates that a forecast in year time interval could be possible.

The second group of countries with high variation of arrivals involves mainly Balkan countries (Bulgaria, Albania, Turkey) and Poland and Russia. Particularly for Bulgaria, Figure 2.6-3 shows that it doubled its touristic activity in years 2014 and 2015. On the other side, Russia had a peak in 2013 and after that a great decrease occurred.

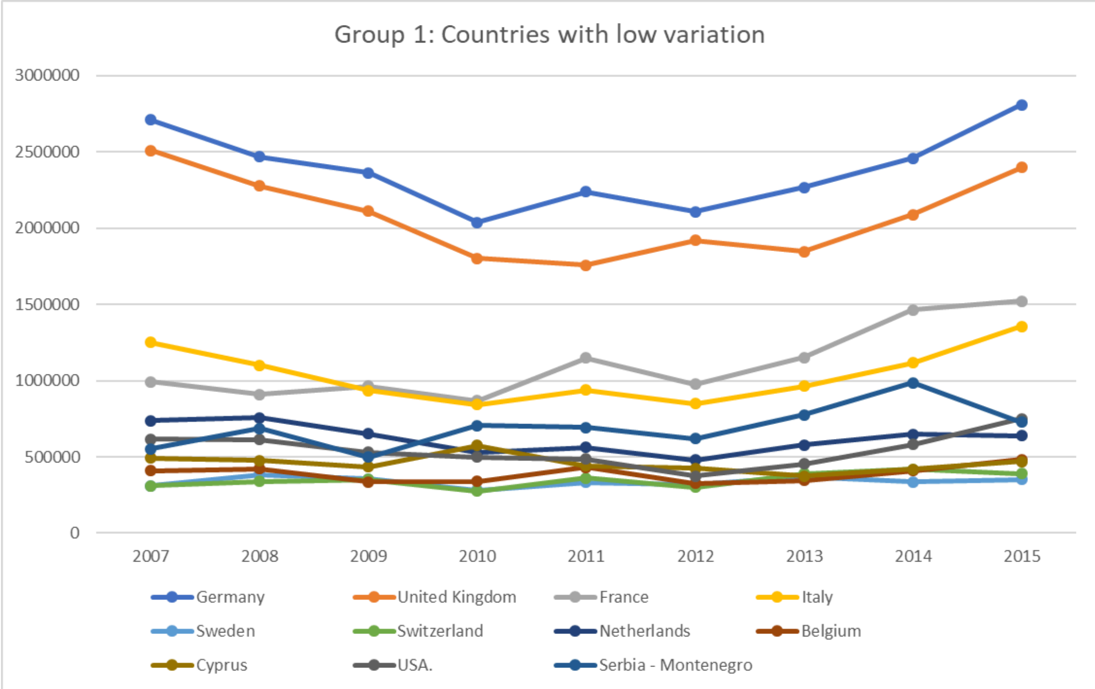


Figure 2.6-2. Countries with low arrival variation

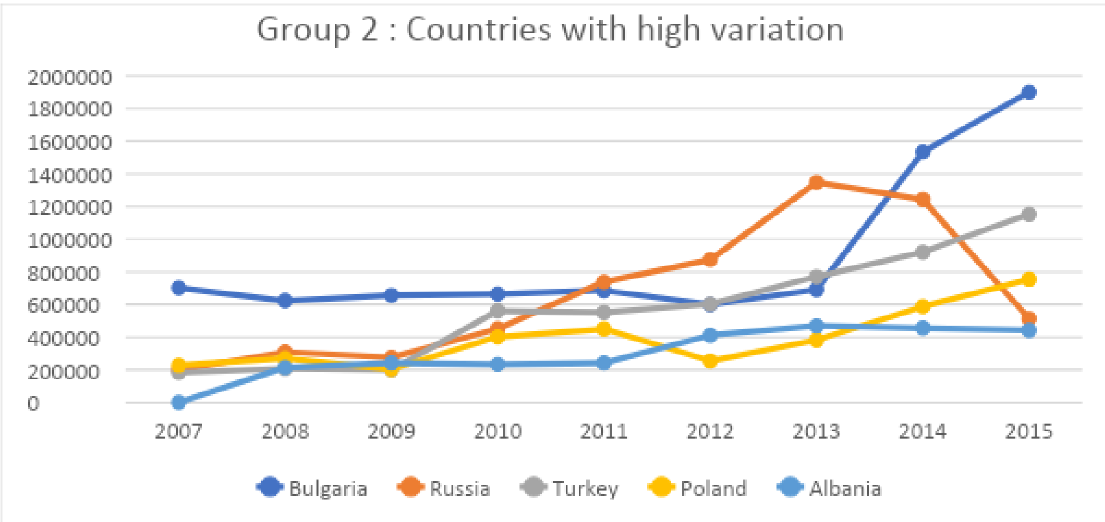


Figure 2.6-3. Countries with high arrival variation

2.6.3. Presentation of Time-series and Trend

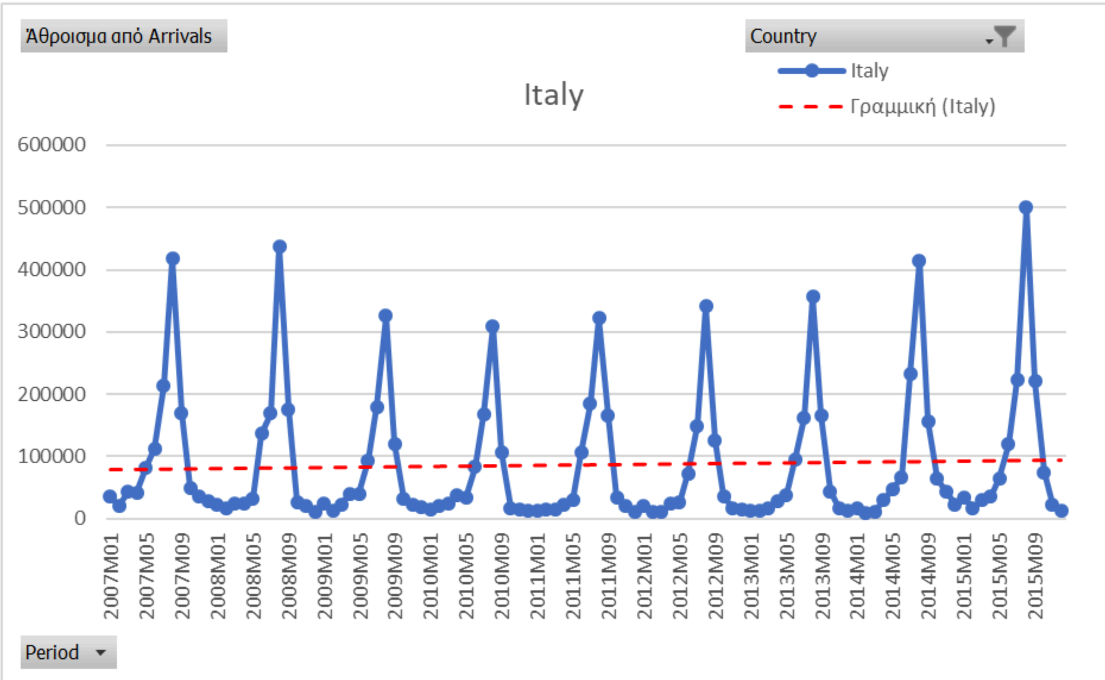
In this section, a time-series presentation of the arrivals for the most important countries is given. In each graph, the trend line is estimated and based on that, the countries have been divided in those that have an almost zero trend, in those that have a significantly positive trend, and those that appear with negative trend.

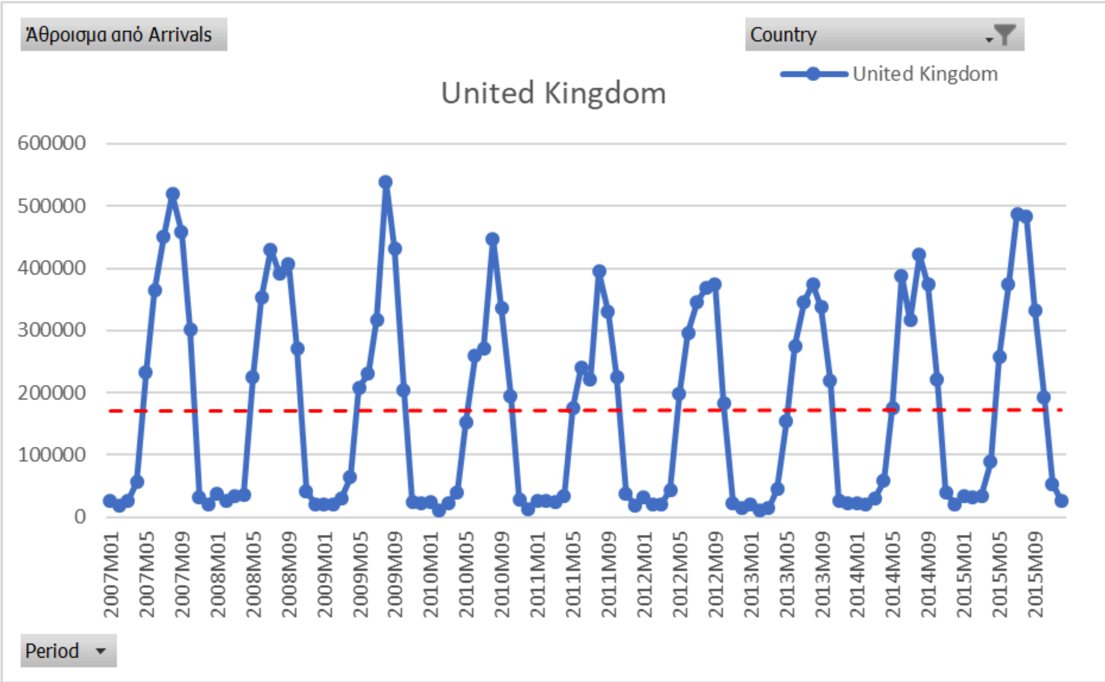
The first group comprises Italy, UK, Germany, Netherlands, USA, Belgium, and Sweden. The group of countries with positive trend involves Russia, Poland, Albania, France, Turkey, Switzerland, Serbia-Montenegro, Romania and Bulgaria. Only Cyprus appears with a relative negative trend.

It is important to note that the time-series pattern varies significantly between countries. For example, Albania, Bulgaria, and Turkey do not show the clear distinction between seasons that has been observed for the total number of arrivals. Furthermore, it is interesting to observe that the maximum peak in high season months does not always occur in August as expected. For example, for Germany the maximum number of arrivals is observed in September and for USA this point varies between July, August, and September, depending on the year of reference.

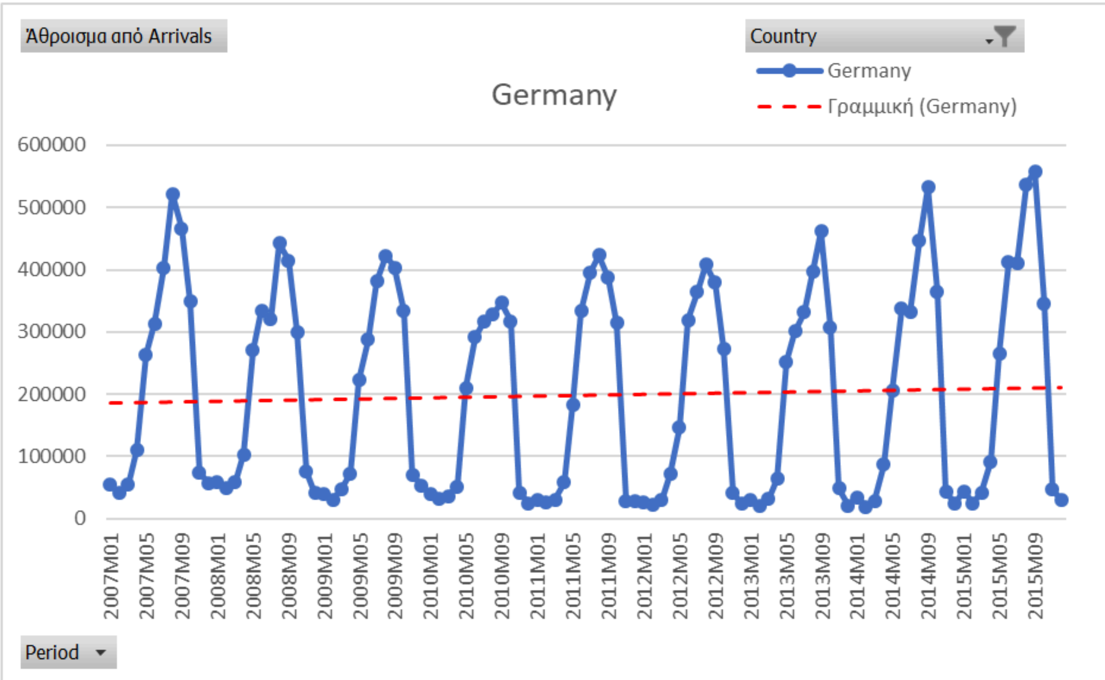
Below are the relevant graphs for each country.

Countries with almost zero trend

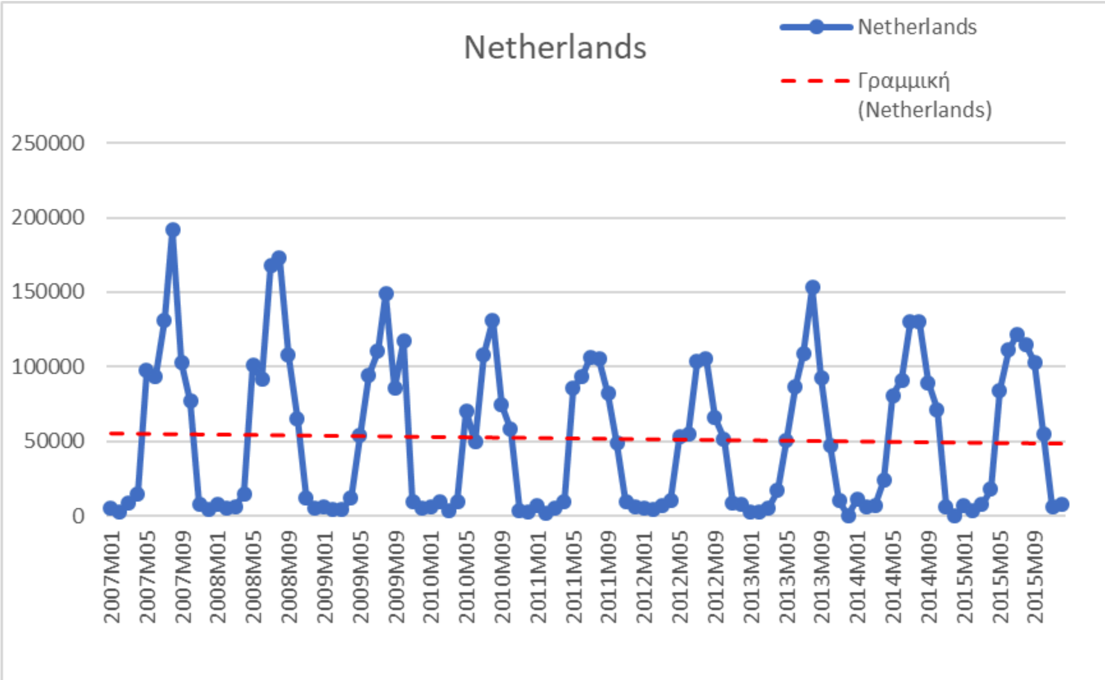


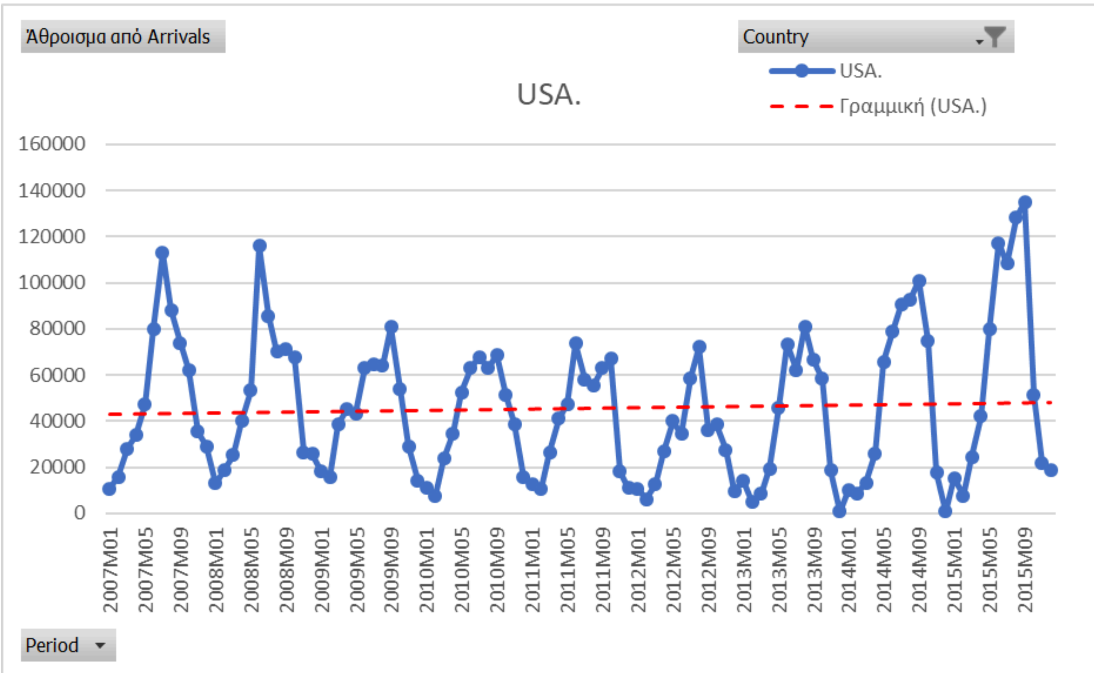


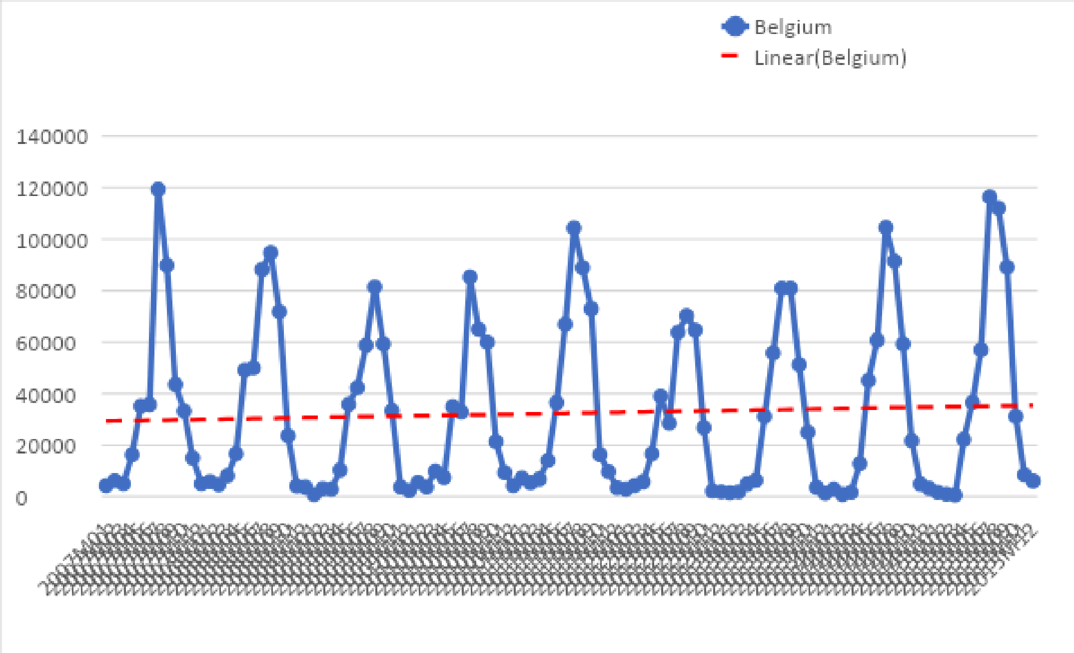
Άθροισμα από Arrivals
Country
United Kingdom
United Kingdom
600000
500000
400000
300000
200000
100000
0
2007M01
2007M05
2007M09
2008M01
2008M05
2008M09
2009M01
2009M05
2009M09
2010M01
2010M05
2010M09
2011M01
2011M05
2011M09
2012M01
2012M05
2012M09
2013M01
2013M05
2013M09
2014M01
2014M05
2014M09
2015M01
2015M05
2015M09
Period

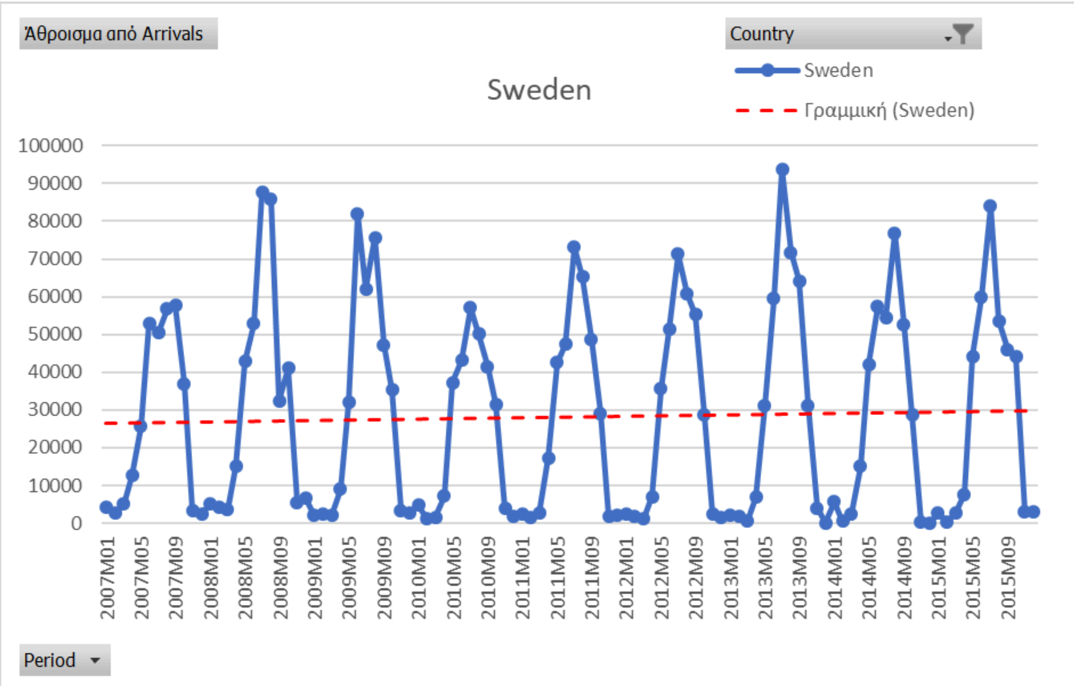


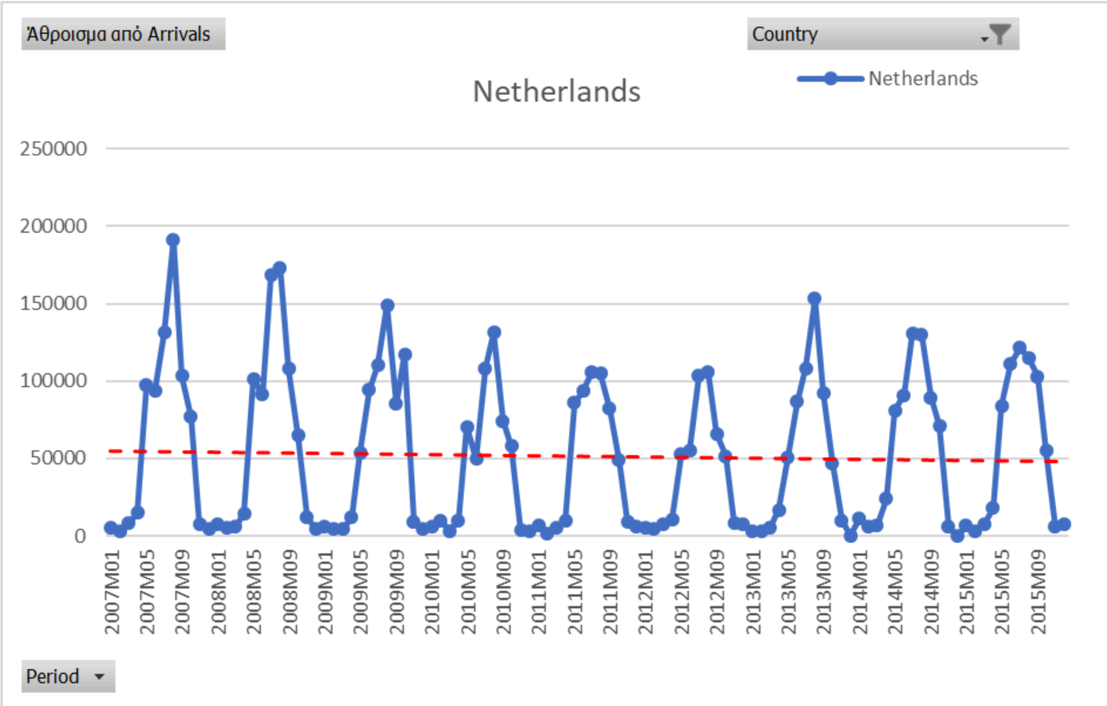
Άθροισμα από Arrivals
Country
Germany
Germany
Γραμμική (Germany)
600000
500000
400000
300000
200000
100000
0
2007M01
2007M05
2007M09
2008M01
2008M05
2008M09
2009M01
2009M05
2009M09
2010M01
2010M05
2010M09
2011M01
2011M05
2011M09
2012M01
2012M05
2012M09
2013M01
2013M05
2013M09
2014M01
2014M05
2014M09
2015M01
2015M05
2015M09
Period


Netherlands
Netherlands
Γραμμική (Netherlands)
250000
200000
150000
100000
50000
0
2007M01
2007M05
2007M09
2008M01
2008M05
2008M09
2009M01
2009M05
2009M09
2010M01
2010M05
2010M09
2011M01
2011M05
2011M09
2012M01
2012M05
2012M09
2013M01
2013M05
2013M09
2014M01
2014M05
2014M09
2015M01
2015M05
2015M09

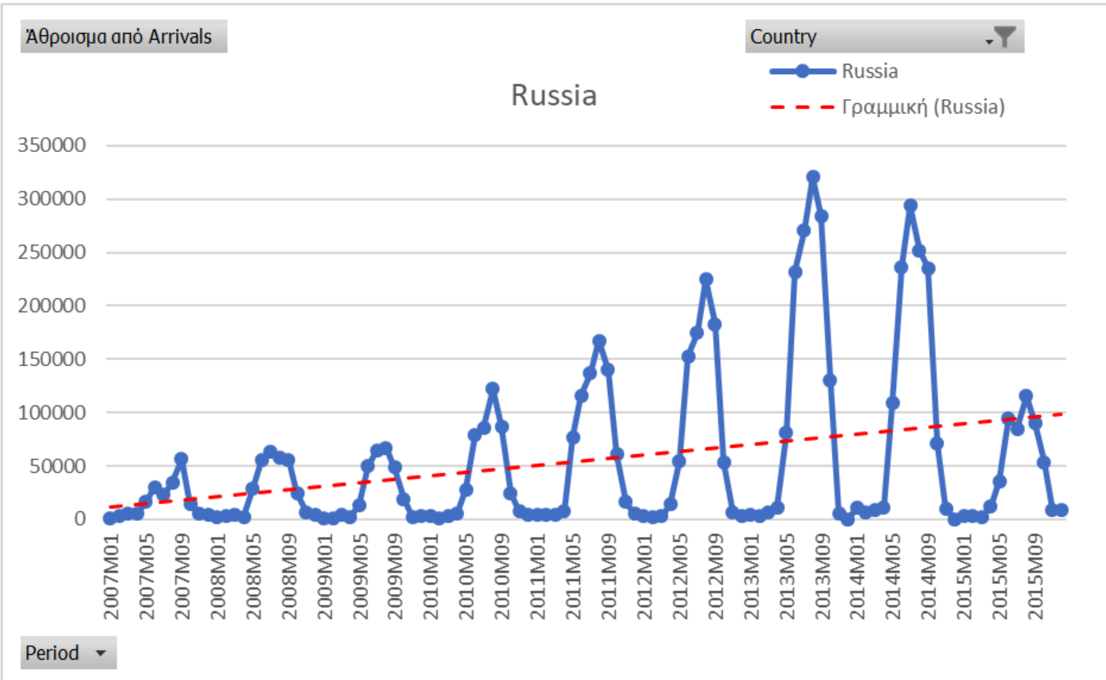

Άθροισμα από Arrivals
Country
USA.
USA.
Γραμμική (USA.)
160000
140000
120000
100000
80000
60000
40000
20000
0
2007M01
2007M05
2007M09
2008M01
2008M05
2008M09
2009M01
2009M05
2009M09
2010M01
2010M05
2010M09
2011M01
2011M05
2011M09
2012M01
2012M05
2012M09
2013M01
2013M05
2013M09
2014M01
2014M05
2014M09
2015M01
2015M05
2015M09
Period

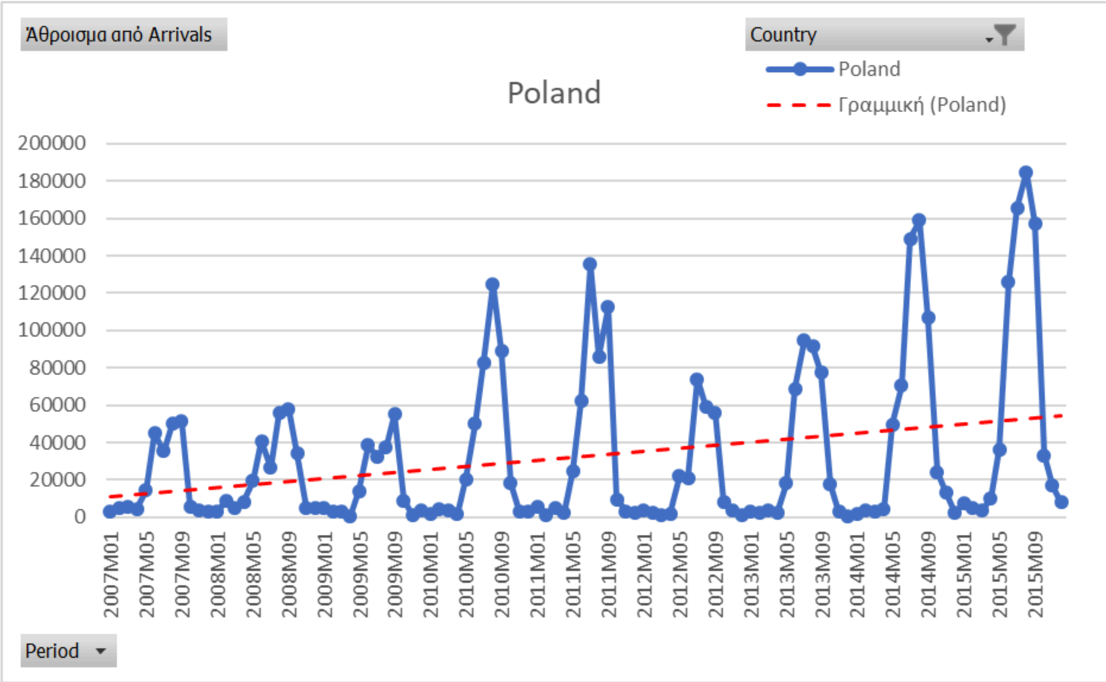

Belgium
Linear(Belgium)
140000
120000
100000
80000
60000
40000
20000
0


Άθροισμα από Arrivals
Country
Sweden
Sweden
Γραμμική (Sweden)
100000
90000
80000
70000
60000
50000
40000
30000
20000
10000
0
2007M01
2007M05
2007M09
2008M01
2008M05
2008M09
2009M01
2009M05
2009M09
2010M01
2010M05
2010M09
2011M01
2011M05
2011M09
2012M01
2012M05
2012M09
2013M01
2013M05
2013M09
2014M01
2014M05
2014M09
2015M01
2015M05
2015M09
Period

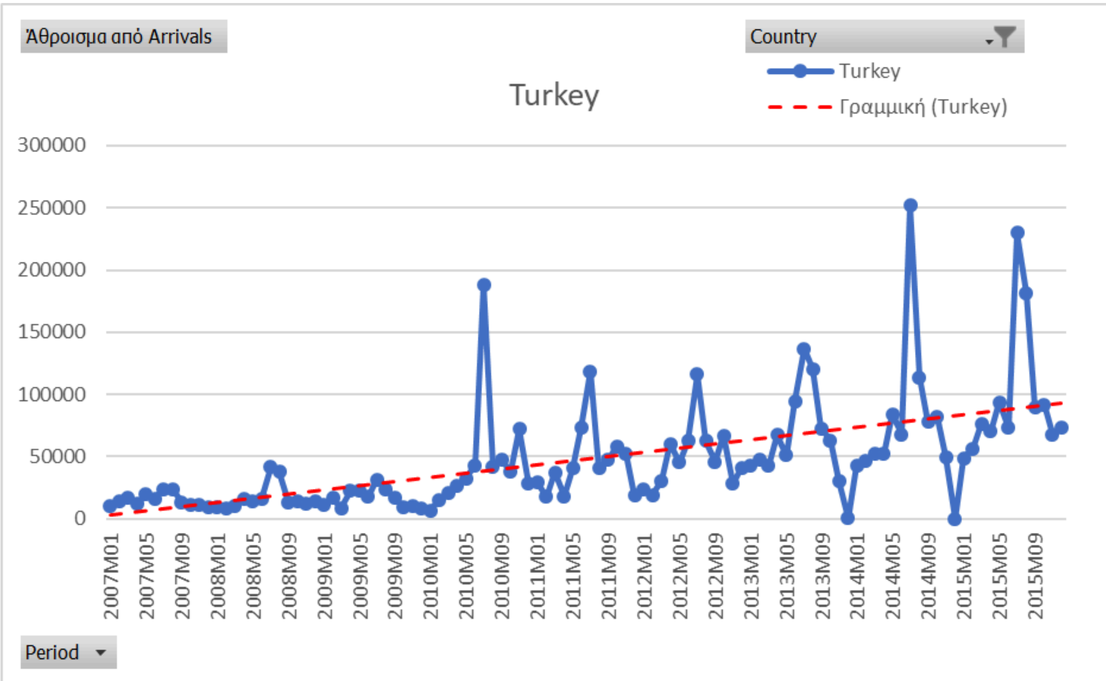


Countries with positive trend

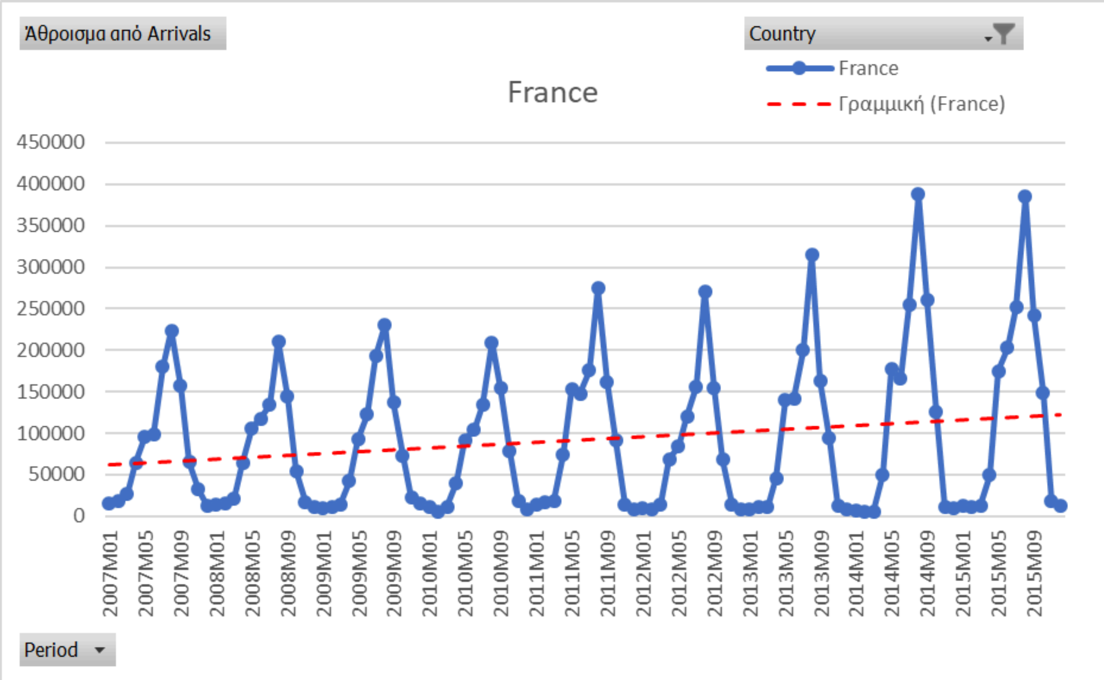




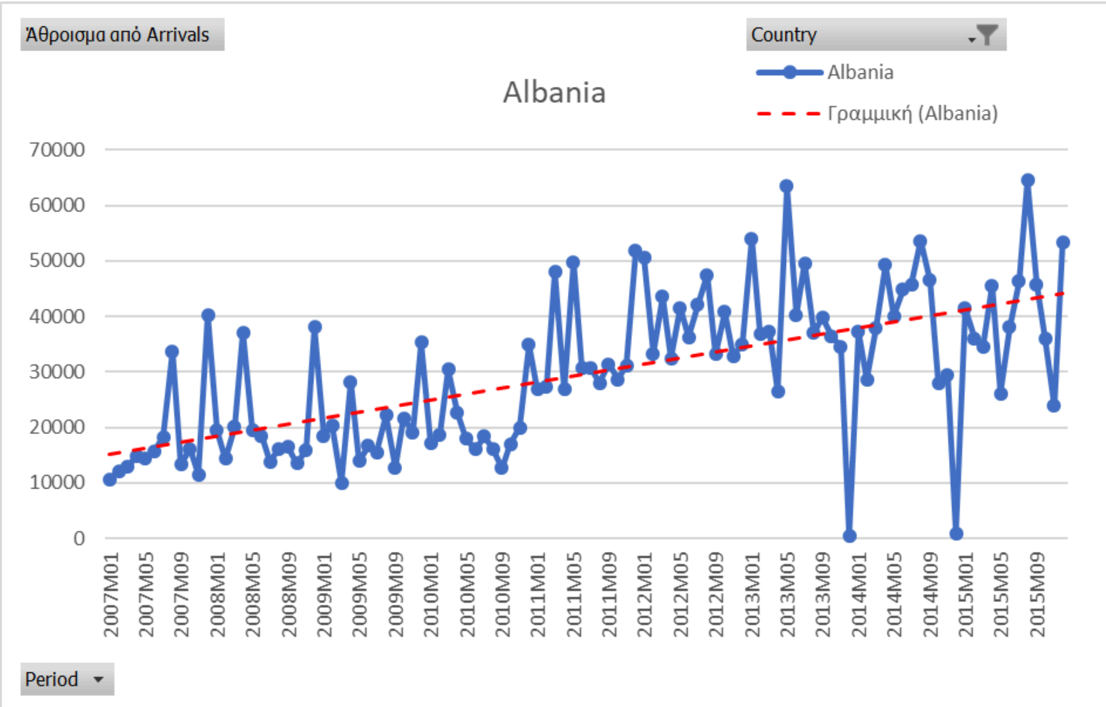
Άθροισμα από Arrivals
Country
Poland
Γραμμική (Poland)
Poland
200000
180000
160000
140000
120000
100000
80000
60000
40000
20000
0
2007M01
2007M05
2007M09
2008M01
2008M05
2008M09
2009M01
2009M05
2009M09
2010M01
2010M05
2010M09
2011M01
2011M05
2011M09
2012M01
2012M05
2012M09
2013M01
2013M05
2013M09
2014M01
2014M05
2014M09
2015M01
2015M05
2015M09
Period



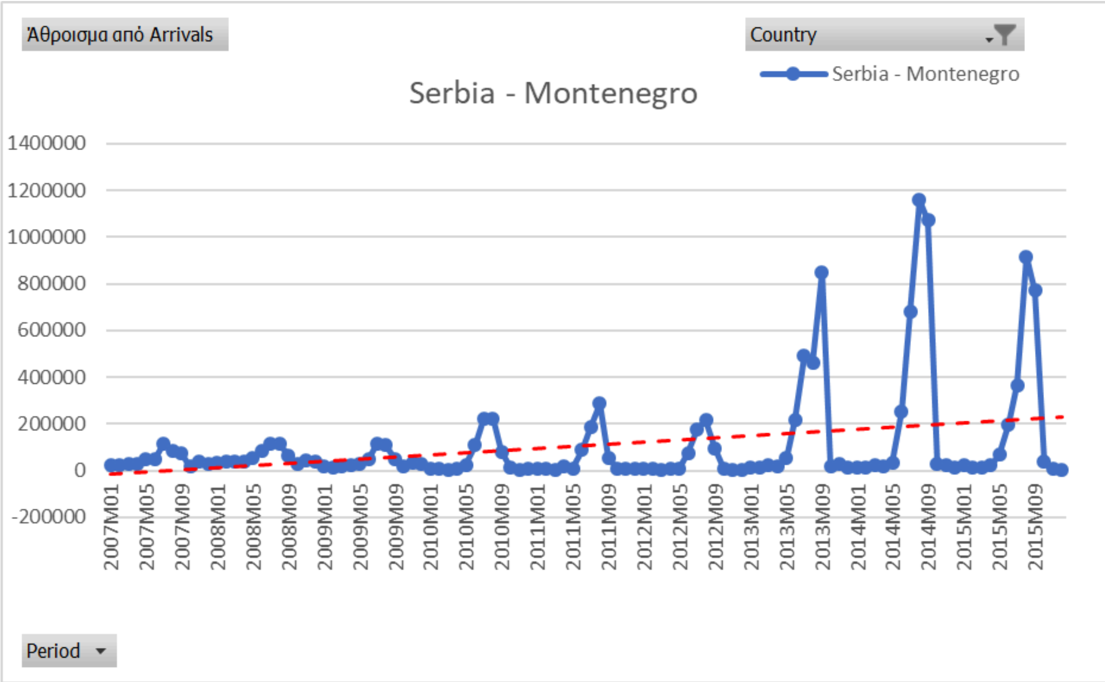
Άθροισμα από Arrivals
Country
Turkey
Γραμμική (Turkey)
Turkey
300000
250000
200000
150000
100000
50000
0
2007M01
2007M05
2007M09
2008M01
2008M05
2008M09
2009M01
2009M05
2009M09
2010M01
2010M05
2010M09
2011M01
2011M05
2011M09
2012M01
2012M05
2012M09
2013M01
2013M05
2013M09
2014M01
2014M05
2014M09
2015M01
2015M05
2015M09
Period

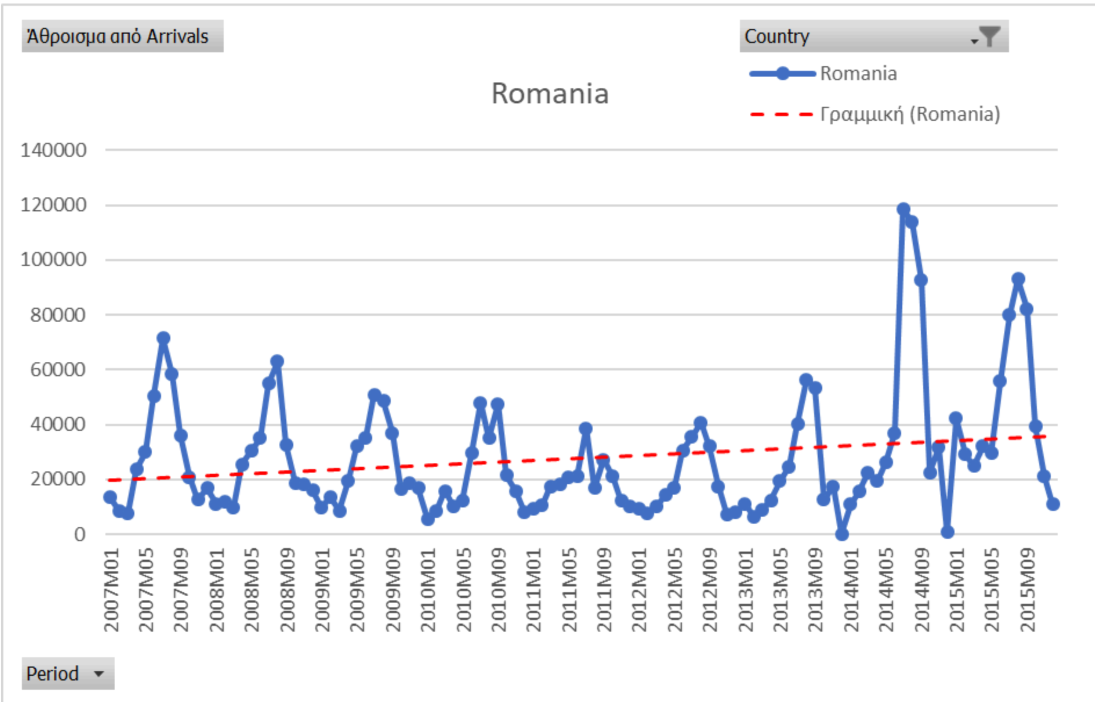


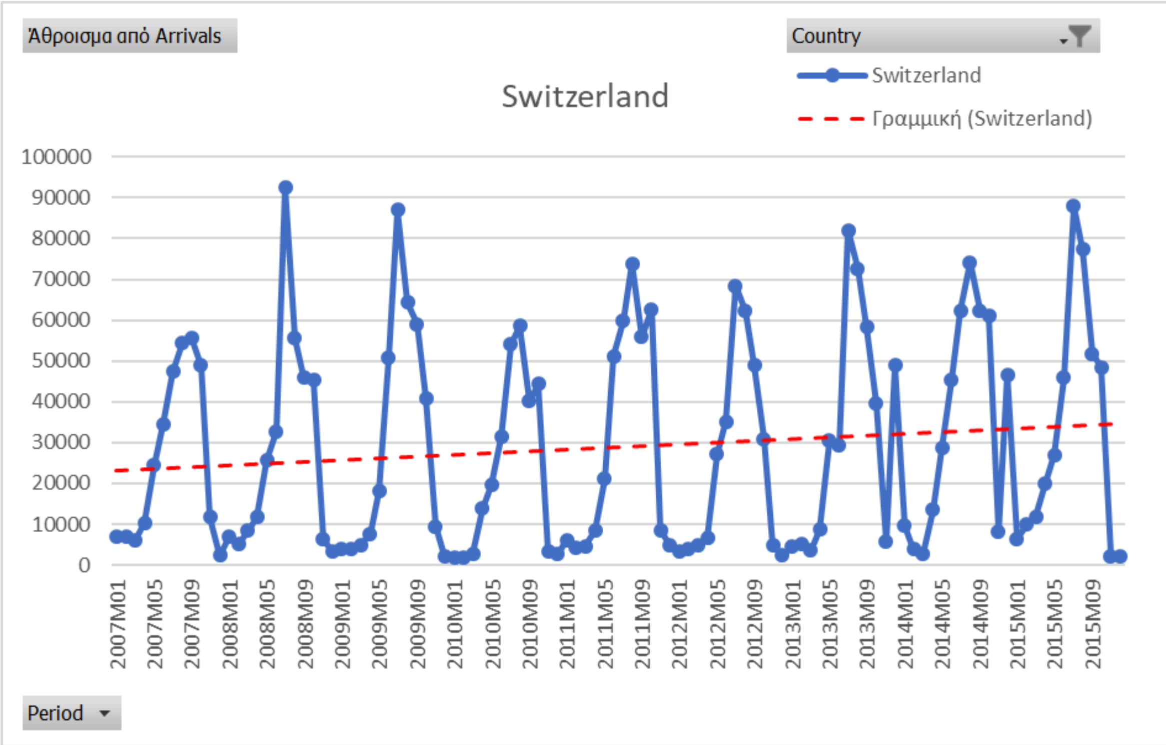
Άθροισμα από Arrivals
Country
France
Γραμμική (France)
France
450000
400000
350000
300000
250000
200000
150000
100000
50000
0
2007M01
2007M05
2007M09
2008M01
2008M05
2008M09
2009M01
2009M05
2009M09
2010M01
2010M05
2010M09
2011M01
2011M05
2011M09
2012M01
2012M05
2012M09
2013M01
2013M05
2013M09
2014M01
2014M05
2014M09
2015M01
2015M05
2015M09
Period



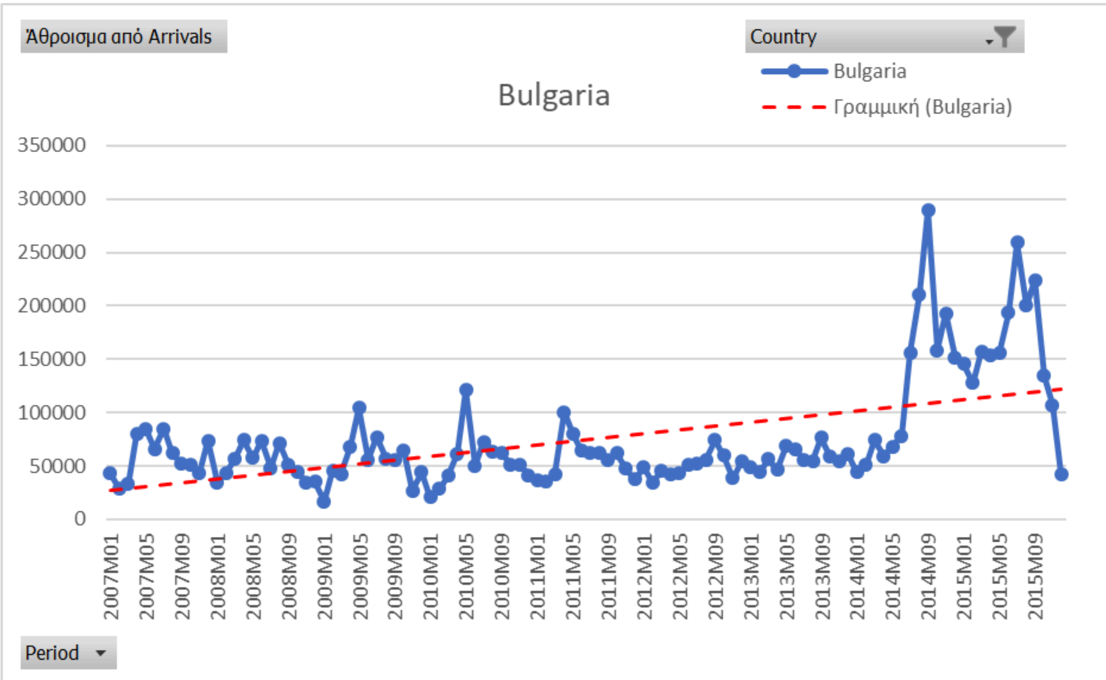
Άθροισμα από Arrivals
Country
Albania
Γραμμική (Albania)
Albania
70000
60000
50000
40000
30000
20000
10000
0
2007M01
2007M05
2007M09
2008M01
2008M05
2008M09
2009M01
2009M05
2009M09
2010M01
2010M05
2010M09
2011M01
2011M05
2011M09
2012M01
2012M05
2012M09
2013M01
2013M05
2013M09
2014M01
2014M05
2014M09
2015M01
2015M05
2015M09
Period


Άθροισμα από Arrivals
Country
Serbia - Montenegro
Serbia - Montenegro
1400000
1200000
1000000
800000
600000
400000
200000
0
-200000
2007M01
2007M05
2007M09
2008M01
2008M05
2008M09
2009M01
2009M05
2009M09
2010M01
2010M05
2010M09
2011M01
2011M05
2011M09
2012M01
2012M05
2012M09
2013M01
2013M05
2013M09
2014M01
2014M05
2014M09
2015M01
2015M05
2015M09
Period

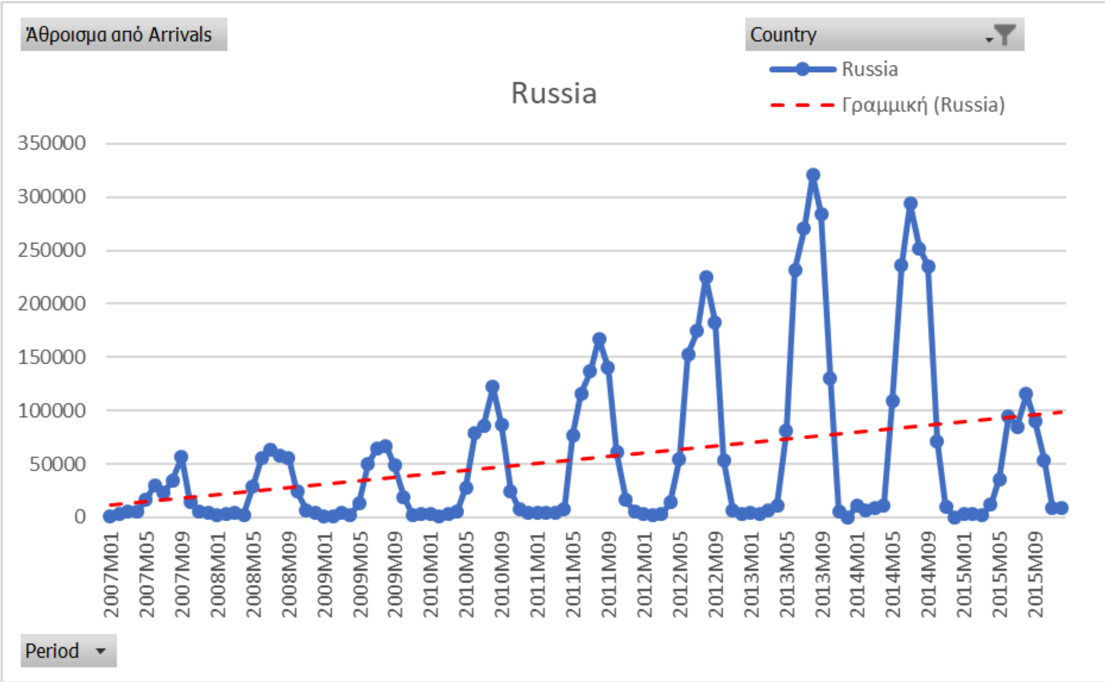

Άθροισμα από Arrivals
Country
Romania
Romania
Γραμμική (Romania)
140000
120000
100000
80000
60000
40000
20000
0
2007M01
2007M05
2007M09
2008M01
2008M05
2008M09
2009M01
2009M05
2009M09
2010M01
2010M05
2010M09
2011M01
2011M05
2011M09
2012M01
2012M05
2012M09
2013M01
2013M05
2013M09
2014M01
2014M05
2014M09
2015M01
2015M05
2015M09
Period



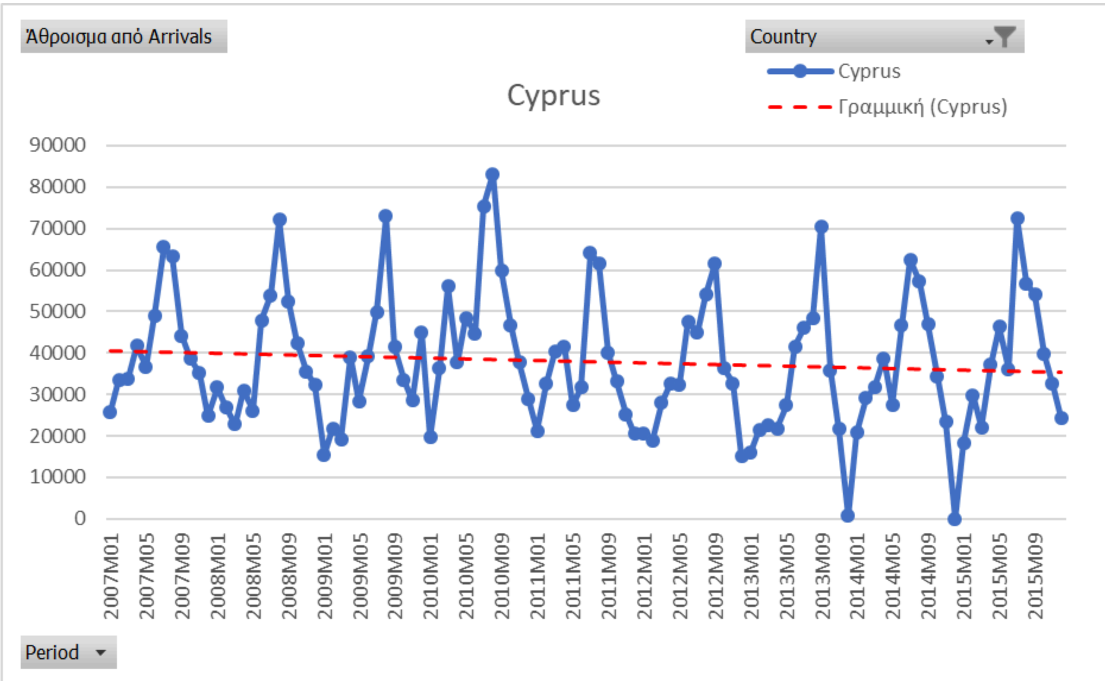
Άθροισμα από Arrivals
Country
Switzerland
Switzerland
Γραμμική (Switzerland)
100000
90000
80000
70000
60000
50000
40000
30000
20000
10000
0
2007M01 2007M05 2007M09 2008M01 2008M05 2008M09 2009M01 2009M05 2009M09 2010M01 2010M05 2010M09 2011M01 2011M05 2011M09 2012M01 2012M05 2012M09 2013M01 2013M05 2013M09 2014M01 2014M05 2014M09 2015M01 2015M05 2015M09
Period



Άθροισμα από Arrivals
Country
Bulgaria
Bulgaria
Γραμμική (Bulgaria)
350000
300000
250000
200000
150000
100000
50000
0
2007M01 2007M05 2007M09 2008M01 2008M05 2008M09 2009M01 2009M05 2009M09 2010M01 2010M05 2010M09 2011M01 2011M05 2011M09 2012M01 2012M05 2012M09 2013M01 2013M05 2013M09 2014M01 2014M05 2014M09 2015M01 2015M05 2015M09
Period



Country with negative trend



1.

3. Forecasting

3.1. Introduction

The study aims at predicting the tourism flows in Greece. A set of monthly data from ELSTAT is used for the period 2000 - 2015. The variables under consideration include the number of tourist arrivals (total, residential, non-residential) and the number of overnights total. For this purpose, the study employs two forecasting techniques, Triple Exponential Smoothing and Seasonal Autoregressive Integrated Moving-Average (SARIMA). Each approach provides insights into the future tourism flows from a different angle.

The investigation of the methods involves a comparison of the forecasting performance of each approach in order to determine the most accurate one. This can be achieved using a variety of forecast error measurements. In this context, the outcome of multiple forecasting tests will be evaluated in order to decide upon the most robust technique.

Focusing on the total tourist arrivals, Figures 3.1 – 3.4 present the patterns they follow.

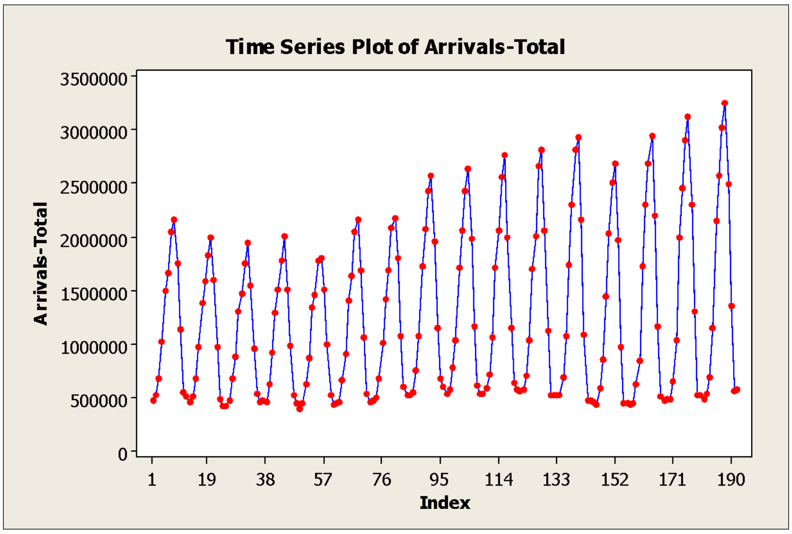


Figure 3.1. Time-series plot for total number of arrivals

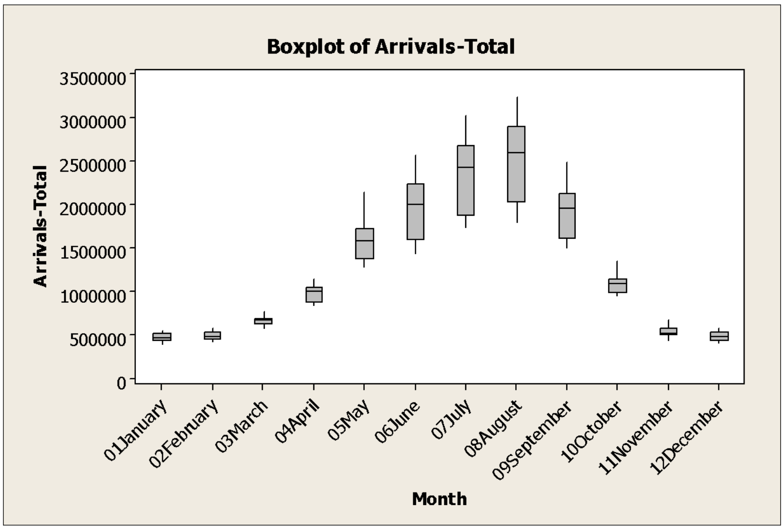


Figure 3.2. Boxplot for arrivals in months.

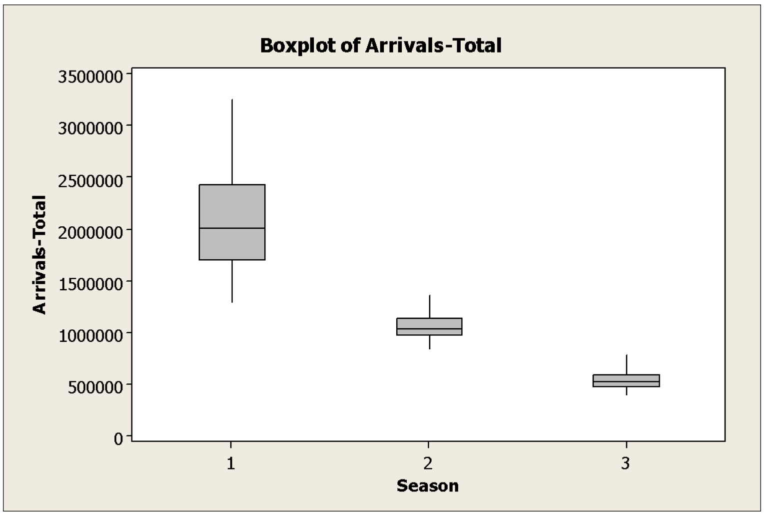


Figure 3.3. Boxplot of Arrivals-Total by season.

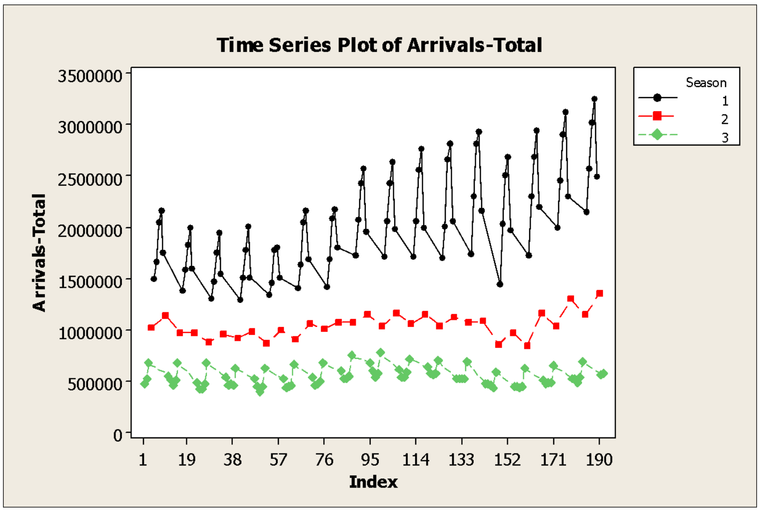


Figure 3.4. Time-series composite graph for Arrivals-Total by Seasons

Figure 3.1 indicates that tourist arrivals are characterized by seasonality. They follow a standard pattern whereby they reach a peak during the summer months and then they fall. According to Figure 3.2 the most active month in terms of arrivals is August, followed by July. This is hardly surprising, given that the most popular tourist destinations in Greece are the islands. Most tourists come from North European countries where the climate and the geographical characteristics do not favor the development of seaside resorts. Therefore, Mediterranean countries, such as Greece, is an attractive holiday destination for North Europeans.

In this context, Figure 3.3 illustrates the categorization of months into 3 tourist seasons: Low, Medium and High. Low season months involve November, December, January, February, and March and correspond to the lowest points in Figure 3.1. Those troughs hover around 500,000 and do not exhibit any trends. Medium season starts from October and ends on April, while the high season is from May to September. There is a trend in high season months, which is declining from period 1 to 60 and becomes increasing from period 60 to 192, with the exception of the interval (140, 160). The trends during the high season are extrapolated to the entire year and determine the peaks and troughs. Any annual increase or decrease in tourist arrivals comes as a result of equivalent fluctuations during those months. This is also illustrated by Figures 3.2 – 3.4; those boxplots indicate high variability on the high season months.

Another noteworthy observation is that the number of tourist arrivals is relatively low from 2000 to 2004 with a slightly decreasing trend. There was a spike in 2004 and since then they remain at higher levels. This increase is mainly attributed to Athens 2004 Olympics that gave a boost to Greek tourism.

3.2 Short review on forecasting methods in tourism

Due to the strong seasonality of the data, the traditional forecasting methods such as simple exponential smoothing, ARIMA etc. produced unacceptable results – the deviations between observed and forecasted values were found to be 20 – 30% - and thus they were discarded.

The Box-Jenkins approach is one of the most widely used methodologies in tourism forecasting and many authors find that it outperforms alternative techniques.

Kim & Uysal (1998) develop an ARMAX model for the numbers of nights spent in hotels in Seoul, Korea, and they find that the variables: price of rooms, trade volume, and events organized, such as conferences and exhibitions, have a significant impact on hotel demand.

Cho (2001) focuses on Hong Kong tourist arrivals and formulates an ARIMAX type model (adjusted ARIMA). This model involves ARIMA residuals of the following variables: GDP/GNP, Consumer Price Index (CPI), money supply, unemployment rate, imports, exports, and discount rate. The results suggest that ARIMAX is the most accurate forecasting method for inbound tourists from Japan, while univariate ARIMA is the best predictor for tourists coming from the US and UK. Interestingly, according to the results, both of these models appear to perform better than exponential smoothing.

Akal (2004) attempts to predict the tourism revenues in Turkey using tourist arrivals as an explanatory variable in an AR(I)MAX model. Then the author shows that the specified model outperforms the simple cause–effect technique.

Gounopoulos, Petmezas, & Santamaria (2012) provide evidence that ARIMA performs better than exponential smoothing models. ShuiKi, ShinHuei, & ChiKeung (2013) and Baldigara and Mamula (2015) view SARIMA type models as the most appropriate framework to predict tourist arrivals and tourist flows respectively. In particular, ShuiKi et al. (2013) compare SARIMA with Seasonal moving average and Holt-Winter models and find that SARIMA produces more accurate forecasts. More recently, Hassani, Silva, Antonakakis, Filis, & Gupta (2017) attempt to predict tourist arrivals to Europe using ARIMA among other parametric and non-approaches, such as Autoregressive Fractionally Integrated Moving Average (ARFIMA), Exponential Smoothing (ETS), Neural Networks (NN), Trigonometric Box-cox ARMA Trend Seasonal model (TBATS), Moving Average (MA), Weighted Moving Average (WMA), Singular Spectrum Analysis (SSA-R and SSA-V). The comparison reveals that none of these models stands out.

A more detailed analysis of the relevant literature is provided in Appendix IV.

Two seasonality-based methods have been selected as the most appropriate for the Greek tourism data: Triple exponential smoothing, the Holt-Winters method, and Seasonal Autoregressive Integrated Moving-Average (SARIMA). Triple exponential smoothing breaks forecasts into three components, i.e. level, trend and seasonality, and is suitable for times series that exhibit trend and seasonality, such as the ones analyzed in this study. SARIMA extends the typical ARIMA model by including an additional seasonal term.

3.3. Methods

3.3.1. Exponential Smoothing

Exponential Smoothing is a widely used forecasting technique. It is based on the most recent forecast, the actual value for the previous period, and one or more smoothing parameters. The distinctive characteristic of this method is that recent observations are assigned more weight than older ones.

Depending on the number of smoothing constants that are incorporated into the model, there are three variations of Exponential Smoothing:

- Single Exponential Smoothing which is the simplest form and uses only one parameter, the smoothing constant *a* that corresponds to the reaction rate to differences between forecast and actual values.
- Exponential Smoothing with Trend Adjustment (Holt's Model), which incorporates an additional parameter, the smoothing constant β. This parameter is essentially an adjustment for trend.
- Exponential Smoothing with Trend and Seasonality or Triple Exponential Smoothing, the Holt-Winters (HW) Method.

This study will consider the third and more complex form of Exponential Smoothing, given that the data show seasonality, besides trend.

The equations to compute the forecasts are as follows:

$$FIT_t = F_t + T_t$$

$$F_t = FIT_{t-1} + a\left(A_{t-1} - FIT_{t-1}\right)$$

$$T_t = T_{t-1} + \beta\left(F_t - FIT_{t-1}\right)$$

where F_t the exponentially smoothed forecast without trend for period t, FIT_t the forecast including trend, and T_t the exponentially smoothed trend for period t.

The Triple Exponential Smoothing includes one more constant, γ, which is the smoothing parameters for the seasonal component.

The above mentioned smoothing constants determine the sensitivity of forecasts to changes. When the parameters are given high values, they become more responsive to recent levels, rather than older estimates.

3.3.2. The Box-Jenkins approach (ARMA) – SARIMA framework

Box-Jenkins (1970) introduced the AutoRegressive Moving Average (ARMA) model. This model encompasses the AR(p) and MA(q) models. An ARMA(p,q) model can be mathematically represented as follows:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

where X_t is a time-series c is a constant, the random variables ε_t, ε_{t-i} are white noise, p the order of autocorrelation, q the order of the moving average, and φ_i, θ_i are parameters.

An important limitation of the ARMA models is that they require stationary data. This inevitably narrows down their range of applications, since most series have unit roots. Yet, Box and Jenkins managed to overcome this weakness within the ARMA framework. They handled this by differencing the successive observations of a series as many times as it is necessary until they become stationary.

In this context, non-stationary time-series can be modelled using an extension of ARMA which is known as AutoRegressive Integrated Moving Average ARIMA (p,d,q). ARIMA (p,d,q) is based on ARMA (p,q) and includes an extra parameter d representing the number of differencing to achieve stationarity.

Another modification of ARMA is the Seasonal ARIMA (SARIMA) model, which can be employed when seasonality is present. The SARIMA model can be expressed as SARIMA (p,d,q) (P,D,Q), where the capital letters P,D,Q are the counterparts of the parameters p,d,q for the seasonal model.

The ARIMA (or 'Box-Jenkins approach) involves the following modelling steps:

1) Identification

Initially, the outcome of stationarity tests dictates if the modelling framework should be based on ARMA or ARIMA. Also, correlograms are used to specify the appropriate parameters (p,q).

2) Model Specification

The models specification can be broken down into the following sub-steps:

2.1) The most reliable criterion would be based on the precision of results (Yokum and Armstrong, 1995). Given that there is no such measure which is universally accepted, the model is specified on the basis of the examination of the autocorrelation (ACF) and partial autocorrelation (PACF) functions.

2.2) The optimal lag length can also be determined on the basis of the Akaike Information Criterion (AIC) or the Schwarz criterion.

3) Estimation

Based on the values (p, q), the ARMA terms are estimated using Least Squares.

4) Diagnostic checking

This step includes residual diagnostics (e.g. residual serial correlation and residual heteroscedasticity tests)

5) Forecasting

Generation of ex-post and ex-ante forecasts.

6) Evaluation of the forecasting accuracy

The performance of the model is assessed on the basis of the following criteria: Mean Absolute Deviation (MAD), Mean absolute percent error (MAPE), Mean Absolute Deviation Percent (MADP), and Mean squared deviation (MSD)

The SARIMA model

The Seasonal ARIMA (SARIMA) model, is an extension of ARIMA (p,d,q) whereby a seasonal factor is added. The SARIMA model can be written as SARIMA (p,d,q) (P,D,Q), where the capital letters P,D,Q refer to the counterparts of the parameters p,d,q for the seasonal model.

3.4. Model fitting

For the Triple exponential smoothing, the multiplicative method has been preferred as the seasonal data variations are not approximately constant but they are changing proportionally through the series. The fitting procedure involved the estimation of the values for the parameters α, β and γ (α=0,15, β=0,06 γ=0,92) so to get error values as minimum as possible. This has been achieved first by selecting greater smoothing effect on level and trend (low values for α and β) and limited smoothing for seasonality (high values for γ) and second by applying a trial and error procedure on a great number of different value combinations.

As far as SARIMA modelling is concerned, the most suitable model proved to be a SARIMA (4,1,2) (1,1,1) for tourist arrivals, a SARMA (3,4) (1,1) for nights total and arrivals – residents, and a SARIMA (3,1,3) (1,1,1) for arrivals non-residents. Seasonality was present in all time-series, therefore we selected SAR(I)MA, rather than AR(I)MA models.

The model selection was based initially on visual inspection of the graph, as well as on stationarity tests (ADF, KPSS) in order to determine the level of differencing. The tourist arrivals were found non-stationary in levels, therefore we applied first differencing to account for the first order of integration. According to the relevant tests, the nights arrivals and the arrivals – residents are stationary, therefore they were both modelled using a SARMA model. Finally, the arrivals-non-residents were found non-stationary and they were handled in a SARIMA framework.

It should be noted that the variable 'arrivals-residents' was the only one that was log-transformed, in order to avoid the presence of heteroscedasticity as the change in the growth rate varied over time.

The parameters of the SAR(I)MA models were determined using the Akaike Information Criterion (AIC) in combination with an examination of the autocorrelation (ACF) and partial autocorrelation (PACF) functions.

3.5. Evaluation of forecasting accuracy

The evaluation of the accuracy of model predictions has always been a challenging endeavor and in fact determines the success or failure of each modelling approach. Therefore, it is important to use sound evaluation criteria and ensure the validity of results.

Forecasting accuracy is judged by means of forecast errors, which are based on the difference between the forecast value and the actual value of each observation. Error occurs even in the best forecasts, but in varying degrees. Error may come from pure randomness of from the bias caused by a consistent mistake.

This study adopts a variety of forecast errors. Specifically, the following criteria will be used to assess the predictive power of each model: Mean Absolute Deviation (MAD), Mean absolute percent error (MAPE), Mean Absolute Deviation Percent (MADP), and Mean squared deviation (MSD)

Those statistics constitute relative measures that can be used for comparison purposes of the same series. The smaller the error, the greater the forecasting accuracy of a given model.

A description of the forecast error statistics used in this study is presented after a brief description of R squared.

- **R squared**

The coefficient of determination (R^2) measures how well the data fit the model. It generally describes the goodness of fit of the regression line to the data.

TSS stands for the Total Sum of Squares and is given by:

$$TSS = \sum y_i^2 = \sum \left(Y_i - \overline{Y}\right)^2$$

RSS is the Residual Sum of Squares (RSS):

$$RSS = \sum \hat{u}_i^2$$

where Y denotes the independent variable, $\overline{Y}$ the sample mean and ut the residual.

The value of R-squared is defined as:

$$R^2 = 1 - \frac{RSS}{TSS}$$

- **Mean Absolute Error (MAE)**

The mean absolute error is defined as:

$$\text{MAE} = \frac{1}{N}\sum_{t=1}^{N}\left|F_t - A_t\right|$$

where F_t is the forecast value and A_t is the actual value.

The MAE represents the average of absolute errors, indicating the proximity of predictions to the actual values. Therefore, the larger the MAE the less accurate the model.

- **Mean absolute percent error (MAPE)**

In the same notation, the mean absolute percent error is defined as:

$$\text{MAPE} = 100\frac{1}{N}\sum_{i=1}^{N}\left|\frac{F_t - A_t}{A_t}\right|$$

MAPE remedies a major weakness of MAE, which is, its dependence on the scaling of the variable. This dependence can become a serious concern when the model comprises varying time intervals or different variables. The way MAPE overcomes this issue is by the division of the difference (F_t – A_t) by the actual value A_t.

However, this technique presumes that there will be no zero values in the sample; otherwise the use of this metric will become problematic, since the division with zero is not possible

- **Mean Absolute Deviation Percent (MADP)**

MADP derives from the division of MAD by the average of the actuals.

This forecast measure has remedies one of the weaknesses of MAPE, as it does not skew the error rates that approach zero.

The following formula is used for the computation of MADP:

$$\frac{\sum_{i=1}^{N}|F_i - A_i|}{\sum_{i=1}^{N}|A_i|}$$

- **Mean squared deviation (MSD)**

MSD is an alternative forecast error measure which is given by the following formula:

$$\frac{\sum_{i=1}^{n}|A_i - F_i|^2}{n}$$

where n is the number of forecasts.

However, the major weakness of this measure is that outliers tend to have a greater impact on MSD than on MAD.

3.6. Application and Results

The evaluation of the two proposed methods was done by means of ex-ante forecasting analysis whereby five different samples of the dataset were specified, with the remaining observations to be considered unknown. The resized samples were used to produce out-of-sample forecasts and ultimately compare the forecasted values with the actual ones.

Then, we conduct out-of-sample analysis for the monthly values of 2016-2018. Due to the lack of data for this period, it is not possible to compare the forecasts with actual values. However, the monthly forecasts are compared with the respective observations of 2015 and we calculate the average rate per year.

For each of the tests, the observed and forecasted values were used to estimate the typical error formulas MAPE, MAD, MADP, MSD and R squared (see spreadsheet).

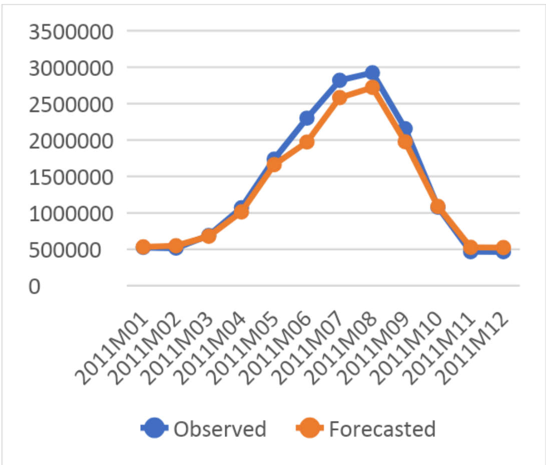
3.6.1. Tourist Arrivals

For tourist arrivals, the first sub-sample spanned 2000-2010 with the aim to forecast each month of 2011, the second started from 2000 to 2011 to forecast the monthly values of 2012 etc. We follow the same procedure for each year, up to 2015, when the available data end. Then we conduct out-sample analysis for 2016-2018.

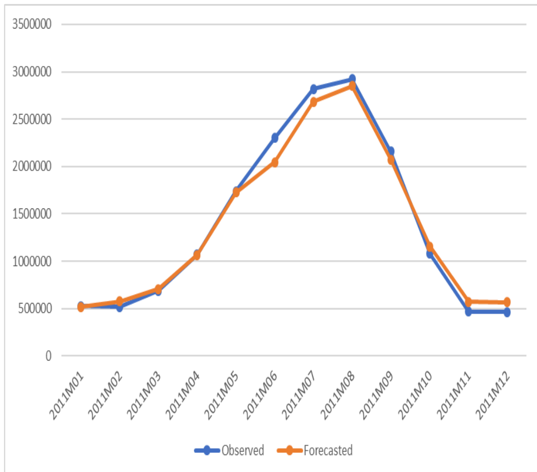
Below are the forecasting tests for each sub-sample.

TEST 1 : 2000 - 2010 => 2011

			HW-Exponential Smoothing	**SARIMA**
Period No	Month	Observed	Forecast	Forecast
133	2011M01	524830	532524,5516	516283.3531
134	2011M02	515934	547524,9946	577678.6746
135	2011M03	689867	678809,3093	704639.6383
136	2011M04	1069357	1013687,828	1067115.697
137	2011M05	1737712	1662439,412	1727533.762
138	2011M06	2299967	1972203,227	2047092.934
139	2011M07	2818308	2581278,775	2682844.725
140	2011M08	2923458	2721735,774	2850771.721
141	2011M09	2156203	1975487,505	2072624.755
142	2011M10	1078490	1088554,312	1156130.385
143	2011M11	466377	525427,7895	573136.5152
144	2011M12	465103	522826,1801	565965.6897
Errors :				
MAPE			**6.89%**	**7.54%**
MAD			**104613**	**77279**
MADP			**7.5%**	**5.5%**
MSD			**21152219307**	**10531284698**
R2			**0.974**	**0.9872**



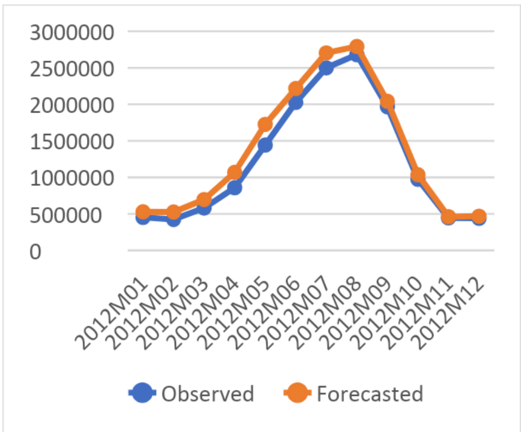
HW-Exponential Smoothing



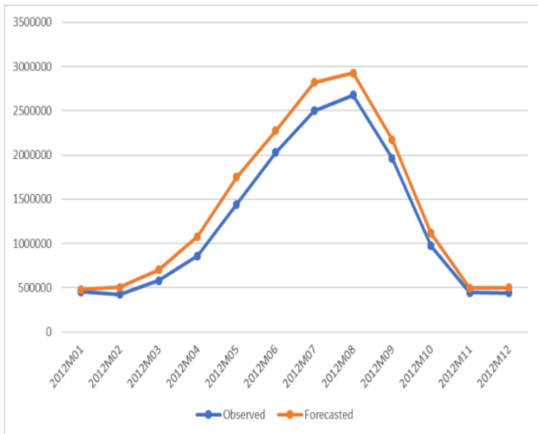
SARIMA

TEST 2 : 2000 - 2011 => 2012

			HW-Exponential Smoothing	SARIMA
Period No	Month	Observed	Forecast	Forecast
145	2012M01	452558	529345,8144	477904.236
146	2012M02	424357	526276,1435	504744.3777
147	2012M03	581144	696948,0355	701007.1143
148	2012M04	858976	1068070,753	1078114.96
149	2012M05	1442049	1725995,788	1750908.11
150	2012M06	2027151	2216641,942	2274888.063
151	2012M07	2500205	2704051,44	2822165.213
152	2012M08	2679376	2792031,219	2928813.823
153	2012M09	1965510	2041464,269	2177569.568
154	2012M10	973555	1035984,214	1116535.551
155	2012M11	445345	461308,798	497083.2787
156	2012M12	440470	468135,2699	500133.7975
Errors :				
MAPE			**12.23%**	**14.76%**
MAD			**122963**	**169931**
MADP			**10.0%**	**13.8%**
MSD			**21239908613**	**38649011460**
R2			**0.9683**	**0.9424**



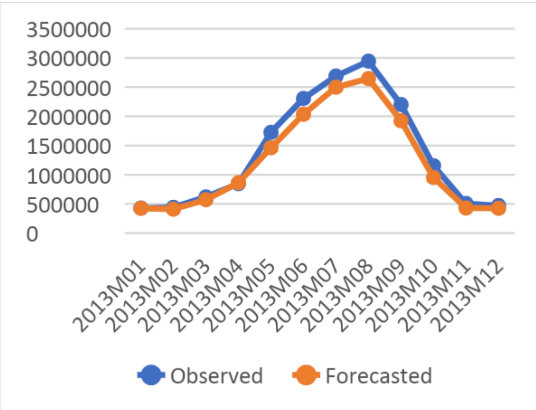
HW-Exponential Smoothing



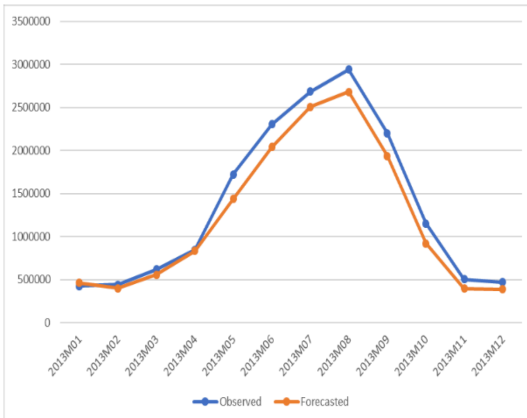
SARIMA

TEST 3 : 2000 - 2012 => 2013

			HW-Exponential Smoothing	**SARIMA**
Period No	Month	Observed	Forecast	Forecast
157	2013M01	427528	426146,2436	463300.6838
158	2013M02	441053	410914,7072	400179.7341
159	2013M03	620089	570310,9054	558670.3416
160	2013M04	846254	861975,6968	837081.1257
161	2013M05	1724551	1460119,937	1438784.894
162	2013M06	2306252	2034483,351	2041531.486
163	2013M07	2687098	2498713,397	2508392.256
164	2013M08	2942170	2646551,441	2683293.28
165	2013M09	2201812	1923836,379	1938428.508
166	2013M10	1154154	950101,6708	922852.1238
167	2013M11	504584	429996,9664	398681.4433
168	2013M12	470217	424267,8947	386920.9429
Errors :				
MAPE			**9.67%**	**11.90%**
MAD			**143316**	**151599**
MADP			**10.53%**	**11.10%**
MSD			**33073223173**	**33210318761**
R2			**0.9607**	**0.9605**



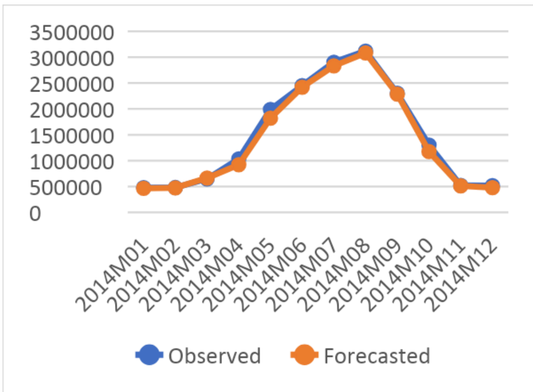
HW-Exponential Smoothing



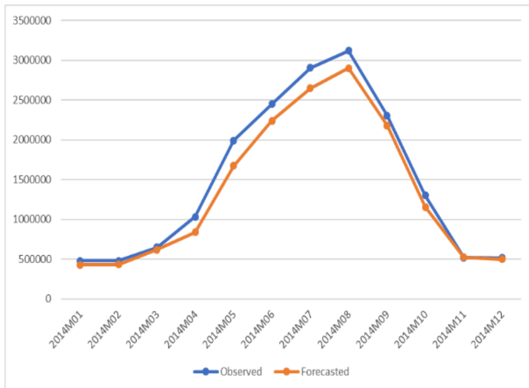
SARIMA

TEST 4 : 2000 - 2013 => 2014

			HW-Exponential Smoothing	SARIMA
Period No	Month	Observed	Forecast	Forecast
169	2014M01	479484	466341,4965	430056.4317
170	2014M02	480858	475990,2277	432114.8437
171	2014M03	647404	664440,3762	618373.1828
172	2014M04	1034259	922710,1202	838539.3112
173	2014M05	1989444	1820893,505	1674549.314
174	2014M06	2450010	2420732,804	2239565.885
175	2014M07	2902722	2832941,063	2645653.58
176	2014M08	3117313	3082170,866	2897020.846
177	2014M09	2302398	2285592,497	2179409.916
178	2014M10	1300758	1175791,681	1155433.396
179	2014M11	522399	511908,5397	526716.9188
180	2014M12	516445	480507,3175	498145.9965
Errors :				
MAPE			**4.14%**	**8.76%**
MAD			**53129**	**134713**
MADP			**3.59%**	**9.1%**
MSD			**5466763011**	**28218747213**
R2			**0.9942**	**0.9702**



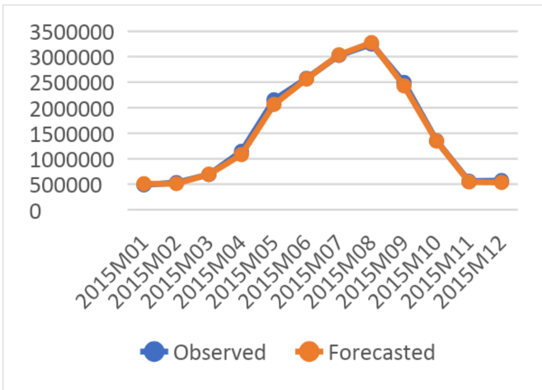
HW-Exponential Smoothing



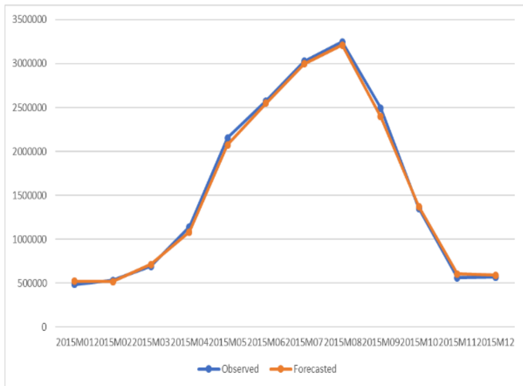
SARIMA

TEST 5 : 2000 - 2014 => 2015

			HW-Exponential Smoothing	SARIMA
Period No	Month	Observed	Forecast	Forecast
181	2015M01	485431	508496,3522	521850.2273
182	2015M02	532593	510920,5711	517061.629
183	2015M03	689505	693725,302	713854.9207
184	2015M04	1141786	1079975,832	1081673.757
185	2015M05	2152897	2062297,636	2074412.458
186	2015M06	2573973	2562402,387	2549569.955
187	2015M07	3025144	3036181,564	2996084.426
188	2015M08	3247472	3273699,86	3211211.302
189	2015M09	2493173	2426855,878	2396866.454
190	2015M10	1351422	1347418,242	1373261.707
191	2015M11	559050	546044,4768	602945.5154
192	2015M12	568733	535136,2409	588124.9662
Errors :				
MAPE			**2.66%**	**3.55%**
MAD			**30594**	**40505**
MADP			**1.95%**	**2.58%**
MSD			**1641978459**	**2228616768**
R2			**0.9984**	**0.9978**



HW-Exponential Smoothing



SARIMA

TEST 6 : 2000 - 2015 => 2016, 2017, 2018

		HW-Exponential Smoothing		**SARMA**	
Month	Observed 2015	Forecast	% Difference	Forecast	% Difference
2016-01	485431	520177	7,16%	531431	9.48%
2016-02	532593	563375	5,78%	582689	9.41%
2016-03	689505	733203	6,34%	748670	8.58%
2016-04	1141786	1199478	5,05%	1199703	5.07%
2016-05	2152897	2253558	4,68%	2197370	2.07%
2016-06	2573973	2706352	5,14%	2602449	1.11%
2016-07	3025144	3190640	5,47%	3073075	1.58%
2016-08	3247472	3436208	5,81%	3288380	1.26%
2016-09	2493173	2624940	5,29%	2538843	1.83%
2016-10	1351422	1427648	5,64%	1422885	5.29%
2016-11	559050	588749	5,31%	632527	13.14%
2016-12	568733	593321	4,32%	645022	13.41%
Average 2016			**5,50%**		**6.02%**
2017-01	485431	544293	12,13%	609156	25.49%
2017-02	532593	589394	10,66%	665537	24.96%
2017-03	689505	766936	11,23%	833999	20.96%
2017-04	1141786	1254452	9,87%	1285166	12.56%
2017-05	2152897	2356448	9,45%	2301412	6.90%
2017-06	2573973	2829447	9,93%	2719439	5.65%
2017-07	3025144	3335214	10,25%	3178204	5.06%
2017-08	3247472	3591323	10,59%	3398995	4.67%
2017-09	2493173	2742989	10,02%	2648944	6.25%
2017-10	1351422	1491613	10,37%	1510489	11.77%
2017-11	559050	615030	10,01%	721129	28.99%
2017-12	568733	619707	8,96%	731224	28.57%
Average 2016			**10,29%**		**15.15%**
2018-01	485431	568410	17,09%	696291	43.44%
2018-02	532593	615413	15,55%	748515	40.54%
2018-03	689505	800668	16,12%	916634	32.94%
2018-04	1141786	1309425	14,68%	1368129	19.82%
2018-05	2152897	2459337	14,23%	2369900	10.08%
2018-06	2573973	2952541	14,71%	2777349	7.90%
2018-07	3025144	3479787	15,03%	3247712	7.36%
2018-08	3247472	3746438	15,36%	3464465	6.68%
2018-09	2493173	2861038	14,75%	2716109	8.94%
2018-10	1351422	1555578	15,11%	1597822	18.23%
2018-11	559050	641310	14,71%	808772	44.67%
2018-12	568733	646093	13,60%	821765	44.49%
Average 2016			**15,08%**		**23.76%**

First of all, it should be noted that R-squared is very high, as it is above 0.96 in all cases and many times it exceeds 0.99. This is indicative of the goodness of fit of the proposed models.

Overall, the HW approach appears to be superior to SARIMA (2,1,4) (1,1,1). All of the forecasting exercises indicate that the forecast errors of HW are lower than those of SARIMA. The difference is not too wide, as it ranges between 0.65% (Test 1) to 4.62% (Test 4) in terms of MAPE. Notably in Test 5, the HW reaches a high level of accuracy (MAPE: 2.66%, MADP: 1.95%). On the other hand, SARIMA achieves its best performance again in Test 5 (MAPE 3.55%, MADP 2.58%), but its accuracy is still lower than HW's. The fact that both models are more effective in Test 5 is mainly attributed to the largest number of observations. The sample size for this test is larger than for Tests 1 – 4 and this enables the models to track the underlying patterns more effectively. Furthermore, the R^2 obtained in Test 5 is the highest for both models. This suggests that when the dataset is updated with new observations, there is upside potential for both models in terms of their performance. However, it should be noted that SARIMA models are more dependent on sample size than Exponential Smoothing, which relies more heavily on the prior period of each forecast. Yet, a larger sample enhances also the adaptive forecasting employed under the HW approach as it facilitates the better selection of β and γ smoothing constants.

A point that deserves special attention is the way the two methods behave in the tourist arrivals' fluctuations from 2011 to 2013. Focusing on August's peak, it is observed that arrivals dropped from 2,923,458 in 2011 to 2,679,376 in 2012 and they went back up again in August 2013 (2,942,170). It turns out that none of the models manages to track those changes. Both models predict an increase for 2012 and a decrease in 2013 (with HW generating forecasts which are closer to the actual values). This failure has its roots in the structure of those models. They both rely on past values and they largely base their predictions on patterns of past periods. In all of the above-mentioned cases, the forecasts are affected by the trend of the previous year and this prevents them from capturing those unexpected changes. This goes down as a weakness of this kind of modelling approaches. However, we should also take into account the small number of observations in those tests. Especially ARIMA models require large data sets in order to perform satisfactorily.

For 2016-2018 both models predict a rising trend of tourist arrivals, which is in line with expectations. With 2015 as a reference year, Exponential Smoothing estimates a 5.5% average increase for 2016, 10.3% for 2017, and 15.1% for 2018. The corresponding figures for SARIMA are 6%, 15.2%, and 23.8% respectively. It seems that SARIMA provides more optimistic projections for the long term, drawing on the rising trend that came up from 2014 onwards. It should be noted that the growing number of arrivals is not limited to the high season, but they also spread to the middle and low seasons.

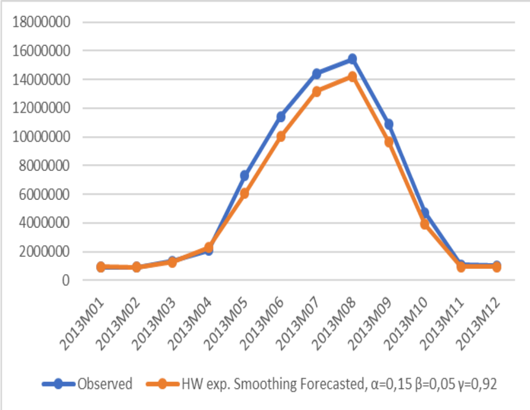
3.6.2. Nights – Total

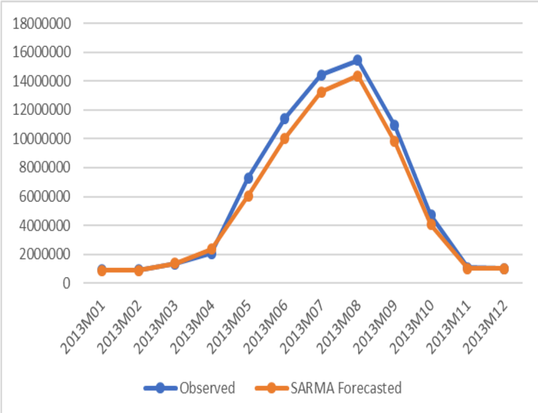
Nights total are divided into 4 sub-samples: The first one is from 2000 to 2012 and the forecast period is 2013, the second is from 2000 to 2013 with the purpose of forecasting the monthly values of 2014, the third one is from 2000 to 2014, with the forecast period being 2015, and finally, as before, we conduct out-of-sample analysis for 2016 – 2018.

Below are the forecasting tests for each sub-sample.

TEST 1: 2000 - 2012 => 2013

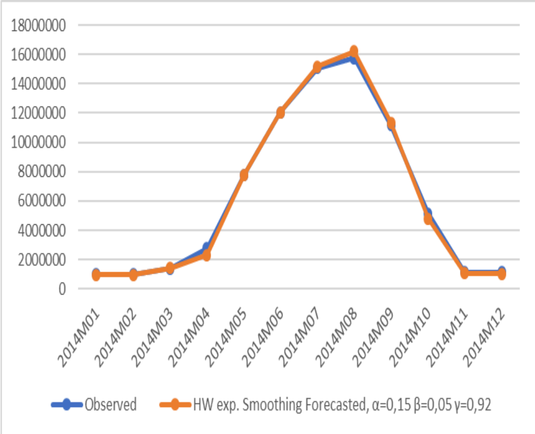
Period No	Month	Observed	HW Forecast	SARMA Forecast
157	2013M01	904955	936116	889961
158	2013M02	905347	909640	889255
159	2013M03	1327380	1293263	1368634
160	2013M04	2075559	2294957	2345894
161	2013M05	7280843	6058044	6042948
162	2013M06	11411713	10034667	10037858
163	2013M07	14418211	13182747	13260248
164	2013M08	15422707	14225147	14350920
165	2013M09	10907114	9656625	9813667
166	2013M10	4720176	3901027	4039961
167	2013M11	1066638	952261	1019830
168	2013M12	1028546	961903	1000943
Errors :				
MAPE			**9.02%**	**7.92%**
MAD			**631041**	**586021**
MADP			**10.6%**	**0.0000020%**
MSD			**721213006270**	**637167106892**
R2			**0.9756**	**0.9784**

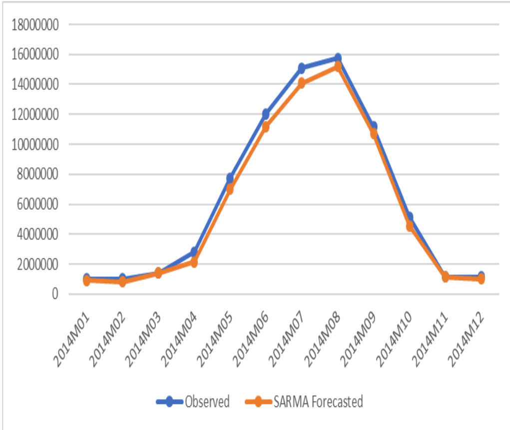




TEST 2: 2000 - 2013 => 2014

Period No	Month	Observed	HW Forecast	SARMA Forecast
169	2014M01	1011944	984737	927393
170	2014M02	1017317	986746	804270
171	2014M03	1386833	1442674	1387425
172	2014M04	2789288	2318459	2152589
173	2014M05	7753192	7755269	6977704
174	2014M06	12040088	12042344	11198975
175	2014M07	15084228	15178375	14085440
176	2014M08	15731420	16198844	15200416
177	2014M09	11148789	11328773	10692549
178	2014M10	5149045	4796008	4547384
179	2014M11	1136678	1086957	1125866
180	2014M12	1141623	1056673	1012304
Errors :				
MAPE			**4.21%**	**8.93%**
MAD			**151504**	**439943**
MADP			**2.4%**	**0.0000014%**
MSD			**51712427970**	**302775986075**
R2			**0.9983**	**0.9902**





TEST 3: 2000 - 2014 => 2015

Period No	Month	Observed	HW Forecast	SARMA Forecast
181	2015M01	1054362	1066867	1105566
182	2015M02	1117262	1069349	967976
183	2015M03	1456316	1476722	1426479
184	2015M04	2994177	2843791	2731084
185	2015M05	8331185	8050607	7584523
186	2015M06	12148665	12551711	11916078
187	2015M07	15419780	15804359	14861569
188	2015M08	16527563	16634258	15606194
189	2015M09	11578112	11833333	11061044
190	2015M10	5288263	5386078	5042859
191	2015M11	1187823	1187948	1168206
192	2015M12	1228834	1181679	1134566
Errors :				
MAPE			**2.47%**	**5.63%**
MAD			**150535**	**319050**
MADP			**2.3%**	**0.0%**
MSD			**41905715854**	**183665841485**
R2			**0.9987**	**0.9999**

TEST 4: 2000 - 2015 => 2016, 2017, 2018

		HW		**SARMA**	
Month	Observed 2015	Forecast	% Difference	Forecast	% Difference
2016-01	1054362	1100623	4.39%	1252185	18.76%
2016-02	1117262	1153746	3.27%	1248666	11.76%
2016-03	1456316	1514337	3.98%	1579170	8.44%

2016-04	2994177	3075617	2.72%	3097068	3.44%
2016-05	8331185	8536902	2.47%	8187216	-1.73%
2016-06	12148665	12588671	3.62%	12176911	0.23%
2016-07	15419780	16033611	3.98%	15280738	-0.90%
2016-08	16527563	17181081	3.95%	16357939	-1.03%
2016-09	11578112	12089276	4.41%	11498398	-0.69%
2016-10	5288263	5533209	4.63%	5231903	-1.07%
2016-11	1187823	1240512	4.44%	1234802	3.96%
2016-12	1228834	1271847	3.50%	1217886	-0.89%
Average 2016		**3.78%**			**3.36%**
2017-01	1054362	1142307	8.34%	1252519	18.79%
2017-02	1117262	1197304	7.16%	1253792	12.22%
2017-03	1456316	1571329	7.90%	1569492	7.77%
2017-04	2994177	3191006	6.57%	3100645	3.56%
2017-05	8331185	8856186	6.30%	8171014	-1.92%
2017-06	12148665	13058030	7.49%	12139303	-0.08%
2017-07	15419780	16629560	7.85%	15242468	-1.15%
2017-08	16527563	17817708	7.81%	16305419	-1.34%
2017-09	11578112	12535853	8.27%	11474874	-0.89%
2017-10	5288263	5736977	8.49%	5233499	-1.04%
2017-11	1187823	1286057	8.27%	1252384	5.44%
2017-12	1228834	1318399	7.29%	1239851	0.90%
Average 2017		**7.64%**			**3.52%**
2018-01	1054362	1183990	12.29%	1269817	20.43%
2018-02	1117262	1240862	11.06%	1274773	14.10%
2018-03	1456316	1628321	11.81%	1587388	9.00%
2018-04	2994177	3306395	10.43%	3111848	3.93%
2018-05	8331185	9175469	10.13%	8161665	-2.03%
2018-06	12148665	13527389	11.35%	12110857	-0.31%
2018-07	15419780	17225509	11.71%	15202283	-1.41%
2018-08	16527563	18454335	11.66%	16259604	-1.62%
2018-09	11578112	12982429	12.13%	11450232	-1.10%
2018-10	5288263	5940746	12.34%	5236315	-0.98%
2018-11	1187823	1331601	12.10%	1271709	7.06%
2018-12	1228834	1364951	11.08%	1259992	2.54%
Average 2018		**11.51%**			**4.13%**

Again, all models fit the data very well, as shown by the high R^2. The values it takes are greater than 0.97 in all cases.

The results demonstrate the superiority of Exponential Smoothing over SARMA. With the exception of the first test, HW outperforms SARMA (3,4) (1,1) in all other cases. In test 1, MAPE is slightly lower for SARMA (7.92% versus 9.02%), but as the samples get larger the HW approach becomes more accurate. For the 2014 and 2015 forecasts the SARMA's MAPE is almost twice as high as that of HW.

Importantly, Exponential Smoothing manages to capture the upward trend in nights-total. Focusing on August values, they rose by 2% year-over-year from 2013 to 2014 and 5.1% from 2014 to 2015. While SARMA correctly predicts the rising trend from August 2013 to August 2014, it fails to identify that this trend would continue in August 2015 and mistakenly predicts a lower value. On the contrary, the HW approach is successful in tracking those changes.

The above results provide evidence that Exponential Smoothing can yield more reliable predictions for this specific variable than SARMA. Therefore, the out-of-sample forecasts of HW are perceived as more realistic in comparison to the respective figures of SARMA. Indeed, the 7.64% increase that HW predicts for 2016 and the 11.51% for 2017 are much closer to industry expectations than the 3.52% and 4.13% of SARMA.

3.6.3. Arrivals – Residents – Total

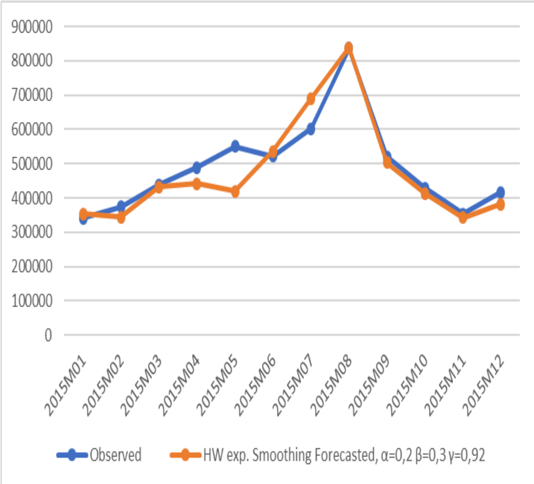
Arrivals – Residents are divided into the sub-sample 2000 – 2014, with the forecast period being 2015. In addition, we produce out-of-sample forecast for 2016 – 2018.

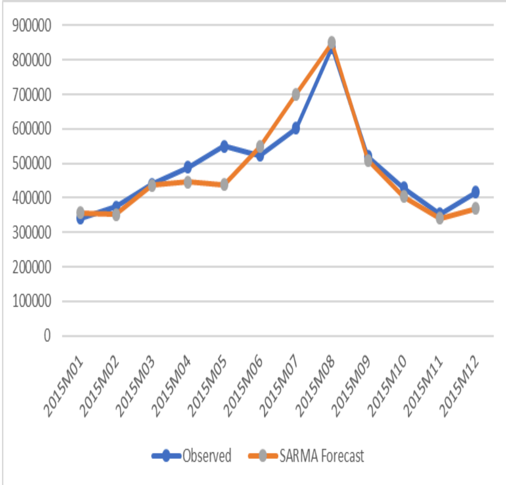
Below are the forecasting tests.

TEST 1: 2000 - 2014 => 2015

Period No	Month	Observed	HW Forecast	SARMA Forecast
181	2015M01	340579	353927	357094
182	2015M02	374333	344732	351473
183	2015M03	439043	432265	436433
184	2015M04	488354	442521	446098
185	2015M05	550000	420032	437993
186	2015M06	522652	536087	548808
187	2015M07	601938	690098	700226
188	2015M08	836737	838141	850680
189	2015M09	520410	502712	508786
190	2015M10	429080	413758	403938
191	2015M11	353463	342972	341023
192	2015M12	415984	382023	369585
Errors :				
MAPE			**6.82%**	**7.19%**
MAD			**33833**	**35853**

MADP			**6.9%**	**0.00021%**
MSD			**2488238280**	**2395613015**
R2			**0.8540**	**0.8594**





TEST 2: 2000 - 2015 => 2016, 2017, 2018

		HW		**SARMA**	
Month	Observed 2015	Forecast	% Difference	Forecast	% Difference
2016-01	340579	364921	7.15%	386265	13.41%
2016-02	374333	391100	4.48%	386495	3.25%
2016-03	439043	459301	4.61%	450467	2.60%
2016-04	488354	498027	1.98%	501970	2.79%
2016-05	550000	524798	-4.58%	517878	-5.84%
2016-06	522652	512161	-2.01%	546431	4.55%
2016-07	601938	611719	1.62%	684422	13.70%
2016-08	836737	847980	1.34%	867190	3.64%
2016-09	520410	527809	1.42%	525280	0.94%
2016-10	429080	436502	1.73%	442503	3.13%
2016-11	353463	361152	2.18%	358914	1.54%
2016-12	415984	420265	1.03%	402733	-3.19%
Average 2016			**1.75%**		**3.38%**
2017-01	340579	369883	8.60%	388191	13.98%
2017-02	374333	396412	5.90%	385937	3.10%
2017-03	439043	465532	6.03%	452723	3.12%
2017-04	488354	504776	3.36%	508792	4.19%
2017-05	550000	531902	-3.29%	514934	-6.38%
2017-06	522652	519086	-0.68%	548528	4.95%

2017-07	601938	619981	3.00%	689742	14.59%
2017-08	836737	859420	2.71%	856762	2.39%
2017-09	520410	534921	2.79%	527985	1.46%
2017-10	429080	442378	3.10%	447212	4.23%
2017-11	353463	366008	3.55%	358126	1.32%
2017-12	415984	425909	2.39%	406306	-2.33%
Average 2017			**3.12%**		**3.72%**
2018-01	340579	374845	10.06%	392119	15.13%
2018-02	374333	401725	7.32%	384817	2.80%
2018-03	439043	471764	7.45%	456339	3.94%
2018-04	488354	511526	4.74%	511400	4.72%
2018-05	550000	539006	-2.00%	511929	-6.92%
2018-06	522652	526011	0.64%	551843	5.59%
2018-07	601938	628243	4.37%	689703	14.58%
2018-08	836737	870860	4.08%	847267	1.26%
2018-09	520410	542034	4.16%	531445	2.12%
2018-10	429080	448253	4.47%	448727	4.58%
2018-11	353463	370864	4.92%	357932	1.26%
2018-12	415984	431553	3.74%	410151	-1.40%
Average 2018			**4.50%**		**3.97%**

The R-squared is satisfactory for both models, as it is greater than 0.85. Thus, the two models are acceptable in terms of goodness of fit.

The forecasting results show that Exponential Smoothing performs slightly better than SARMA (3,4) (1,1) in the context of arrivals of non-residents. MAPE is lower by 0.37% for HW over SARMA. MAD is also lower by 2,020 points. On the other hand, MADP and MSD suggest that SARMA is more accurate than Exponential Smoothing. Overall, the two models have an almost equivalent performance. Yet, the greater reliability of MAPE and MAD measures, coupled with the better performance of HW in the preceding forecasts confer an edge on Exponential Smoothing over SARMA. From this perspective, the out-of-sample forecasts generated by HW are deemed more credible. However, the predictions of the two approaches for 2017 and 2018 do not differ significantly. Based on their forecasts, the expected average growth rate for 2017 is 3.1 – 3.7% and for 2018, 4.0 – 4.5%.

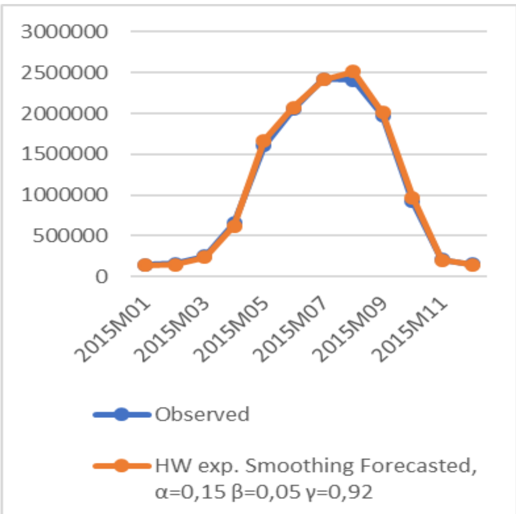
3.6.4. Arrivals – Non-Residents – Total

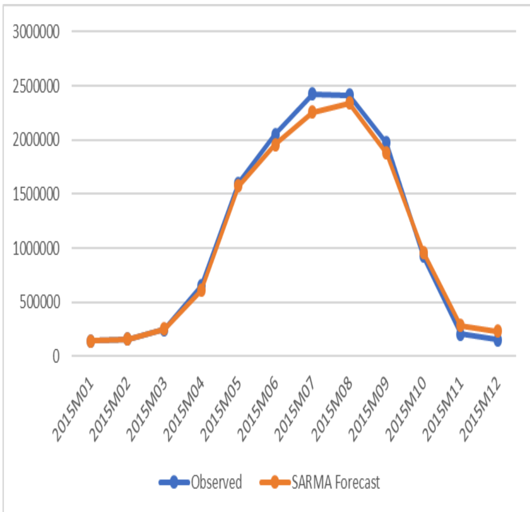
This time-series is divided into the sub-sample 2000 – 2014, with the forecast period being 2015. In addition, we conduct out-of-sample analysis for 2016 – 2018.

Below are the forecasting tests.

TEST 1: 2000 - 2014 => 2015

Period No	Month	Observed	HW Forecast	SARMA Forecast
181	2015M01	144852	137780	144291
182	2015M02	158260	147852	161799
183	2015M03	250462	237190	254443
184	2015M04	653432	623234	609026
185	2015M05	1602897	1669301	1575870
186	2015M06	2051321	2075122	1959918
187	2015M07	2423206	2414304	2256429
188	2015M08	2410735	2514710	2338328
189	2015M09	1972763	2009524	1881238
190	2015M10	922342	972835	962135
191	2015M11	205587	204405	283498
192	2015M12	152749	148314	233731
Errors :				
MAPE			**3.51%**	**10.58%**
MAD			**29742**	**58359**
MADP			**2.8%**	**0.0000071%**
MSD			**1752865401**	**5560950618**
R2			**0.9979**	**0.9932**





TEST 2: 2000 - 2015 => 2016, 2017, 2018

		HW	**SARMA**

Month	Observed 2015	Forecast	% Difference	Forecast	% Difference
2016-01	144852	153891	6.24%	166707	15.09%
2016-02	158260	166324	5.10%	199781	26.24%
2016-03	250462	261816	4.53%	303747	21.27%
2016-04	653432	680248	4.10%	717554	9.81%
2016-05	1602897	1693689	5.66%	1683591	5.03%
2016-06	2051321	2168853	5.73%	2123158	3.50%
2016-07	2423206	2560457	5.66%	2481637	2.41%
2016-08	2410735	2573971	6.77%	2494220	3.46%
2016-09	1972763	2107967	6.85%	2047618	3.79%
2016-10	922342	995354	7.92%	1029734	11.64%
2016-11	205587	220401	7.21%	313747	52.61%
2016-12	152749	162633	6.47%	262594	71.91%
Average 2016			**6.02%**		**18.90%**
2017-01	144852	164172	13.34%	271976	87.76%
2017-02	158260	177375	12.08%	301762	90.68%
2017-03	250462	279115	11.44%	400918	60.07%
2017-04	653432	724946	10.94%	813502	24.50%
2017-05	1602897	1804374	12.57%	1775001	10.74%
2017-06	2051321	2309824	12.60%	2217457	8.10%
2017-07	2423206	2725984	12.49%	2577429	6.36%
2017-08	2410735	2739480	13.64%	2587601	7.34%
2017-09	1972763	2242789	13.69%	2142218	8.59%
2017-10	922342	1058677	14.78%	1120761	21.51%
2017-11	205587	234349	13.99%	404607	96.81%
2017-12	152749	172871	13.17%	355011	132.41%
Average 2017			**12.89%**		**46.24%**
2018-01	144852	174453	20.44%	365174	152.10%
2018-02	158260	188425	19.06%	397174	150.96%
2018-03	250462	296413	18.35%	497147	98.49%
2018-04	653432	769645	17.79%	911419	39.48%
2018-05	1602897	1915060	19.47%	1873704	16.89%
2018-06	2051321	2450794	19.47%	2317022	12.95%
2018-07	2423206	2891512	19.33%	2676799	10.47%
2018-08	2410735	2904989	20.50%	2688650	11.53%
2018-09	1972763	2377611	20.52%	2243184	13.71%
2018-10	922342	1122001	21.65%	1223545	32.66%
2018-11	205587	248296	20.77%	507611	146.91%
2018-12	152749	183109	19.88%	458916	200.44%
Average 2018			**19.77%**		**73.88%**

The R-squared is higher than 0.99 for both models. Therefore, no concerns are raised about the goodness of fit.

In the 2015 forecasting exercise, SARIMA (3,1,3) (1,1,1) performs rather poorly compared to Exponential Smoothing. Its MAPE is about three time larger than HW's (10.6% versus 3.5%). This is consistent with the findings for the rest of the variables examined in this study.

The proposed SARIMA model has been adjusted in such a way as to capture the trend exhibited by this variable. Yet, it seems that the model overpredicts the tourist arrivals by residents and this causes this large error. This tendency passes on to out-of-sample forecasts and yield very high growth rates (i.e. 46.2% for 2017 and 73.9% for 2018). On the other hand, HW produces more conservative forecasts for those years (12.9% for 2017 and 19.8% for 2018).

3.7. Conclusion

The preceding analysis suggests that both Exponential Smoothing and SAR(I)MA are powerful modelling approaches that can generate satisfactory predictions for the future tourism demand in Greece. The R-squared values are greater than 0.95 in most cases, indicating that the proposed models fit very well the sets of observations.

The out-of-sample forecasts for the period 2016 – 2018 reveal a growing rate for all variables of this analysis. In fact, there is consensus between the two modelling approaches that a booming tourism demand is anticipated during this period. This is in line with industry expectations and press announcements that point to higher tourism flows to Greece.

The comparison of pertinent forecast errors shows that Triple Exponential Smoothing manages to predict the future values of almost all variables with remarkable accuracy. On several occasions, MAPE is as low as 2.5 - 3.5%. At the other edge of the spectrum, while in certain cases SAR(I)MA reaches a satisfactory MAPE of about 3.5%, in other cases MAPE exceeds 8%.

Overall, the multiple comparisons illustrated that HW outperforms SAR(I)MA in the majority of forecasting scenarios. These findings contradict several studies from the tourism literature, according to which the ARIMA class of models performs better than exponential smoothing. The outcome of the various forecasting exercises conducted within this study is that the HW approach is more suitable for the Greek tourism data. This is in line with the fact that in cases where the structure of the data generating process is changing – as in the dataset of this study -, HW is more appropriate than SAR(I)MA.

Therefore, Triple Exponential Smoothing is proposed as the major forecasting approach of variables pertaining to Greek tourism demand. On the other hand, SAR(I)MA, although less accurate, is still a robust modelling technique and can be used as a complement in order to enhance the reliability of forecasts. A further alternative could be the combined forecasting based on both the Triple Exponential Smoothing and the SAR(I)MA technique.

4. Final remarks

To finalize the report, a summary is given about the analyzed data as well about the analysis of forecasting methods. The paper is closed with conclusions which also give an outlook on the possible operation of forecasting the Greek tourism in the future, based on the results of this project.

4.1. Summary

The data set: This study is based on a data set of monthly observations, provided by ELSTAT. The focal point of the analysis includes the number of arrivals (in hotels & campsites, total, residents and non-residents) and the number of overnights (in hotels & campsites, total, residents and non-residents).

The analysis of the behavior of each variable indicates that in most cases there is a slight positive trend without any significant changes. The shape of variation over time diverges from linear trend. The number of overnights, total, (variable Nights-Total) behaves differently, as it exhibits a negative trend for three months. At the same time, the projection of the linear trend line in the future period 2017-2018 gives an indication of what will follow in the coming months. This of course is investigated more thoroughly in the forecasting approaches of section 3.

The next step involved the analysis by seasons, which justified the categorization into three groups of months: November - March (Low Season), October and April (Intermediate Season), and May - September (High Season). The mean and Anova tests show that the mean values of the variables Nights-Total and Arrivals-Total in the three seasons are significantly different, confirming the distinction between them. The ensuing correlation analysis showed that there is a high linear correlation between Nights-Total and Arrivals-Total ($R^2 = 0,98$). It also arises that such strong correlation is not present when it comes to composition factors, such as Campsites, Residents and Non-Residents.

The most significant origin countries in terms of number of arrivals are found to be Germany with a share of 15,01%, United Kingdom with 13,09%, France with

6,99%, and Italy with 6,54%. The majority of EU countries, such as Germany, UK, France, Italy, Sweden, Switzerland, Netherlands, Belgium, and additionally Cyprus, Serbia-Montenegro, and USA appear to have a relatively constant flow of arrivals. Balkan countries (Bulgaria, Albania, Turkey), Poland, and Russia exhibit a much higher variation of arrivals.

The analysis of trend lines by country of origin indicated that Italy, UK, Germany, Netherlands, USA, Belgium, and Sweden have an almost zero trend, Russia, Poland, Albania, France, Turkey, Switzerland, Serbia-Montenegro, Romania, and Bulgaria a positive trend, and finally Cyprus a negative trend.

It is noteworthy that time-series patterns vary significantly from country to country. The categorization in seasons made for the total number of arrivals does not match the pattern observed in the arrivals from certain countries, such as Albania, Bulgaria, and Turkey. On top of that, while the peak in total arrivals occurs in August, this is not always the case with arrivals from other countries, such as Germany and the US.

The forecasting analysis demonstrated that both Exponential Smoothing and SAR(I)MA are robust modeling approaches that can yield satisfactory predictions for the variables examined. The high R-squared values (above 0.95 in most cases) provide evidence that the data fit the model very well.

The evaluation of the forecasting accuracy of each model revealed that Triple Exponential Smoothing outperforms SAR(I)MA in most of the tests. This shows that the type of data used in this study can be modeled more effectively by means of Exponential Smoothing. Yet, ARIMA class of models remains a useful forecasting instrument and this is made evident not only by the findings of the relevant literature, but also by the forecast errors of the present study. Those errors may be higher than the ones generated by HW, but they remain within acceptable limits. In a nutshell, the HW approach is proven superior for this kind of analysis, but that is not to say that SARIMA should be discarded. In fact, a combination of the two methods may provide a more comprehensive picture of what lies ahead.

4.2. Conclusions and next steps

The intention of the forecasting project was to analyze forecasting methods with the aim (1) to find the suitable methodology for the routine-wise implementation of forecasting key statistics of Greek tourism in the future and (2) to make a proposal on how to develop a tool for forecasting the tourism development both as a policy tool for the Ministry of Tourism and as a campaigning tool for the Greek National

Tourism Organization (GNTO). The project has been conducted in cooperation with two Greek experts, Dr. Yiannis Smirlis (University of Piraeus) and Dr. Vangelis Tsioumas (The American College of Greece - DEREE) who will be available for the further development of the proposed methodology into a routine-wise operated forecasting tool.

This part of the report discusses the next steps to be taken in order to transform the proposed forecasting methodology in a routine-wise used tool: This tool shall annually or sub-annually provide the Ministry of Tourism and the GNTO, but also the businesses, the media, and the public of Greece with forecasts which are needed for policy planning and developing campaigns in Greek tourism.

The institutional framework: For the future routine-wise operation of the proposed forecasting methods, an institutional arrangement has to be established. The institution which shall have the responsibility for the future operation has to deal with the following tasks:

- Development of an IT system which allows handling the data and estimating the forecasts
- Establishing the data base for the forecasting system, and updating and editing the data
- Running the forecasting procedures according to an agreed schedule
- Production and dissemination of the forecasting reports

The data base: The forecasting project was restricted in the scope of analysis by the availability of tourism data. The main source of tourism data is ELSTAT; the available data were the number of arrivals and the number of overnights in hotels etc. and campsites, with breakdowns corresponding to inbound and domestic visitors and others. These data allow forecasts of certain tourism flows. Further areas of interest for the project are expenditures for tourism consumption, as well as economic determinants of inbound flows from certain countries of residence such as the effect of changes in the disposable income of the visitors, the price levels in Greece and alternative destinations, the travel costs, but also factors of the economic environment like the exchange rates, and factors like the Greek marketing expenditures, events like political unrests, and others.

Based on the experience of the forecasting project, some recommendations are provided that may help to improve the data base for the future forecasting system:

- The project was based on the most recent data available: The time-series were – in late spring of 2017 – available up to the end of 2015. For forecasting tourism flows in 2017 in reasonable quality, input data up to the end of 2016 should be available.

- ELSTAT's data should be provided in a form that will not require time-consuming transformations each time they are to be used. Downloading the time-series from the ELSTAT-website should be possible. A suitable format is proposed in section 2.1 of the report.
- The available data need to be enriched with the number of overnights by country of origin, at least for the important source countries of Greek tourism. This will allow a more complete analysis of the tourism flows and to this extent the development of region-specific forecasting models.
- ELSTAT's data base should be supplemented (1) by regional data (NUTS 2 level), at least for the tourism-relevant regions, as well as (2) by the expenditures of tourists at a reasonable level of detail.
- The consistency of the data provided by ELSTAT with corresponding data from other data sources like Eurostat and SETE and of the definitions given in the metadata reports of all these agencies should be checked; discrepancies should be documented.

The forecasting methods: The project report generally surveys forecasting methods which are reported in the statistical literature as relevant for tourism forecasting. Given the fact that only tourism flow data were available for the empirical part of the forecasting project, the range of methods which could be analysed was rather limited. Due to the lack of data and also of time, the involvement was also restricted with respect to the used statistical method.

The main result of the forecasting project is the demonstration that for tourism flows (number of arrivals, numbers of overnights), exponential smoothing and also the SAR(I)MA technique can yield satisfactory predictions. Given the fact that tourism flows and their forecasts are an important and crucial ingredient for policy planning and for developing campaigns, the results of the project are a reasonable starting point for the future routine-wise operation of the forecasting methods.

Methods that are based on more sophisticated models like Vector Autoregressive models, Error Correction models, Time Varying Parameter (TVP) models, etc. allow for deeper analyses of Greek tourism, in particular the analysis of the economic background of the tourism key statistics. For example, analysing the economic determinants of inbound flows from certain countries of residence such as the effect of changes in the disposable income of the visitors, the price levels in Greece and alternative destinations, the travel costs, but also factors of the economic environment like the exchange rates, and factors like the Greek marketing expenditures, events like political unrests, and others may result in more sophisticated models which allow for assessing the effects of changes in these economic determinants on the inbound flows; the forecasts may, e.g., reflect the increased travel costs or the reduced unemployment rate in Germany on the inflow of German visitors. The further development of forecasting models should be in the responsibility of the institution which shall deal with the future routine-wise operation of forecasting Greek tourism; cooperation with research institutions is highly recommended for this purpose.

Appendices

Appendix I. Descriptive Statistics of all variables included in the data set

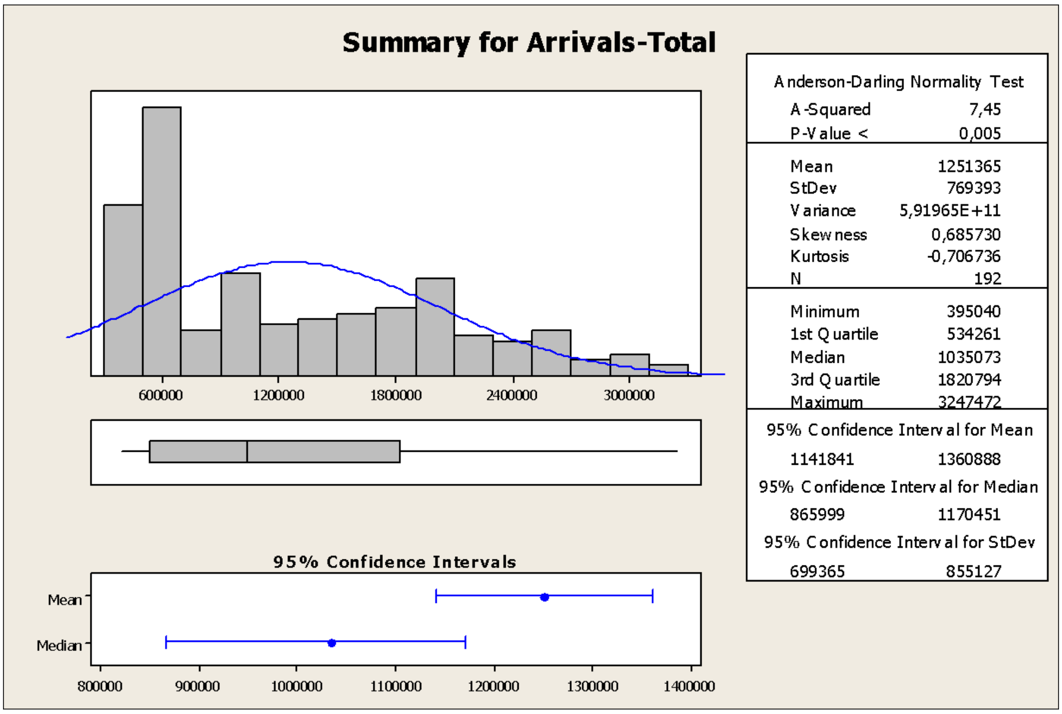


Figure II-4 Descriptive Statistics for Arrivals-Total

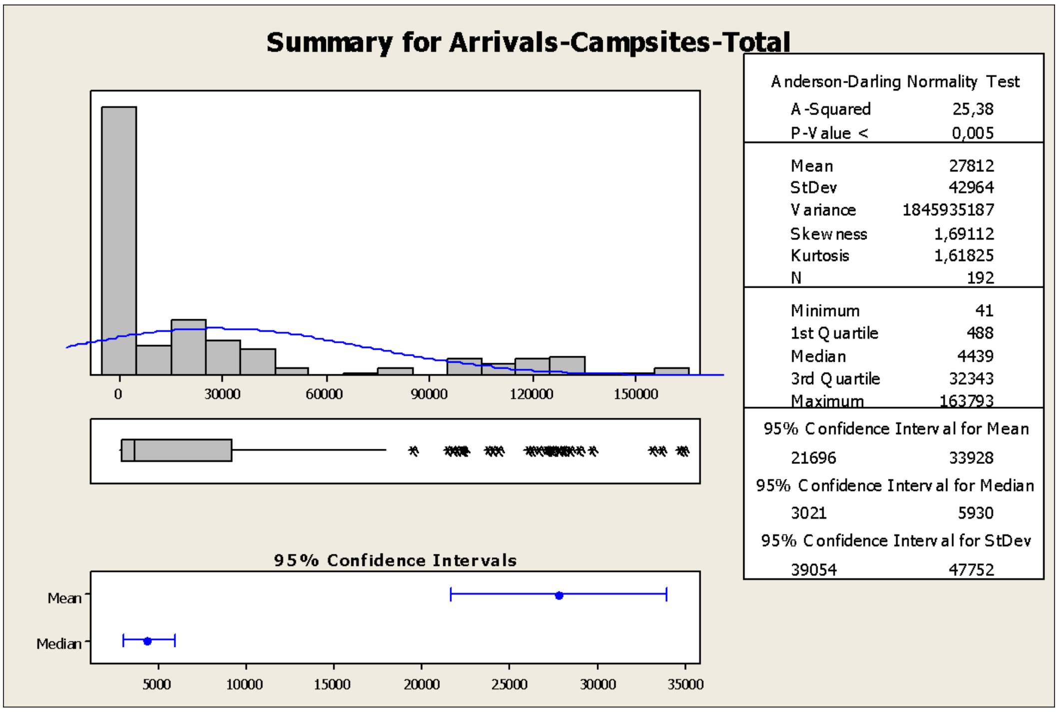


Figure II-5 Descriptive Statistics for Arrivals-Campsites-Total

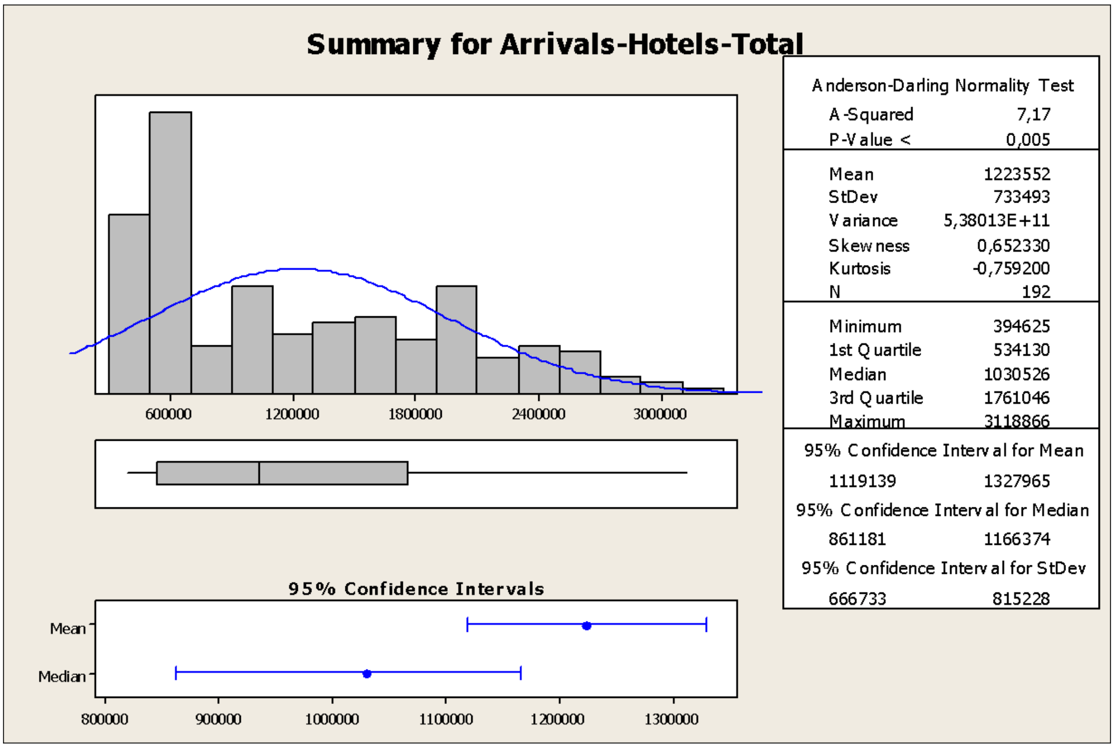


Figure II-6 Descriptive Statistics for Arrivals-Hotels-Total

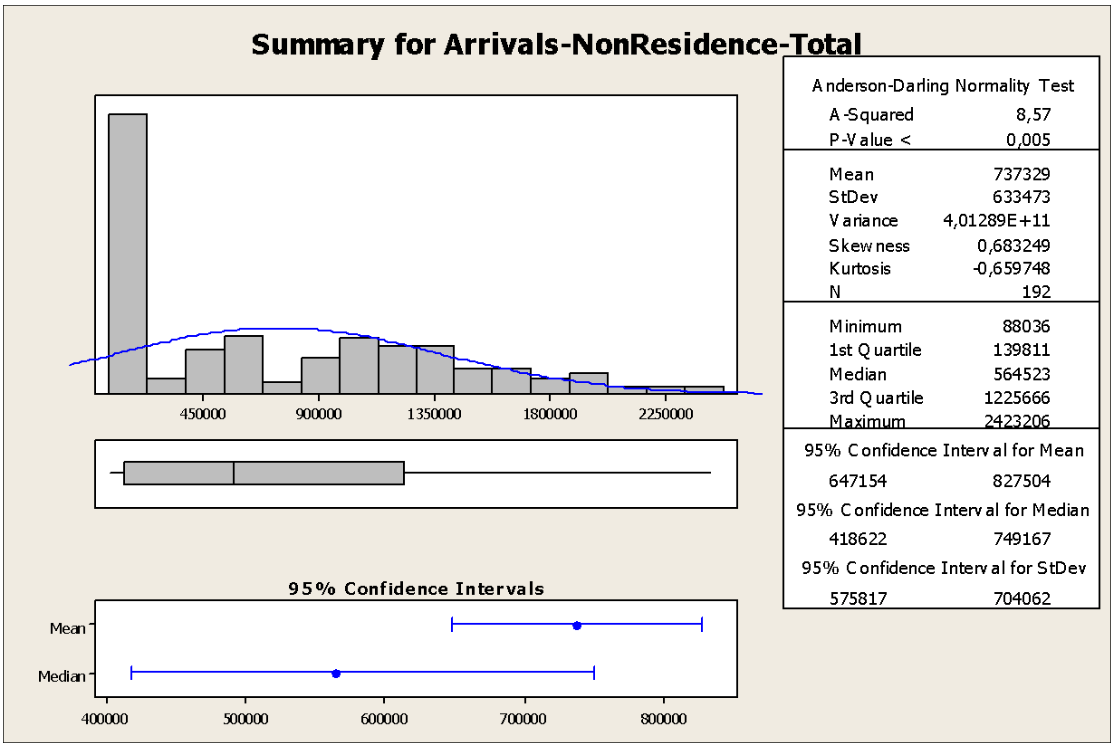


Figure II-7 Descriptive Statistics for Arrivals-Non-Residents-Total

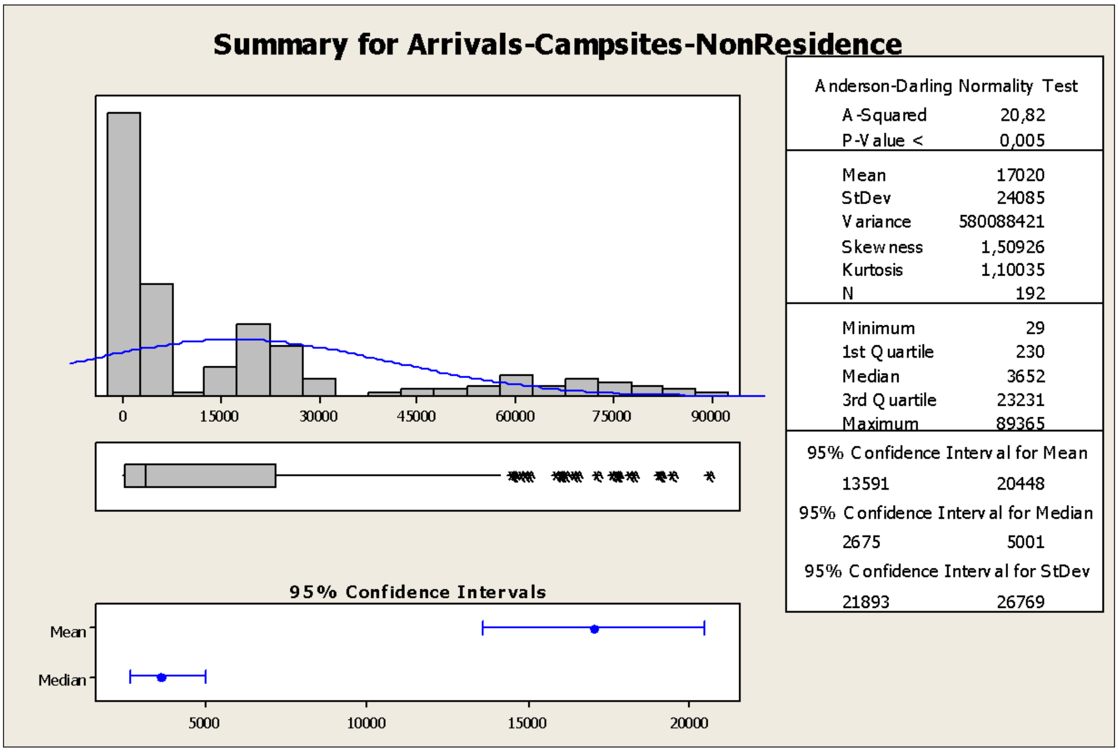


Figure II-8 Descriptive Statistics for Arrivals-Campsites-Non-Residents

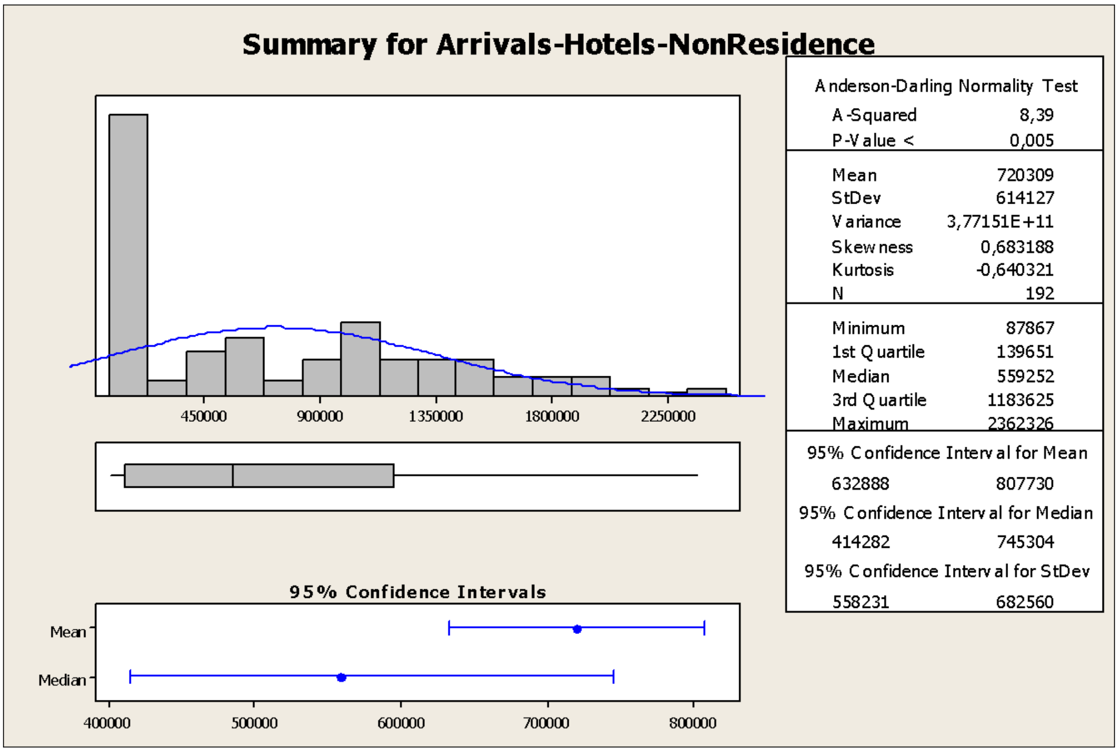


Figure II-9 Descriptive Statistics for Arrivals-Hotels-Non-Residents

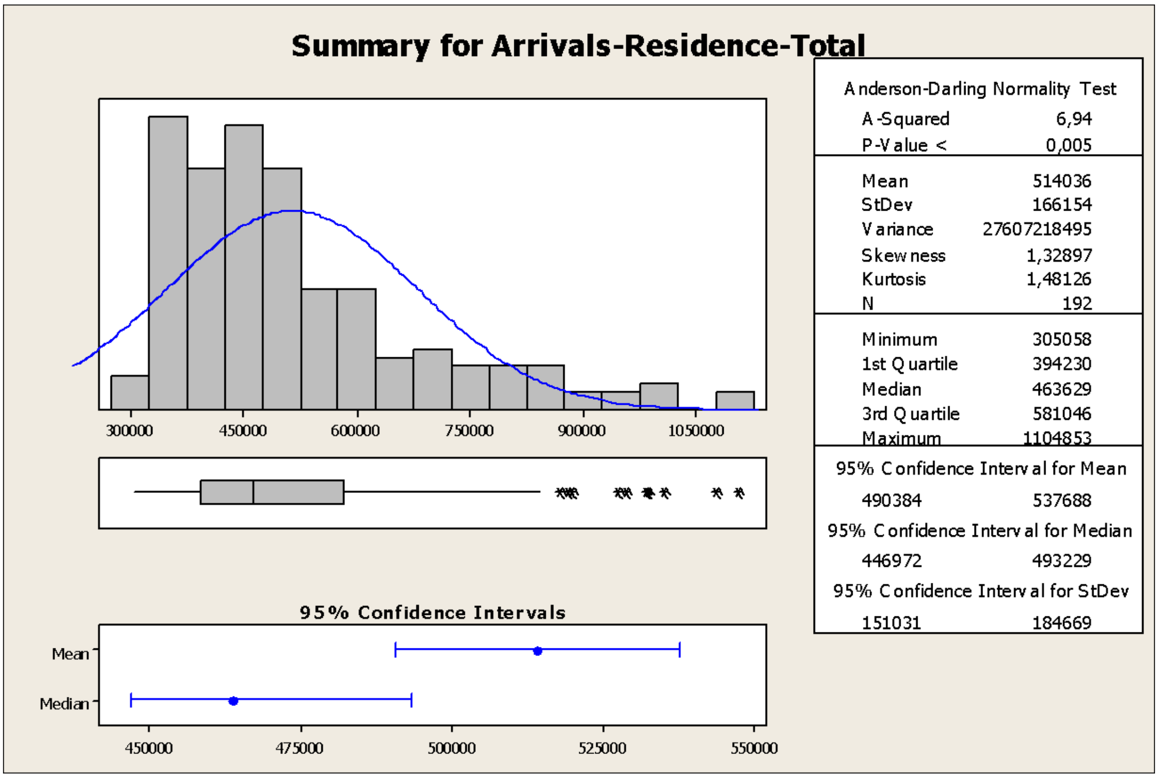


Figure II-10 Descriptive Statistics for Arrivals-Residents-Total

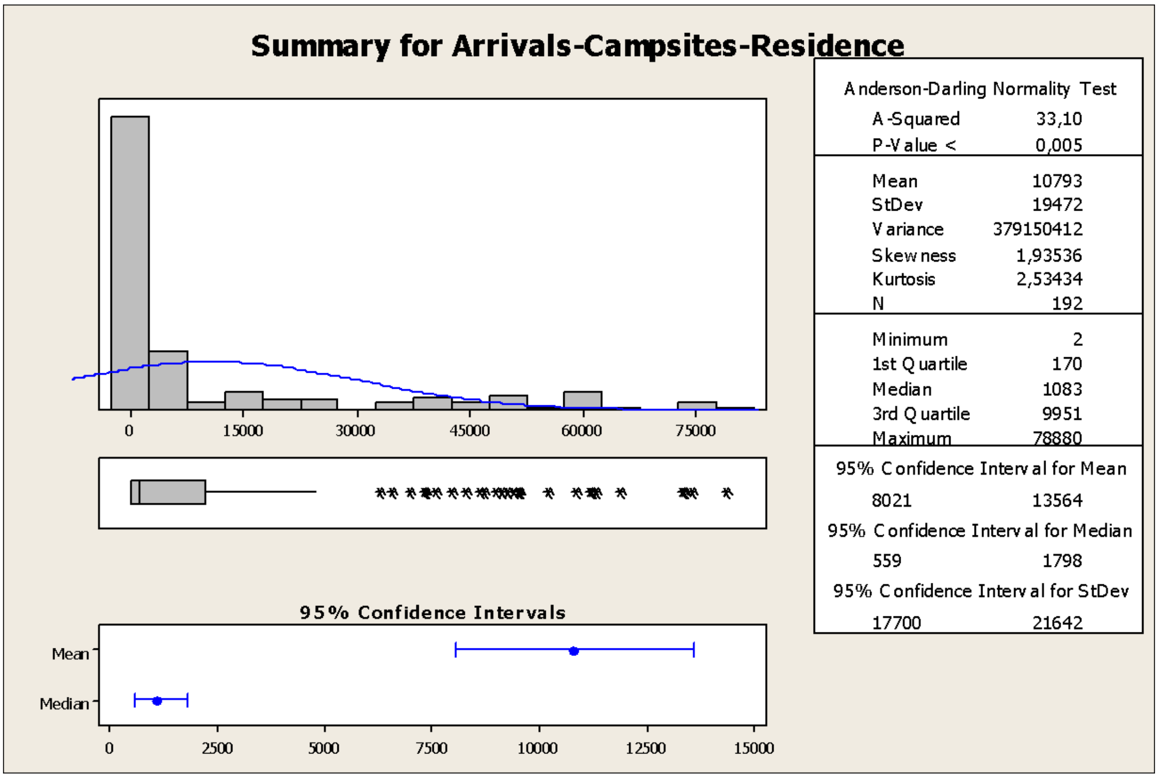


Figure II-11 Descriptive Statistics for Arrivals-Campsites-Residents

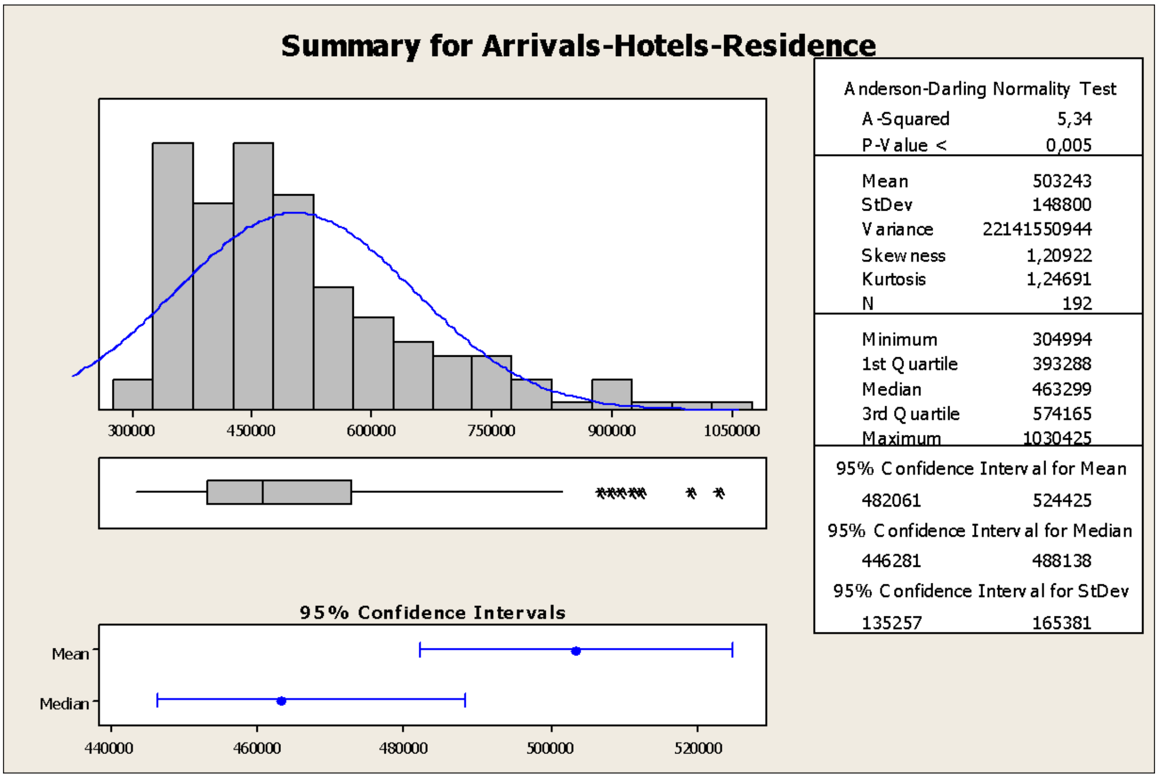


Figure II-12 Descriptive Statistics for Arrivals-Hotels-Residents

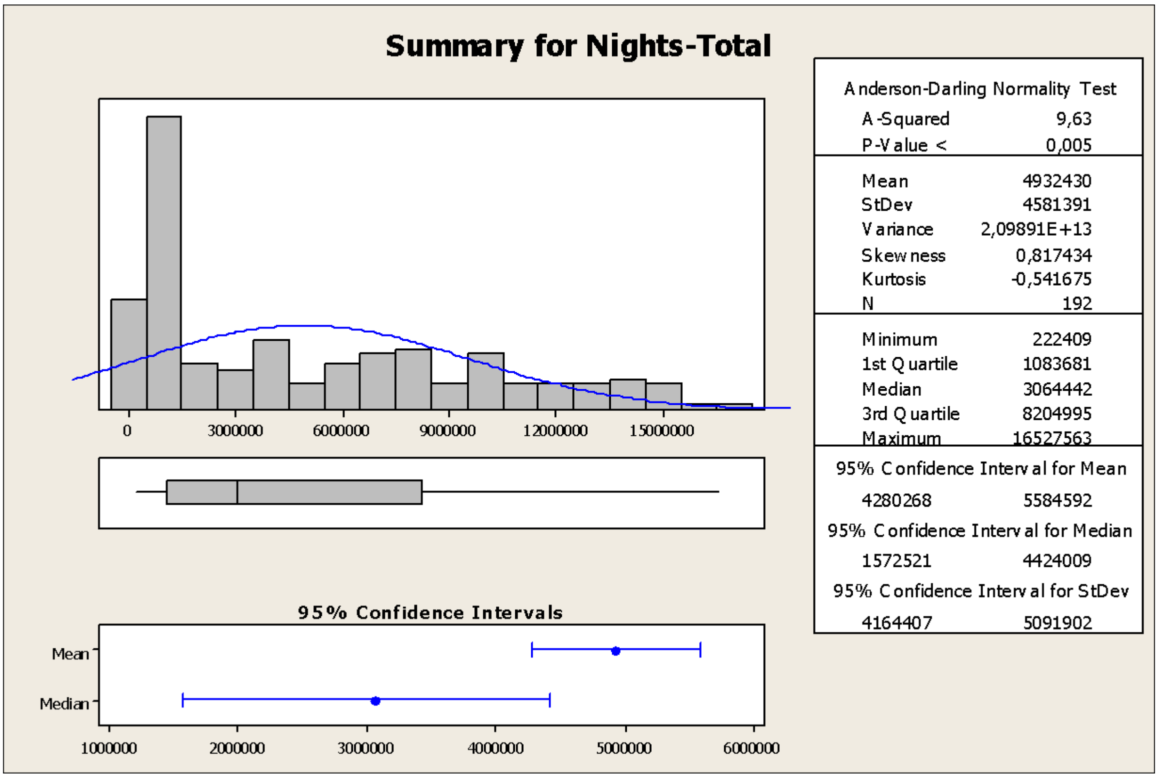


Figure II-13 Descriptive Statistics for Nights-Total

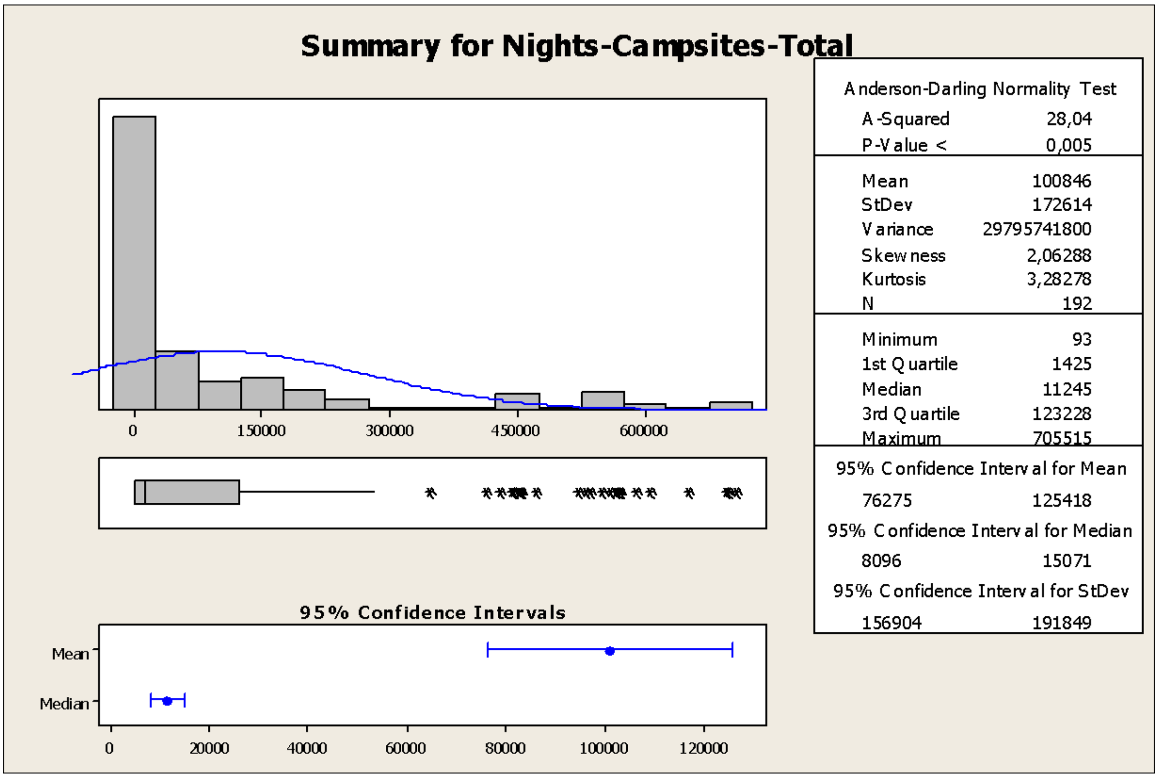


Figure II-14 Descriptive Statistics for Nights-Campsites-Total

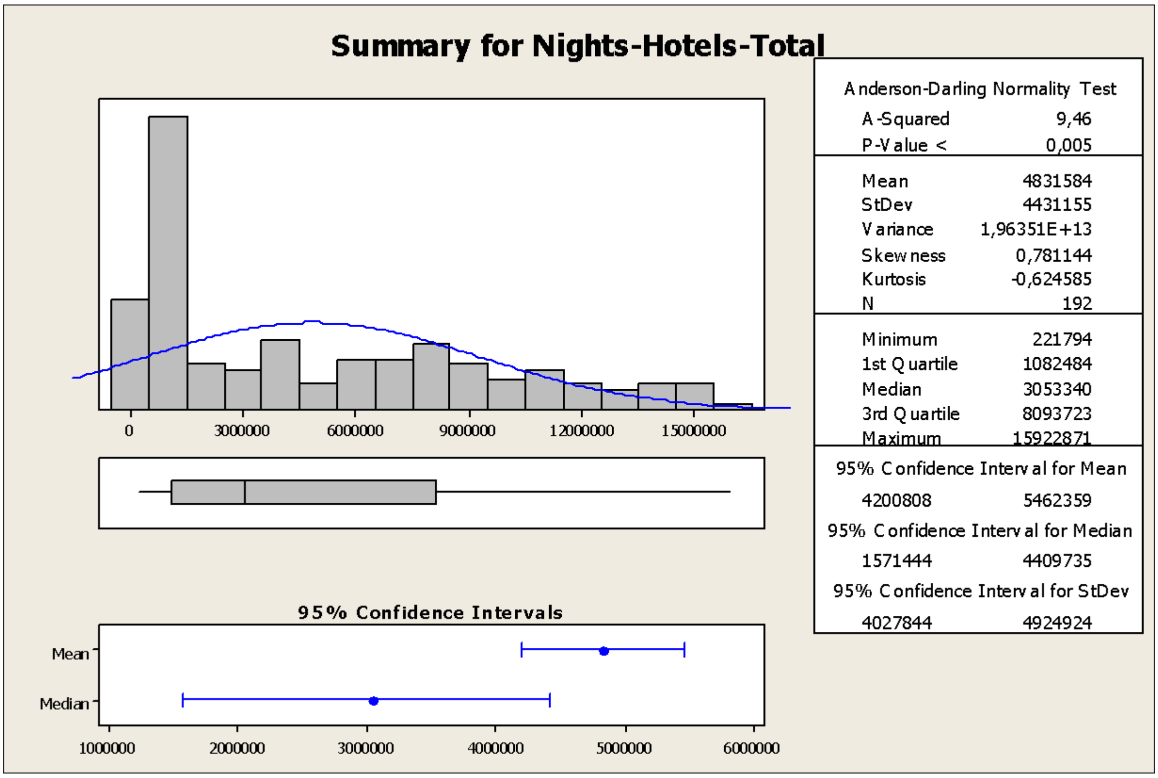


Figure II-15 Descriptive Statistics for Nights-Hotels-Total

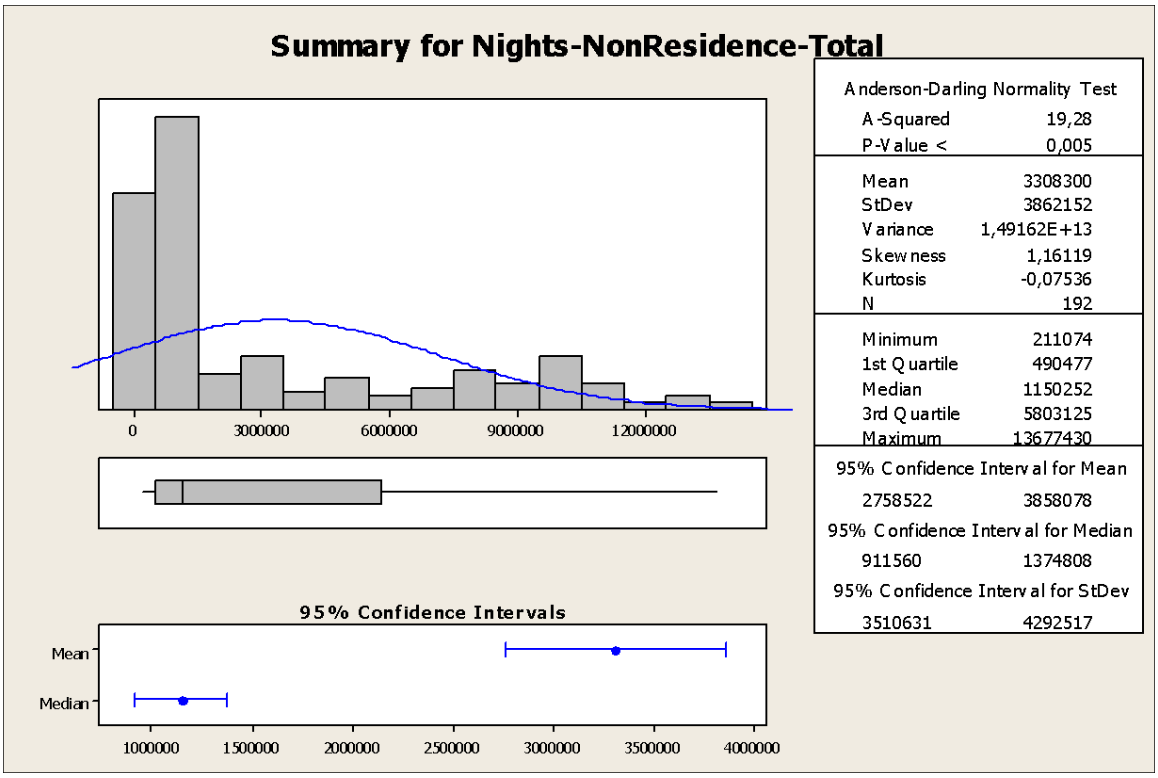


Figure II-16 Descriptive Statistics for Nights-Non-Residents-Total

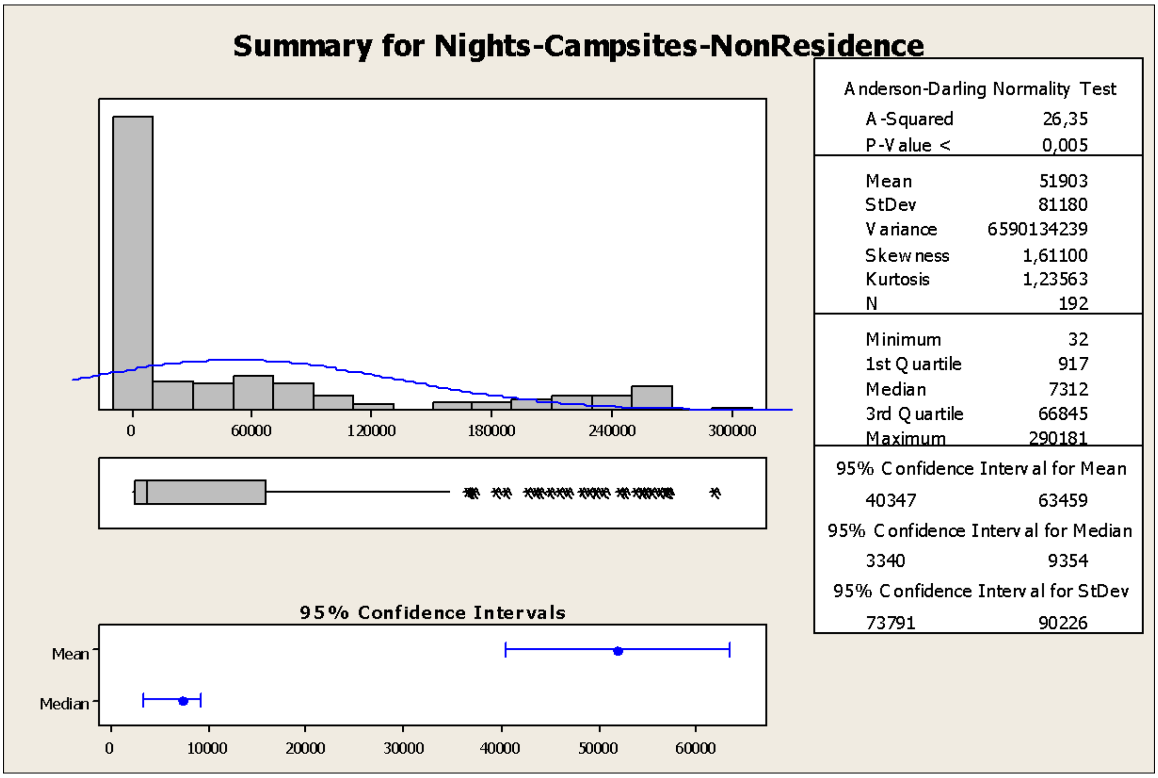


Figure II-17 Descriptive Statistics for Nights-Campsites-Non-Residents

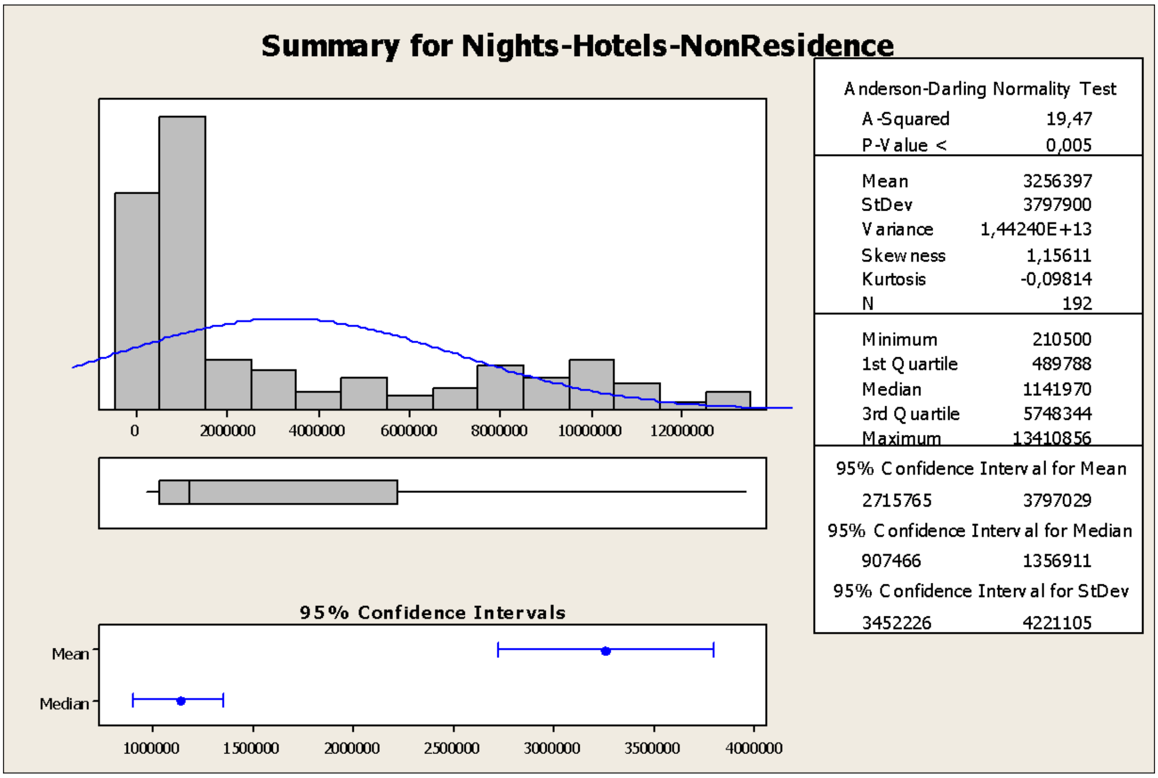


Figure II-18 Descriptive Statistics for Nights-Hotels-Non-Residents

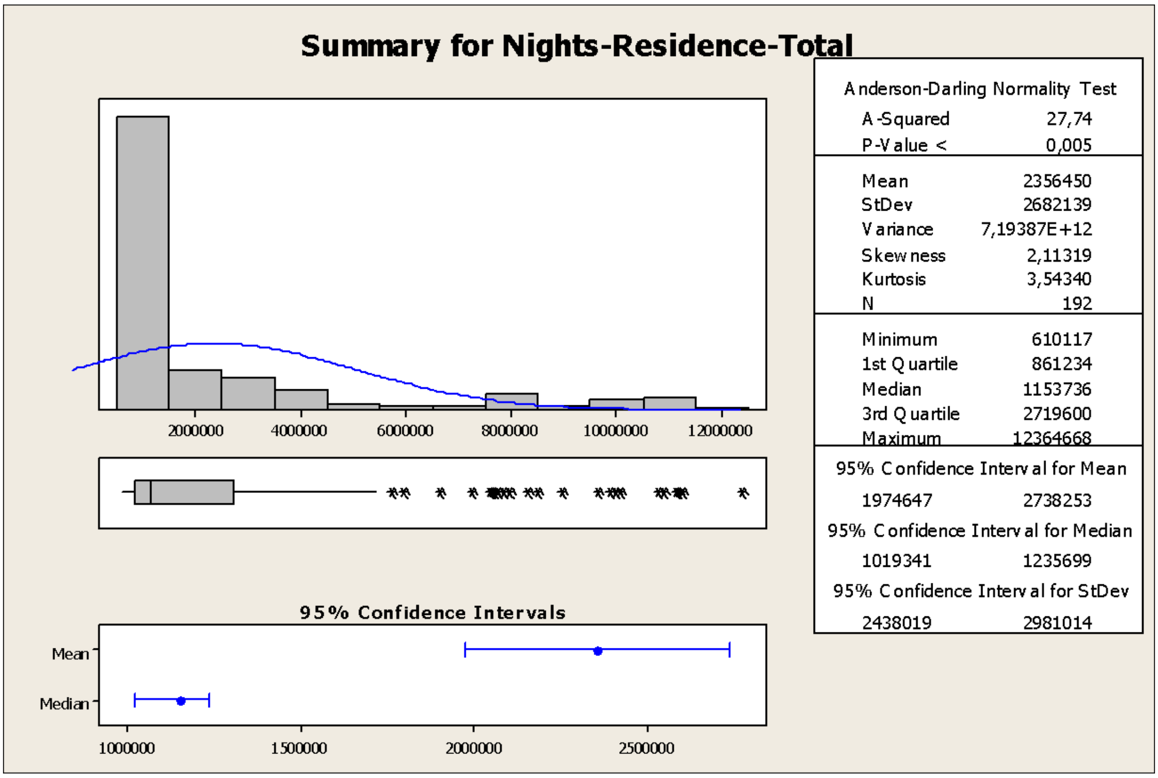


Figure II-19 Descriptive Statistics for Nights-Residents-Total

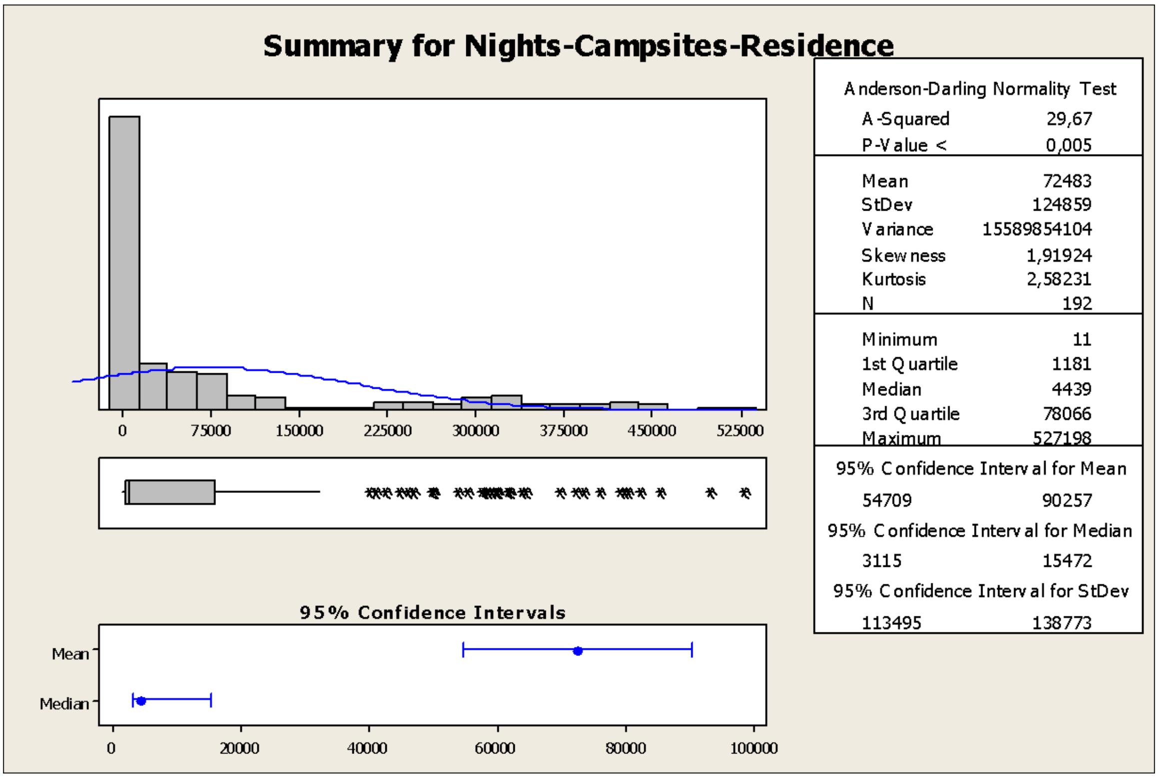


Figure II-20 Descriptive Statistics for Nights-Campsites-Residents

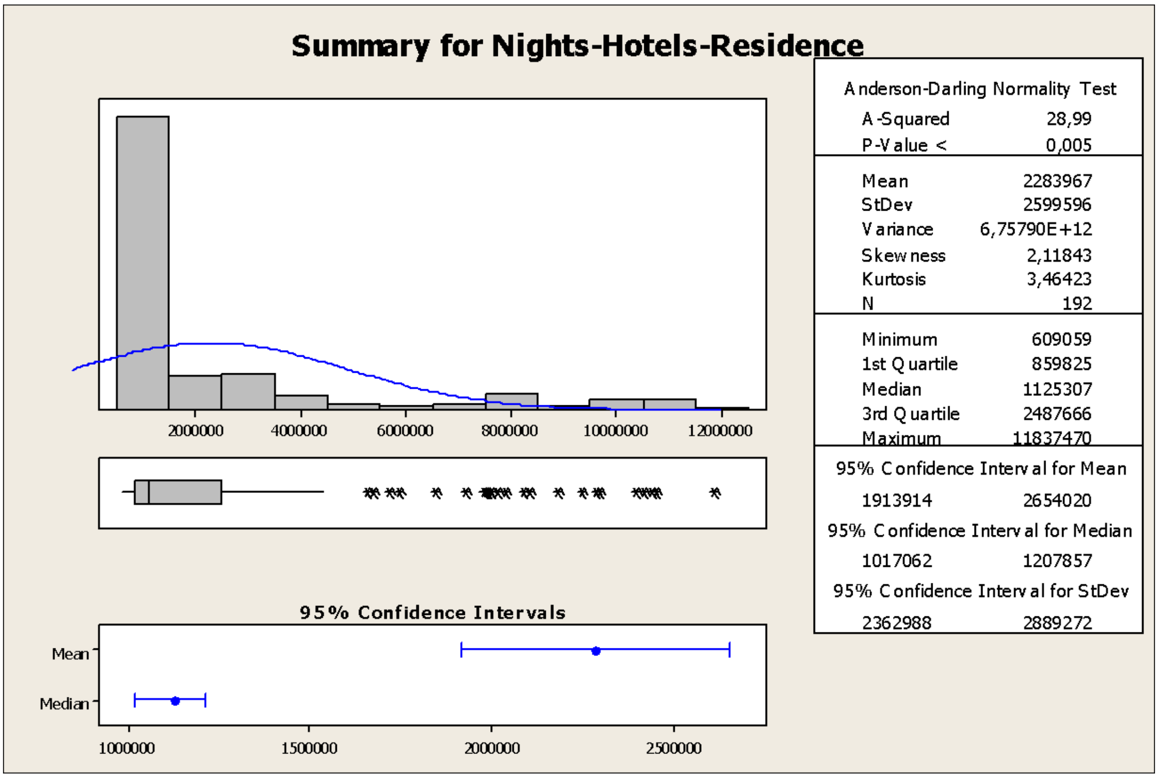


Figure II-21 Descriptive Statistics for Nights-Hotels-Residents

Appendix II. Plots of Nights-Total, Arrivals-Total by Month

01 January, Nights

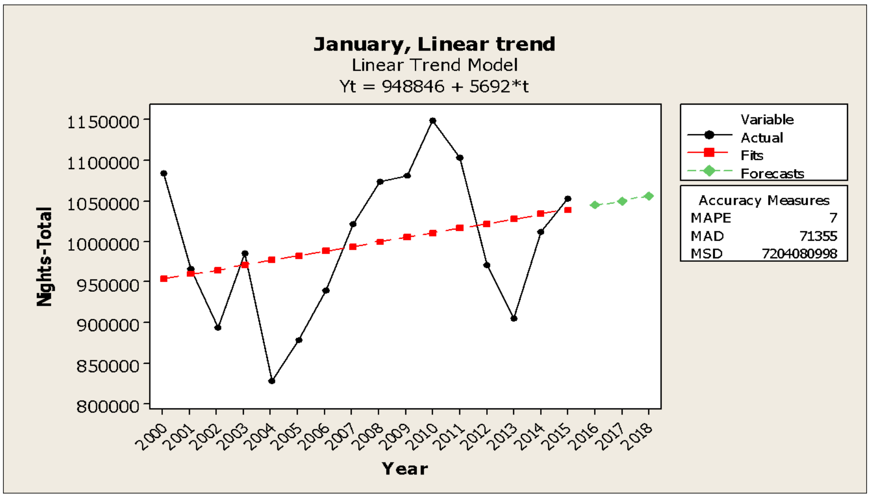


Figure II-1 January, Linear Trend for Nights-Total

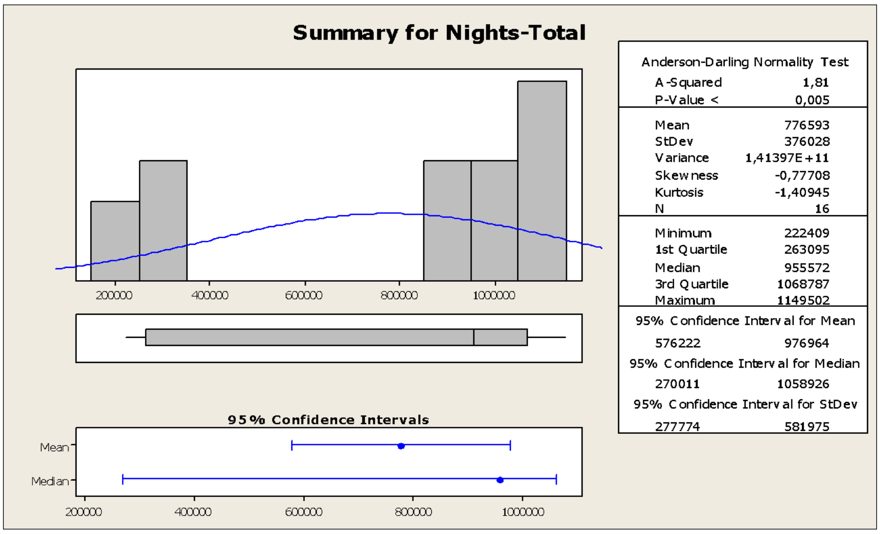


Figure II-2 January, Statistical Summary for Nights-Total

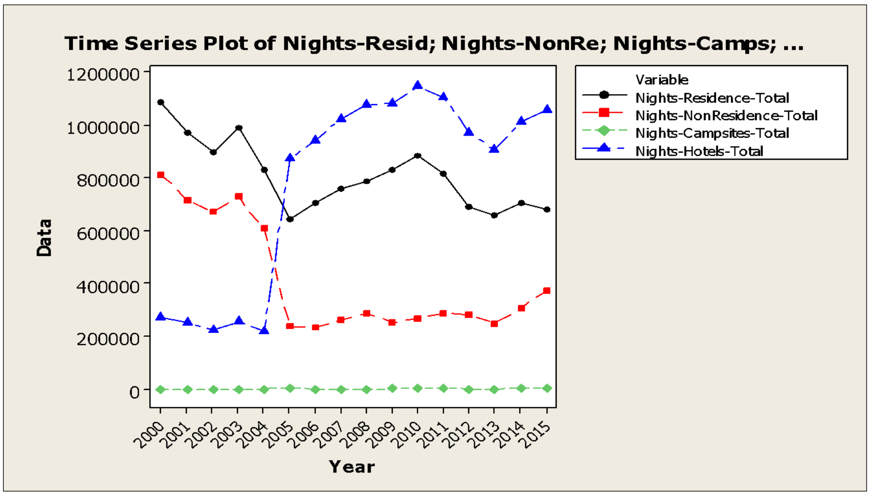


Figure II-3 January, break down time-series plot for Nights-Total

01 January, Arrivals

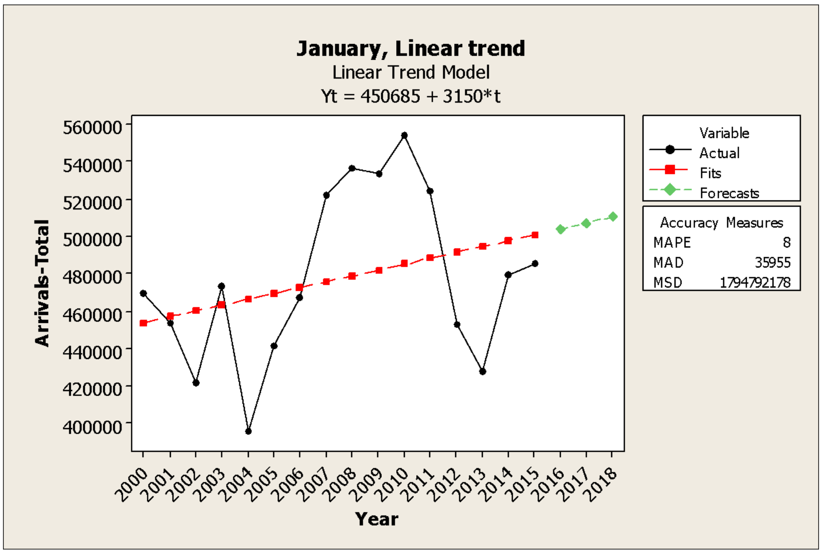


Figure II-4 January, Linear Trend for Arrivals-Total

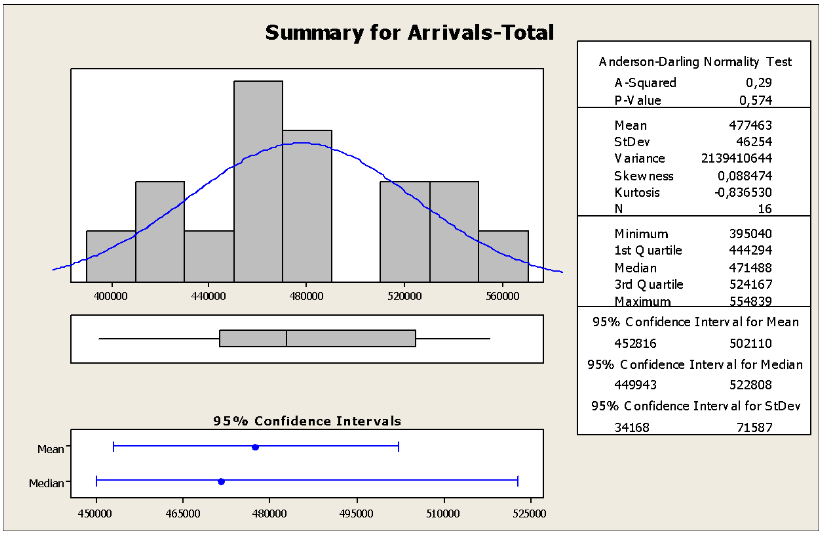


Figure II-6 January, Statistical Summary for Arrivals-Total

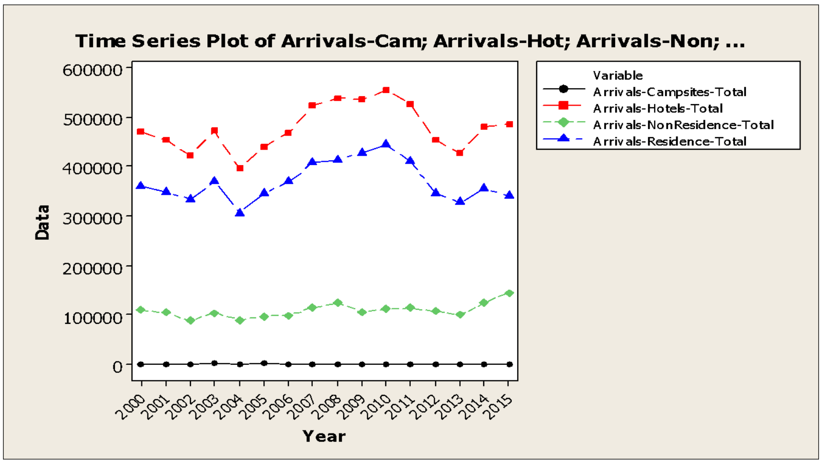


Figure II-7 January, break down time-series plot for Arrivals-Total

02 February, Nights

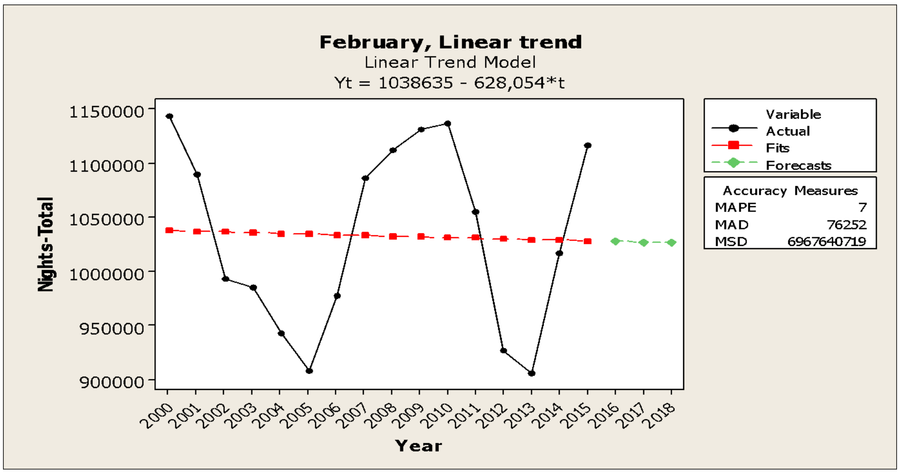


Figure II-8 February, Linear Trend for Nights-Total

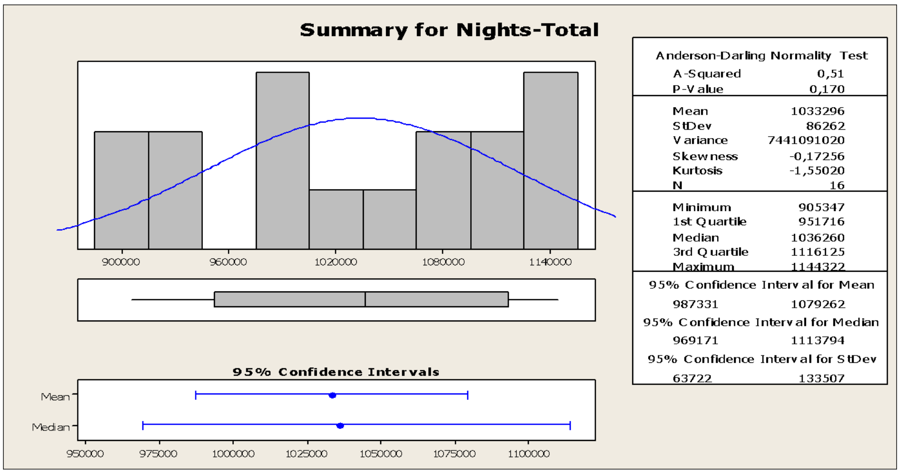


Figure II-9 February, Statistical Summary for Nights-Total

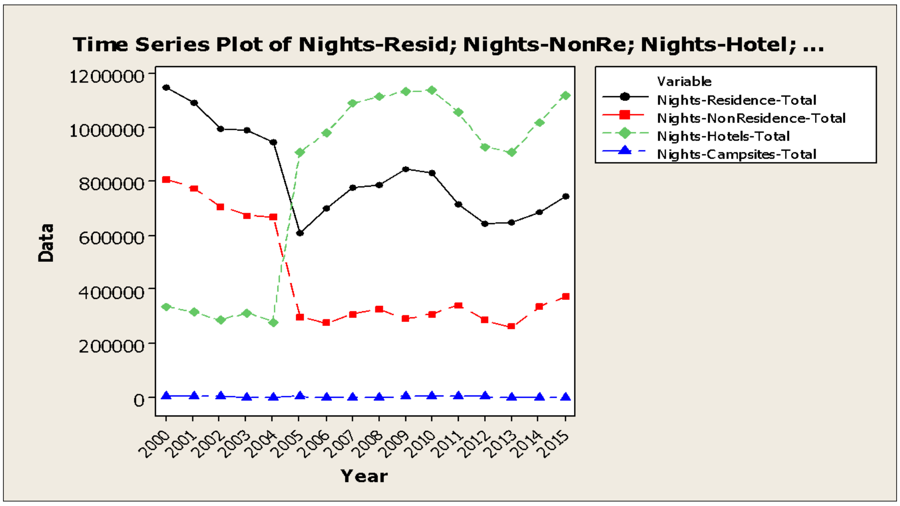


Figure II-10 February, break down time-series plot for Nights-Total

02 February, Arrivals

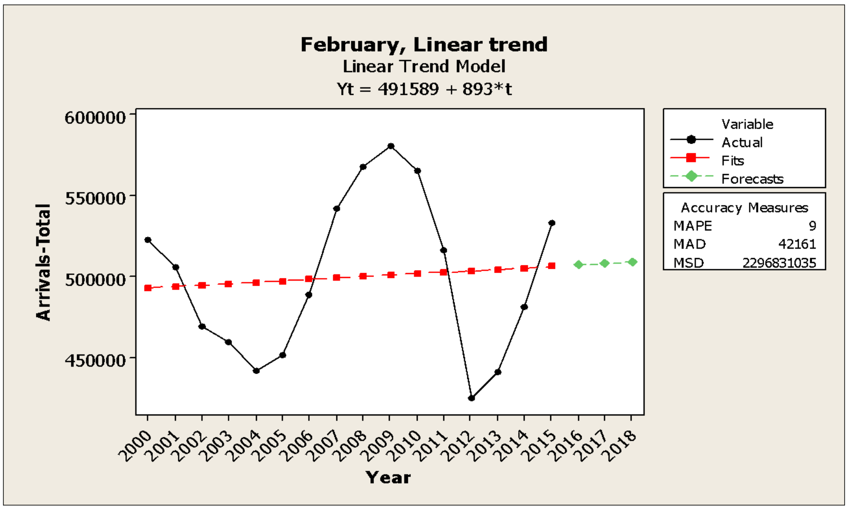


Figure II-11 February, Linear Trend for Arrivals-Total

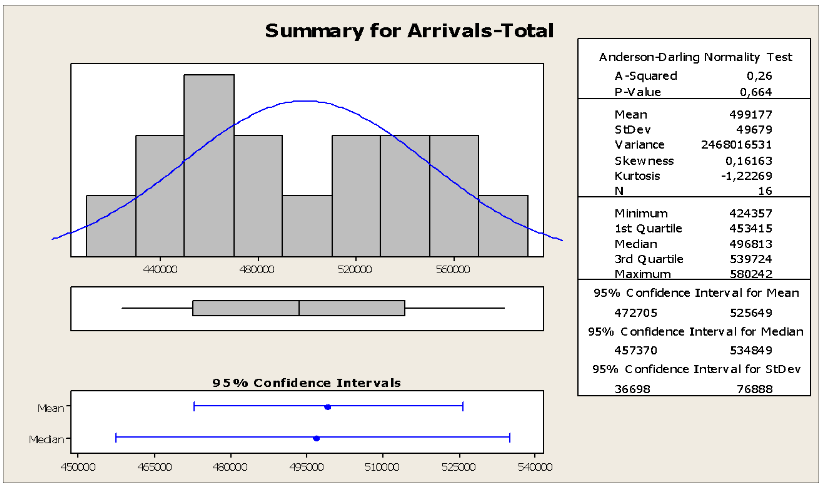


Figure II-12 February, Statistical Summary for Arrivals-Total

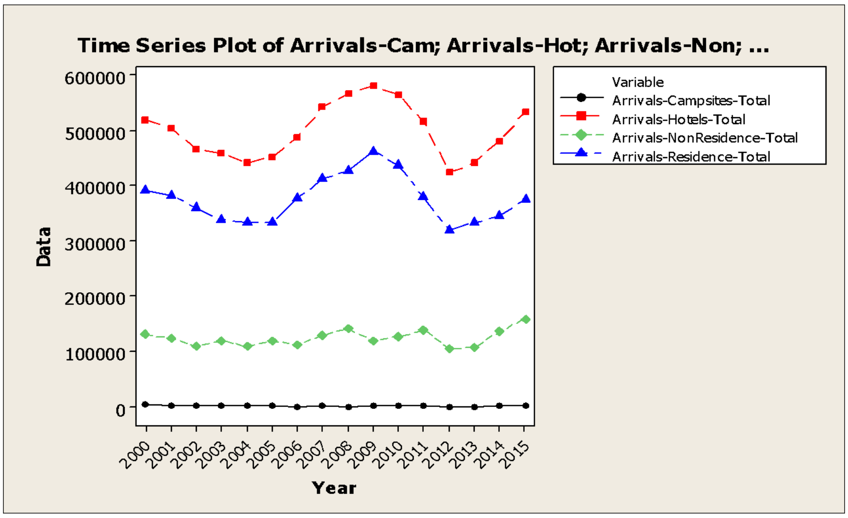


Figure II-13 February, break down time-series plot for Arrivals-Total

03 March, Nights

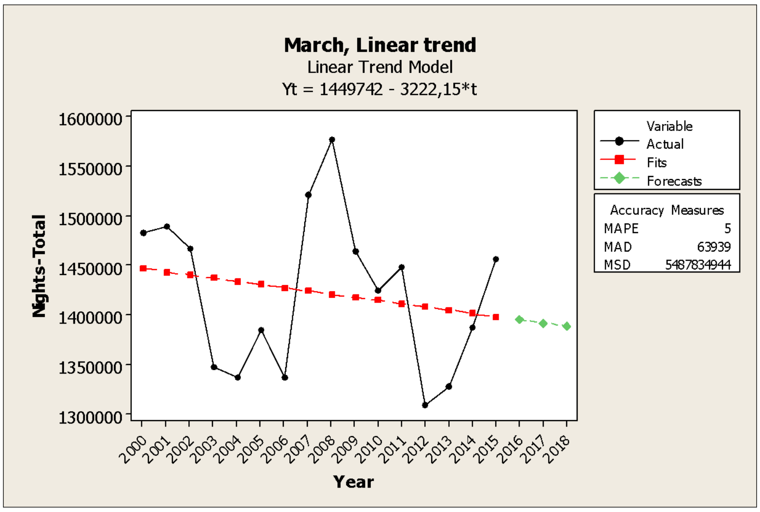


Figure II-14 March, Linear Trend for Nights-Total

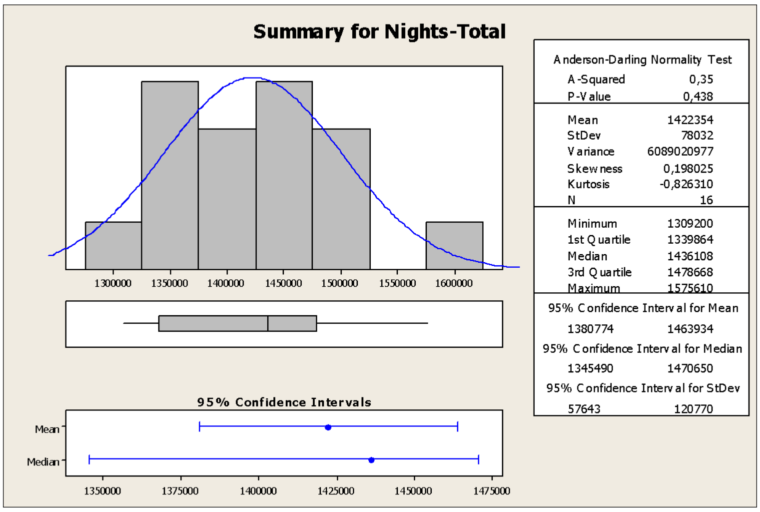


Figure II-15 March, Statistical Summary for Nights-Total

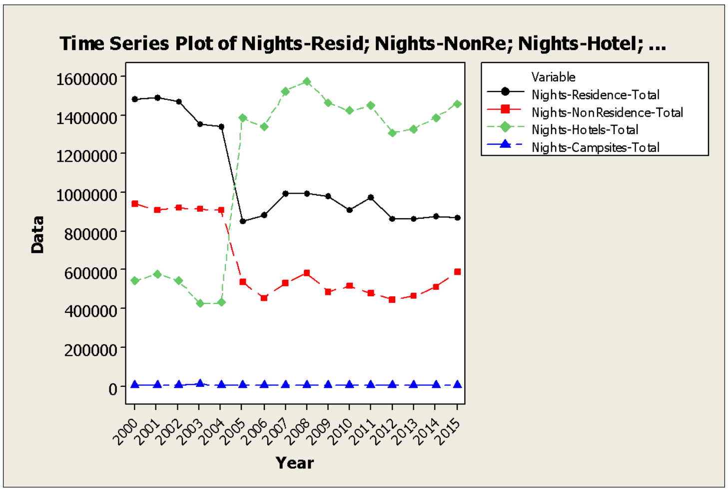


Figure II-16 March, break down time-series plot for Nights-Total

03 March Arrivals

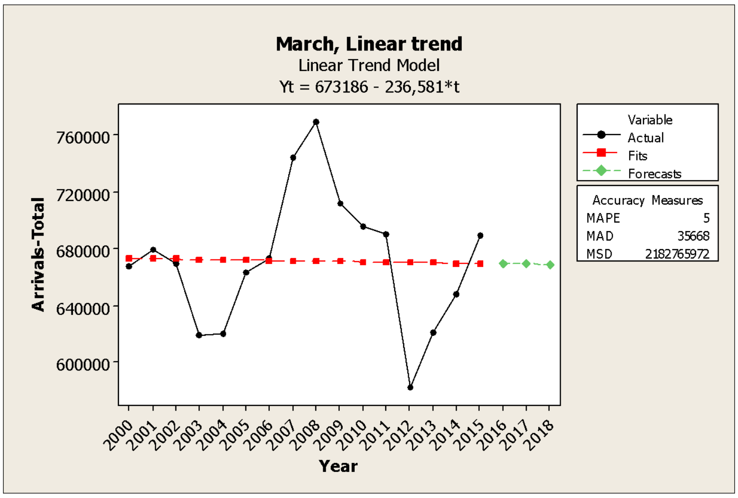


Figure II-17 March, Linear Trend for Arrivals-Total

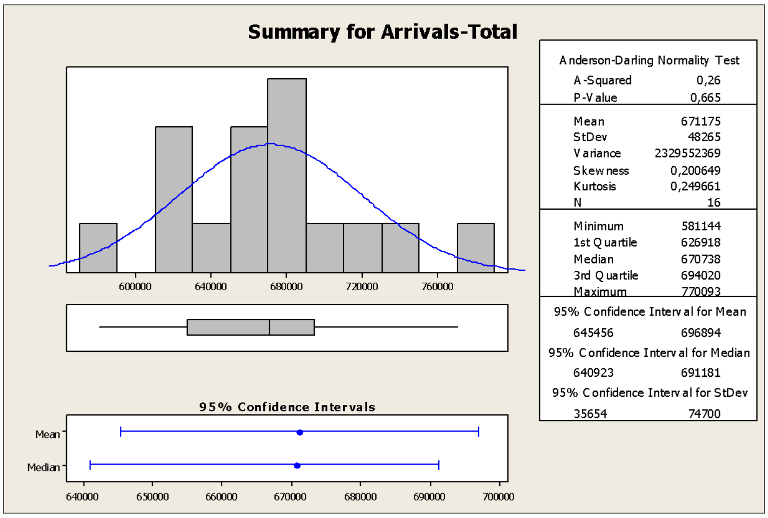


Figure II-18 March, Statistical Summary for Arrivals-Total

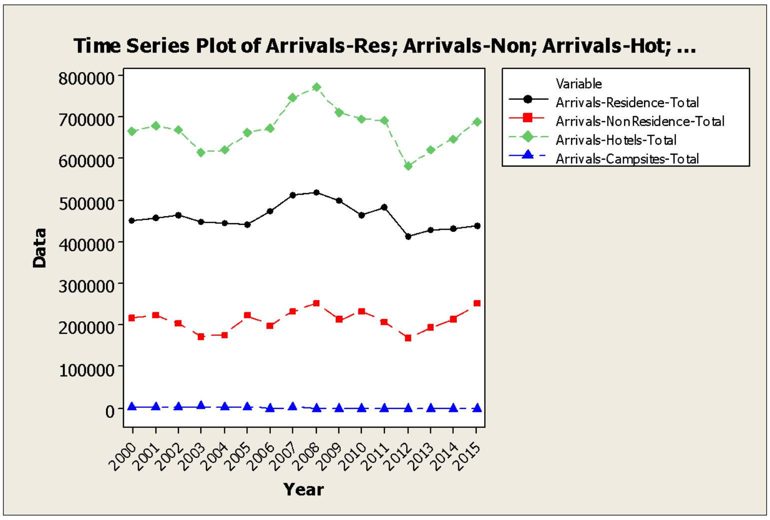


Figure II-19 March, break down time-series plot for Arrivals-Total

04 April, Nights

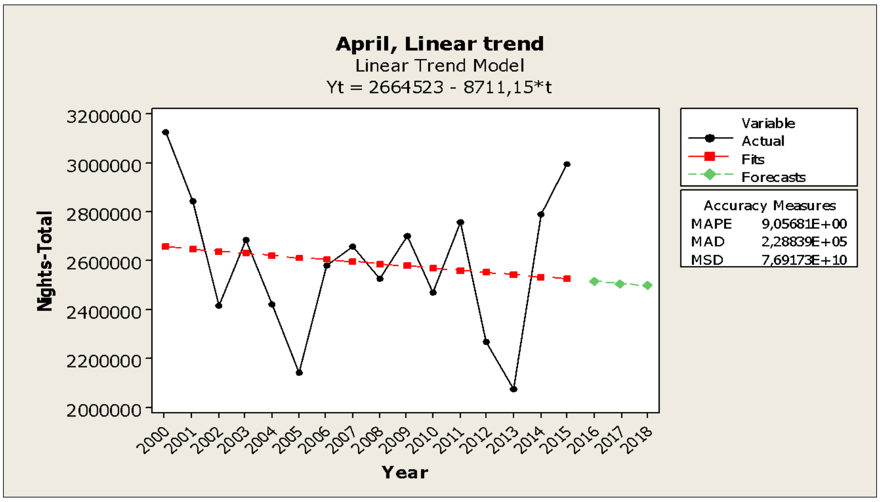


Figure II-20 April, Linear Trend for Nights-Total

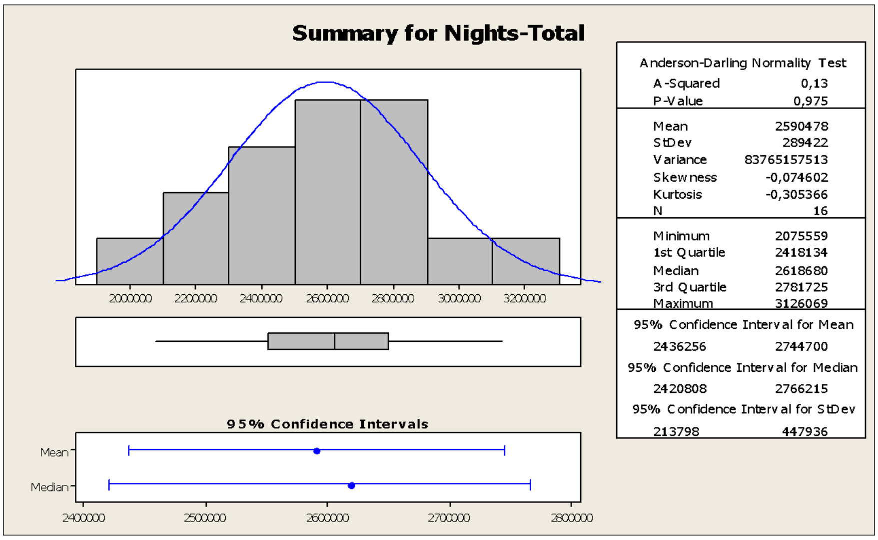


Figure II-21 April, Statistical Summary for Nights-Total

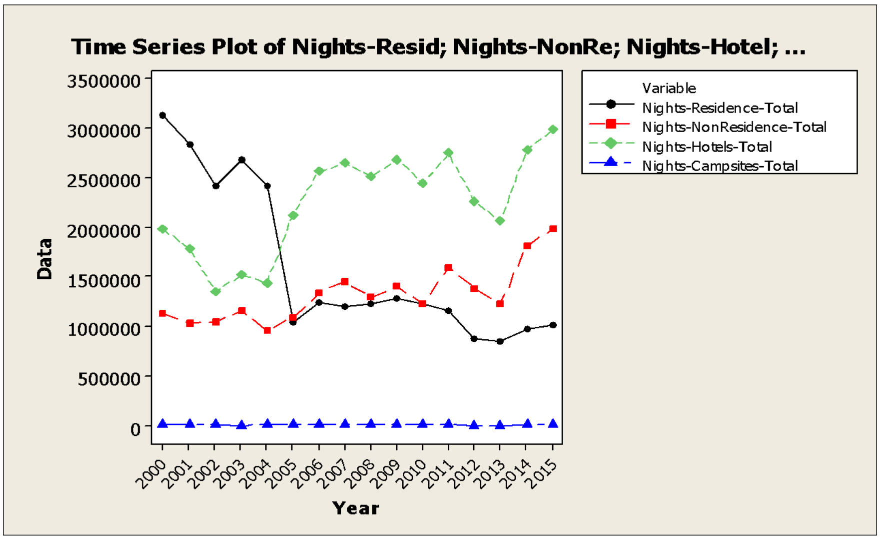


Figure II-22 April, break down time-series plot for Nights-Total

04 April, Arrivals

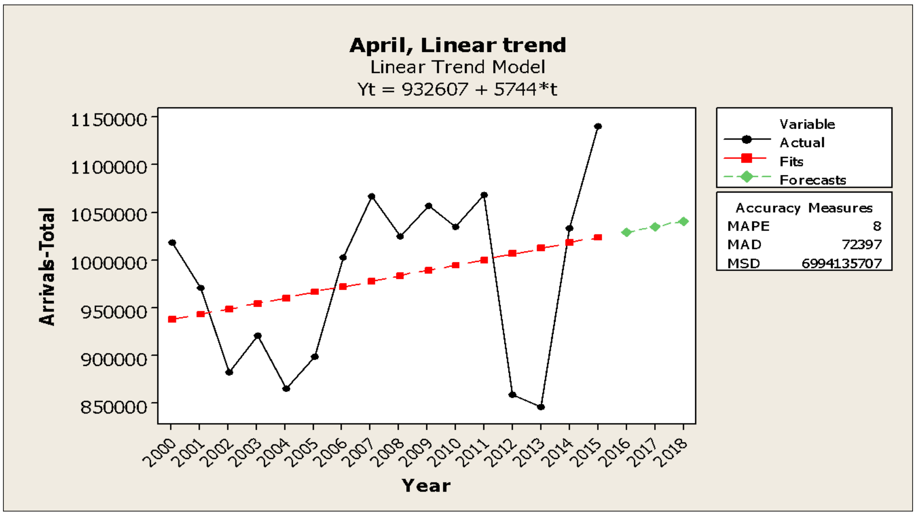


Figure II-23 *April*, Linear Trend for Arrivals-Total

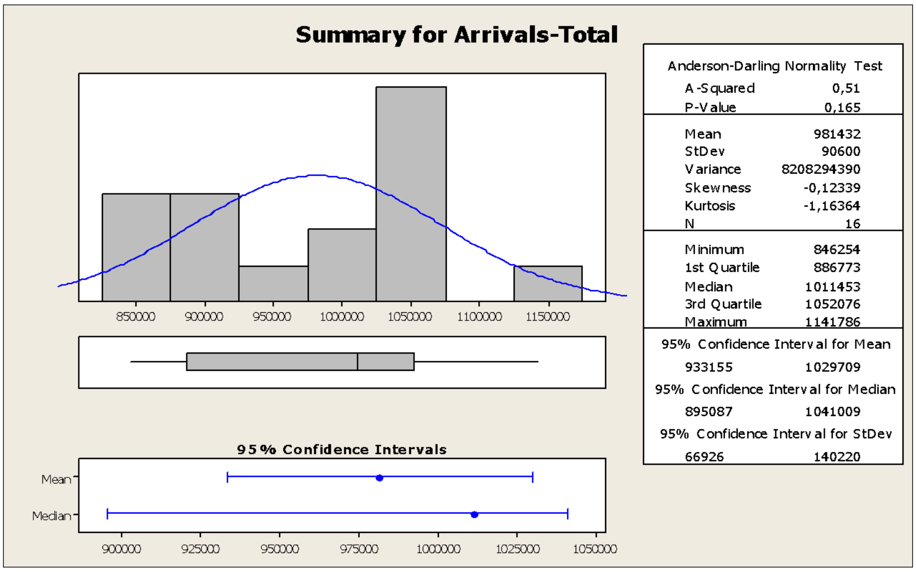


Figure II-24 April, Statistical Summary for Arrivals-Total

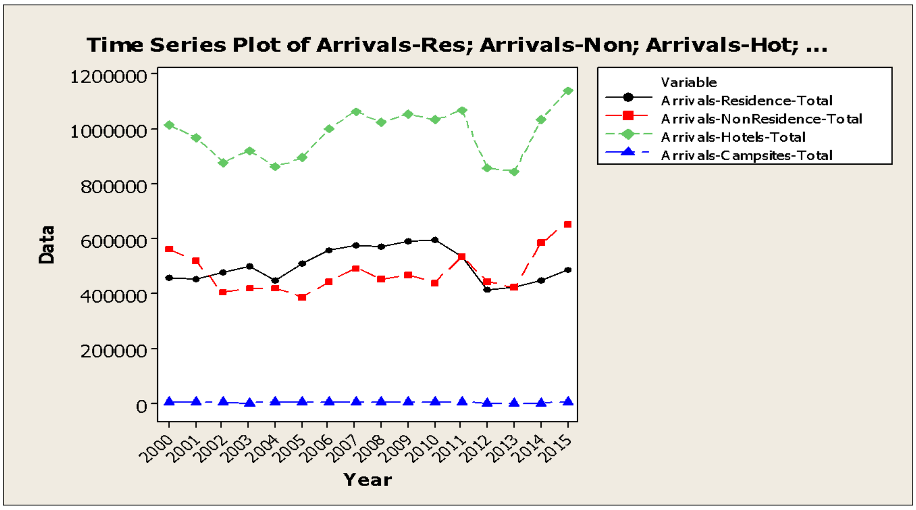


Figure II-25 April, break down time-series plot for Arrivals-Total

05 May, Nights

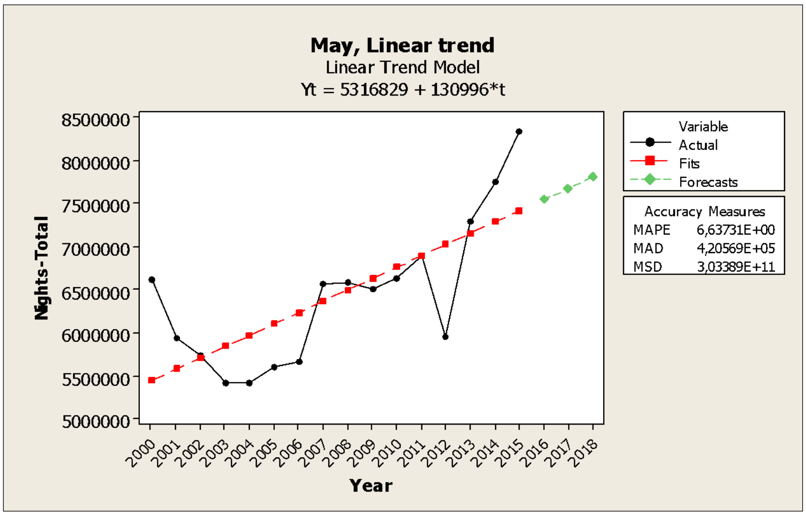


Figure II-26 May, Linear Trend for Nights-Total

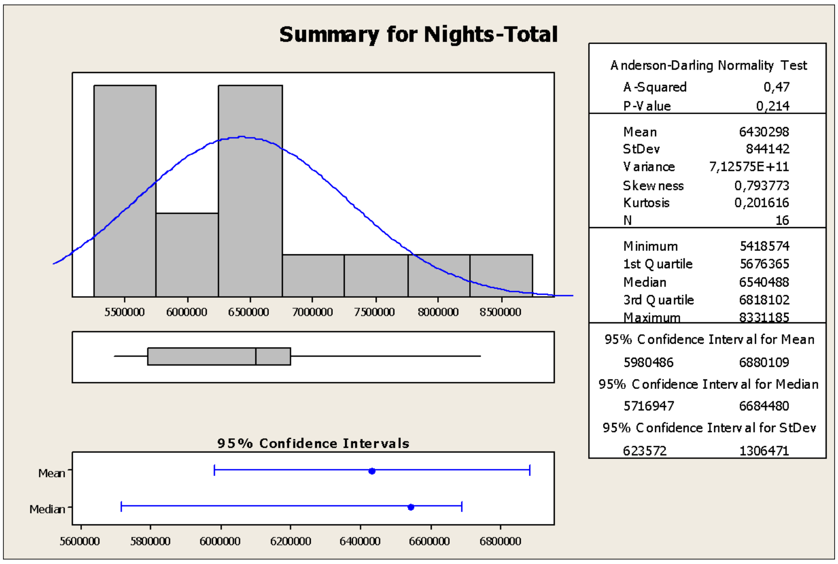


Figure II-27 May, Statistical Summary for Nights-Total

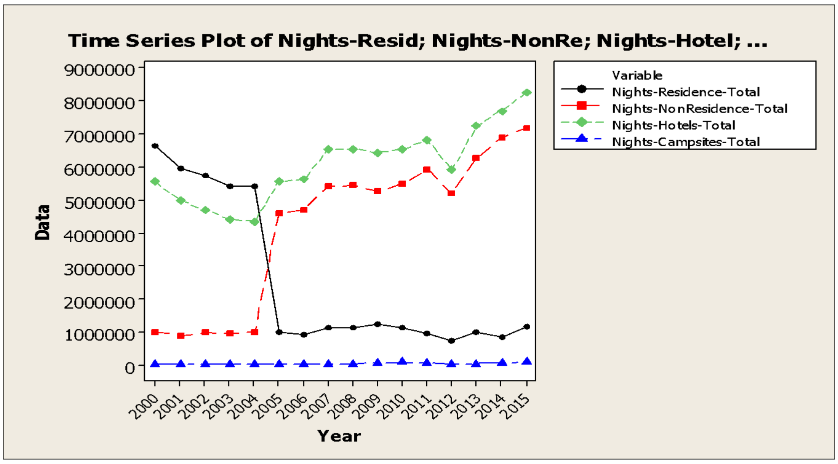


Figure II-28 May, break down time-series plot for Nights-Total

05 May, Arrivals

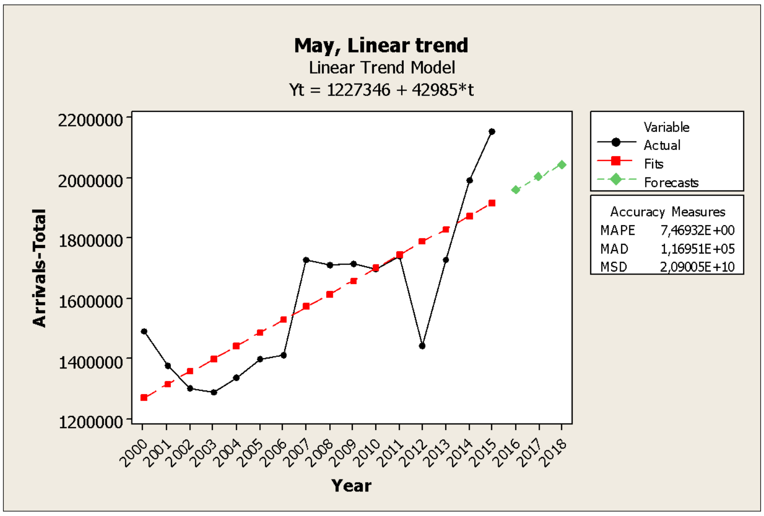


Figure II-29 May, Linear Trend for Arrivals-Total

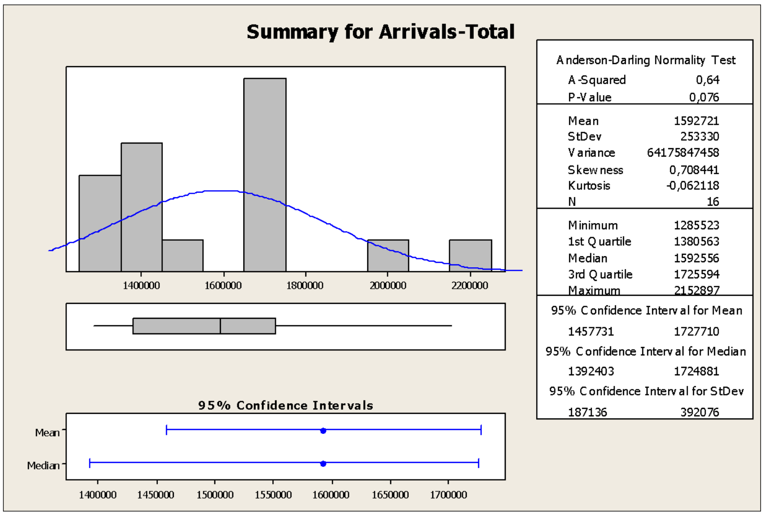


Figure II-30 May, Statistical Summary for Arrivals-Total

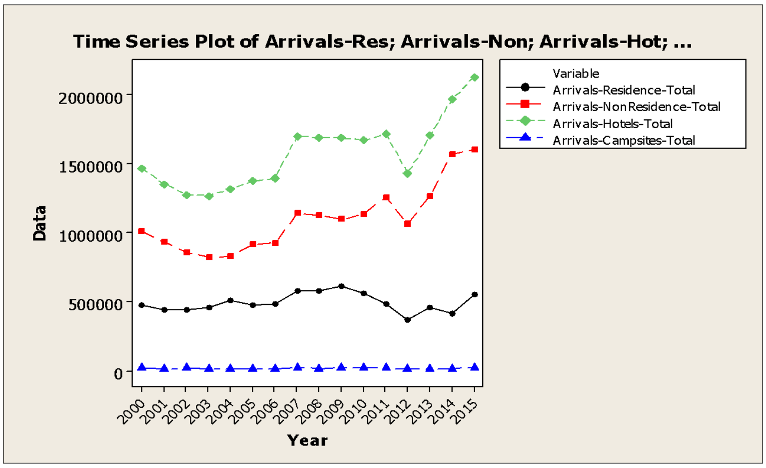


Figure II-31 May, break down time-series plot for Arrivals-Total

06 June, Nights

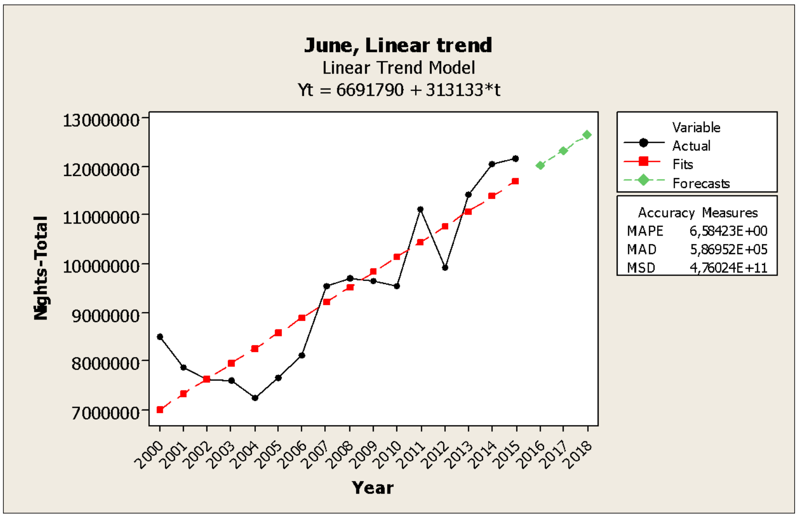


Figure II-32 June, Linear Trend for Nights-Total

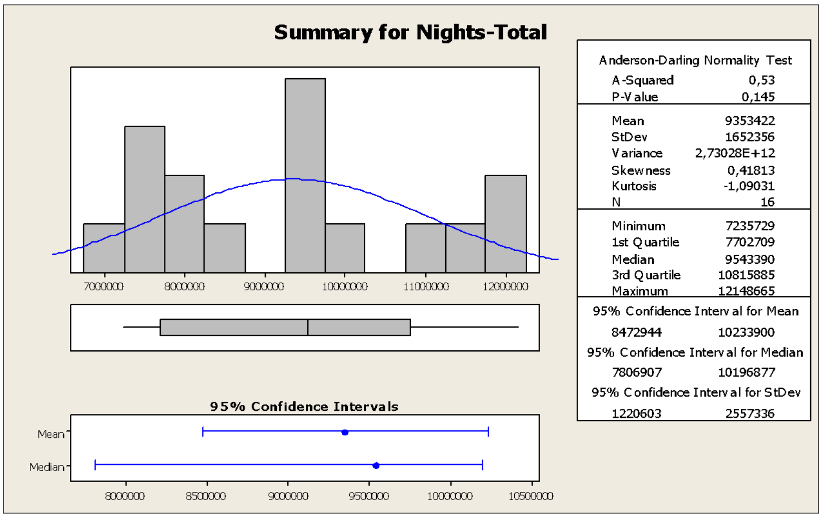


Figure II-33 June, Statistical Summary for Nights-Total

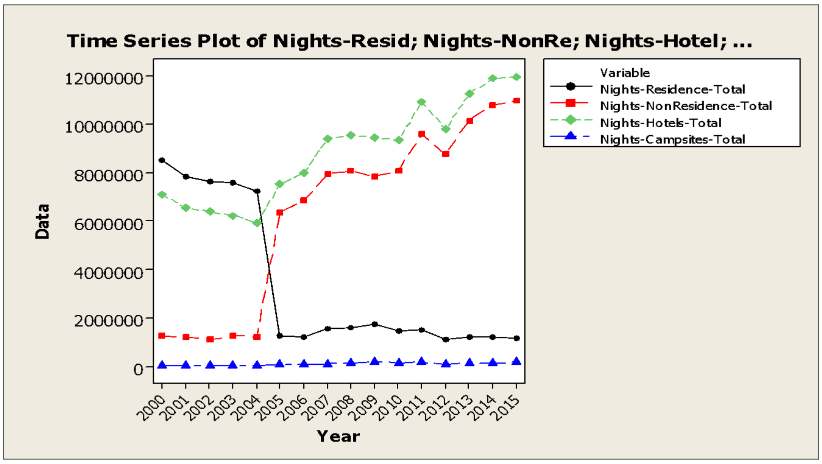


Figure II-34 June, break down time-series plot for Nights-Total

06 June, Arrivals

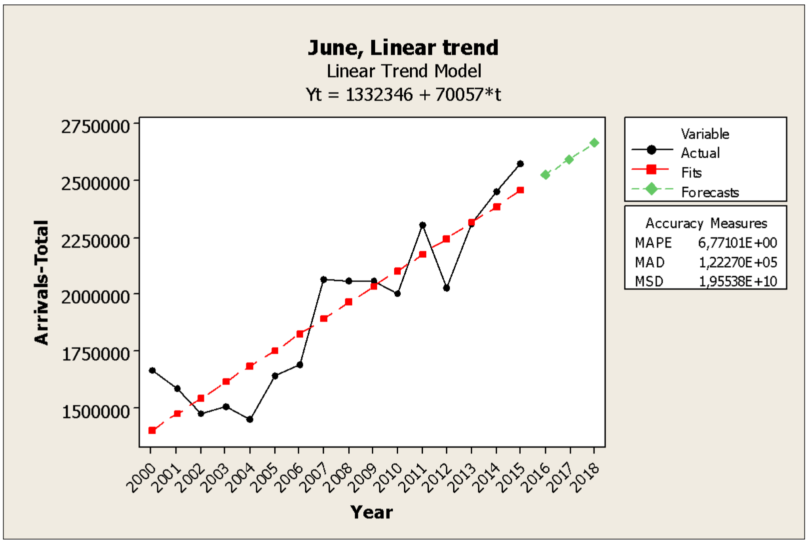


Figure II-35 June, Linear Trend for Arrivals-Total

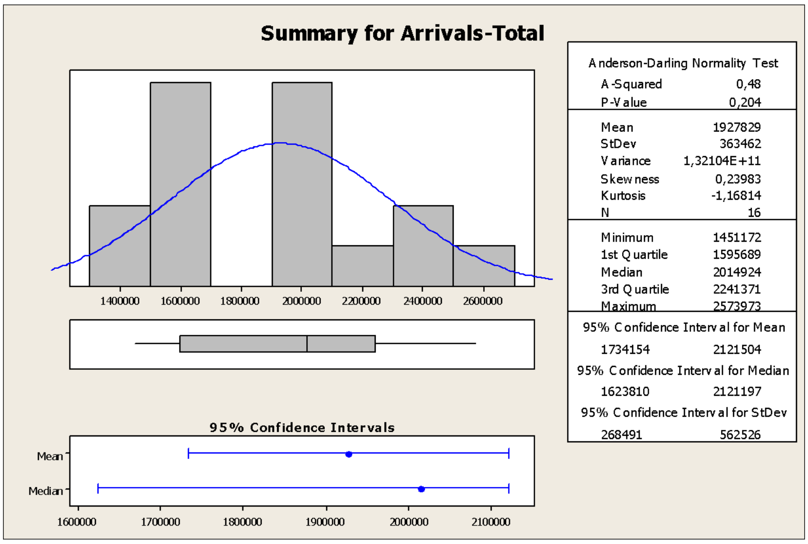


Figure II-36 June, Statistical Summary for Arrivals-Total

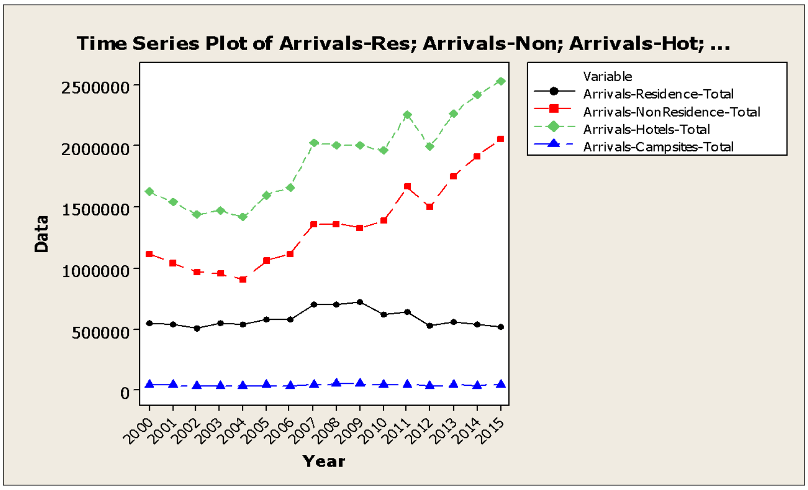


Figure II-37 June, break down time-series plot for Arrivals-Total

07 July, Nights

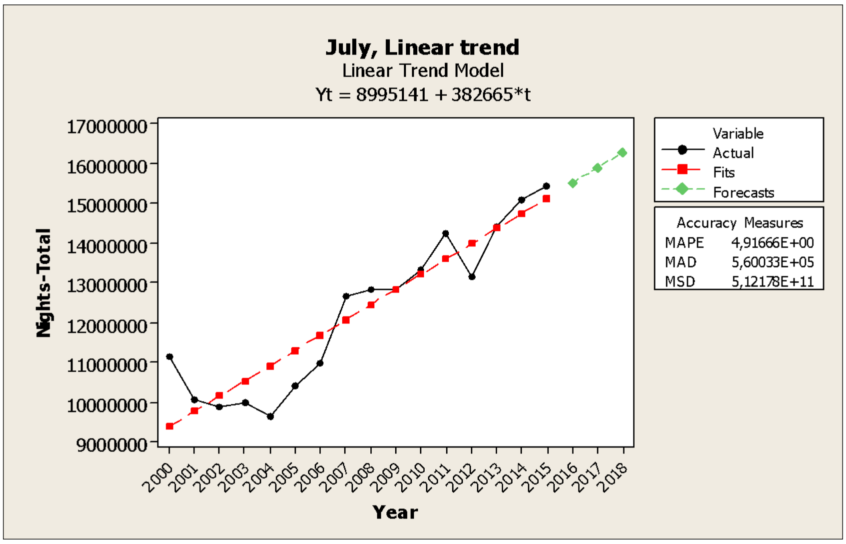


Figure II-38 July, Linear Trend for Nights-Total

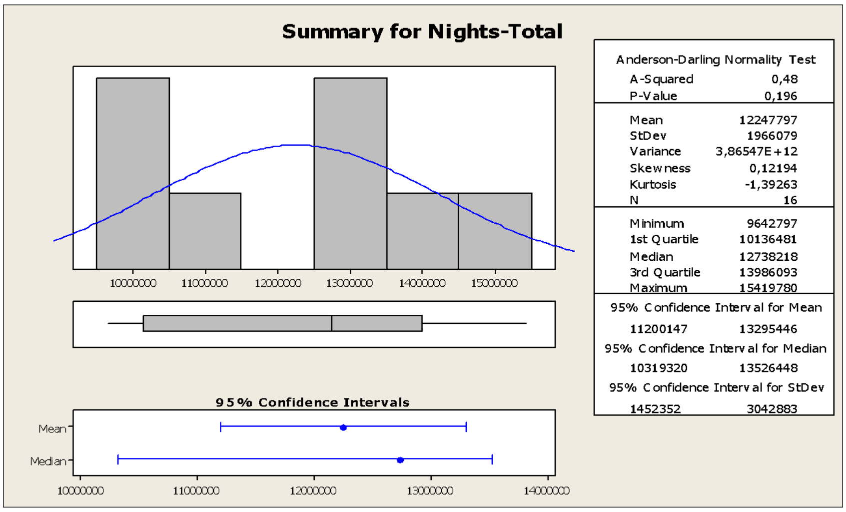


Figure II-39 July, Statistical Summary for Nights-Total

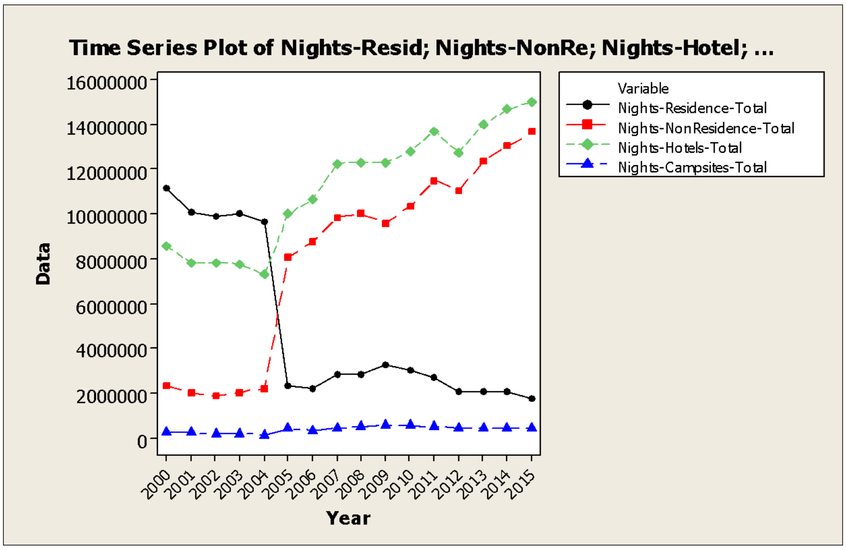


Figure II-40 July, break down time-series plot for Nights-Total

07 July, Arrivals

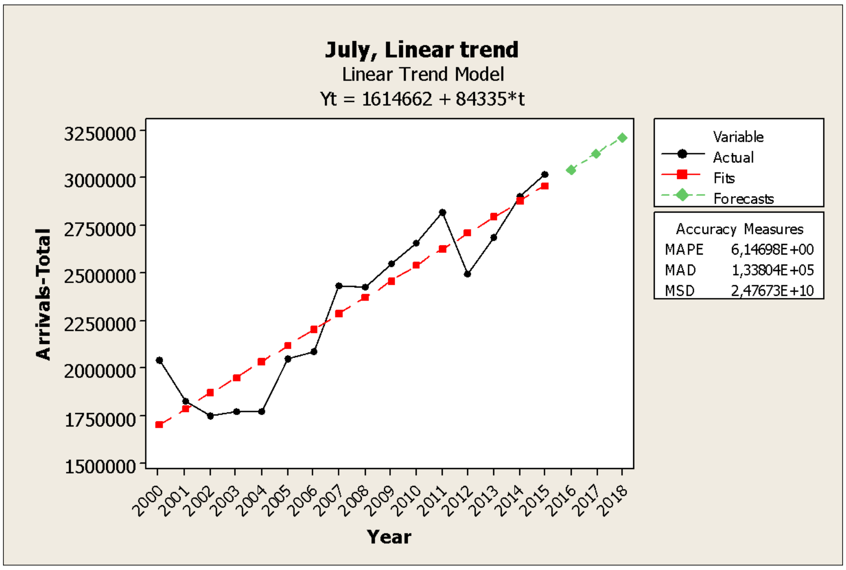


Figure II-41 July, Linear Trend for Arrivals-Total

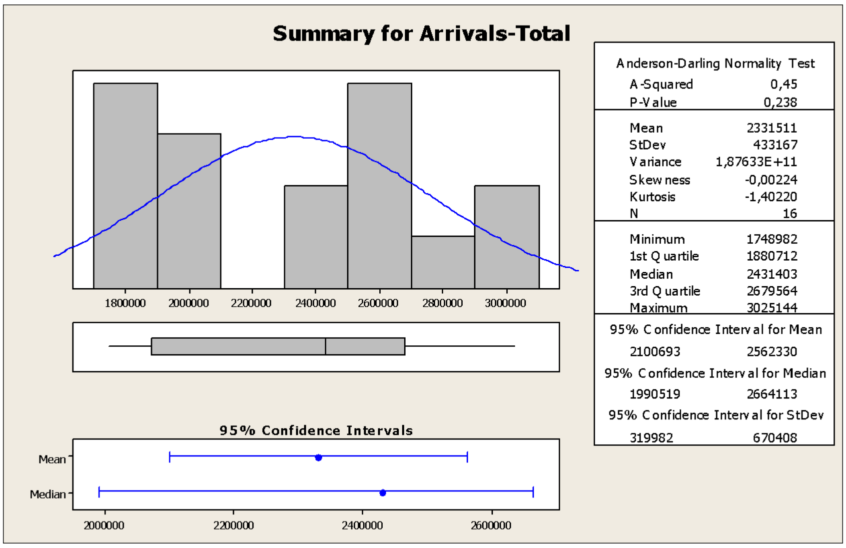


Figure II-42 July, Statistical Summary for Arrivals-Total

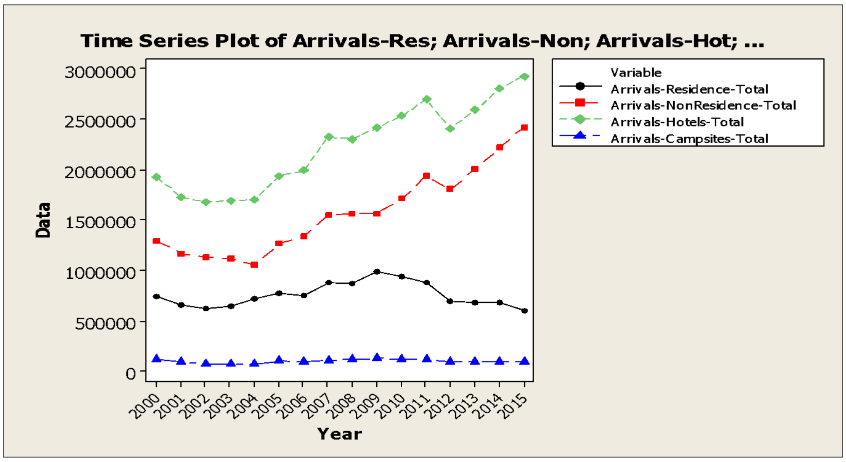


Figure II-43 July, break down time-series plot for Arrivals-Total

08 August, Nights

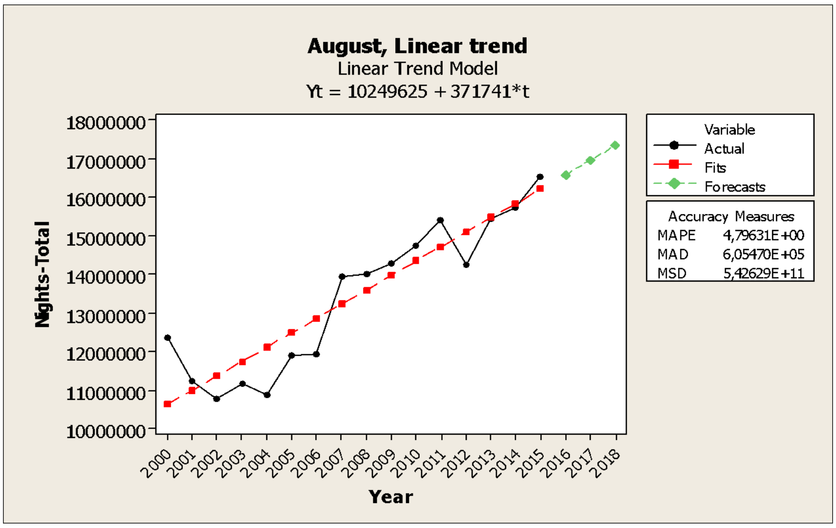


Figure II-44 August, Linear Trend for Nights-Total

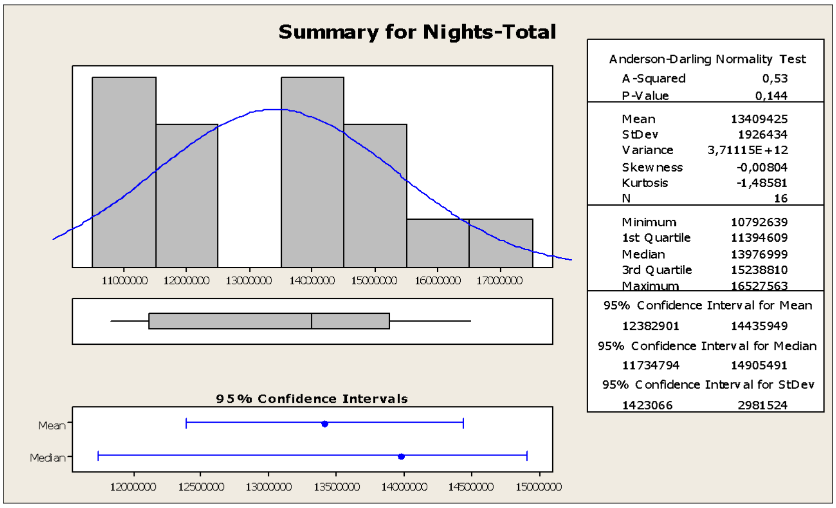


Figure II-45 August, Statistical Summary for Nights-Total

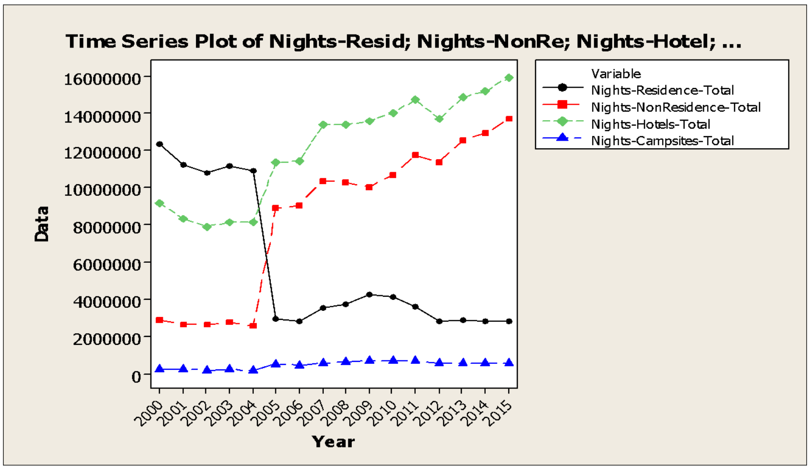


Figure II-46 August, break down time-series plot for Nights-Total

08 August, Arrivals

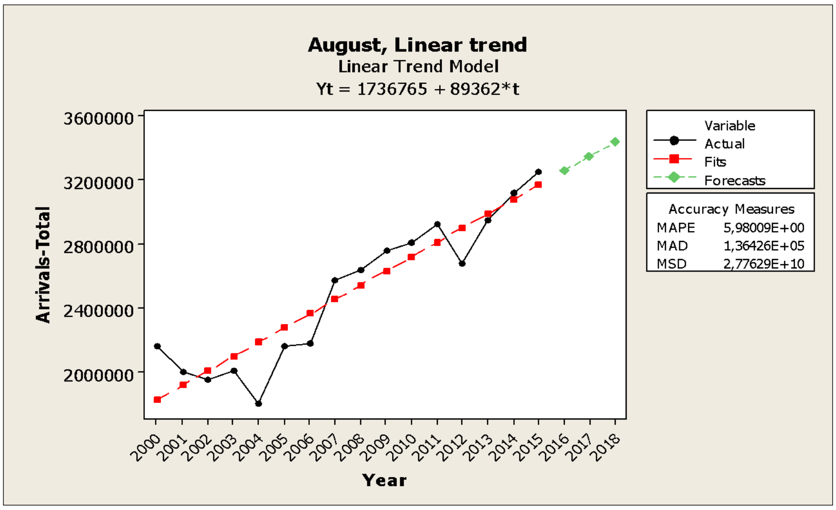


Figure II-47 August, Linear Trend for Arrivals-Total

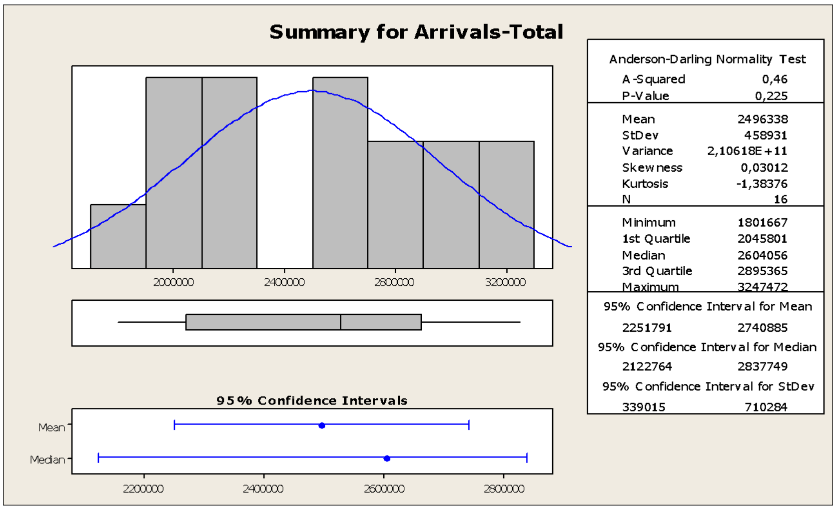


Figure II-48 August, Statistical Summary for Arrivals-Total

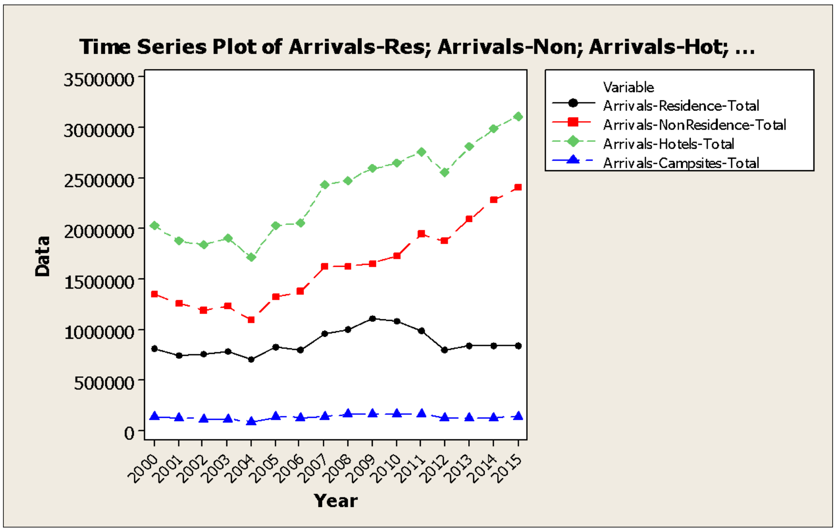


Figure II-49 August, break down time-series plot for Arrivals-Total

09 September, Nights

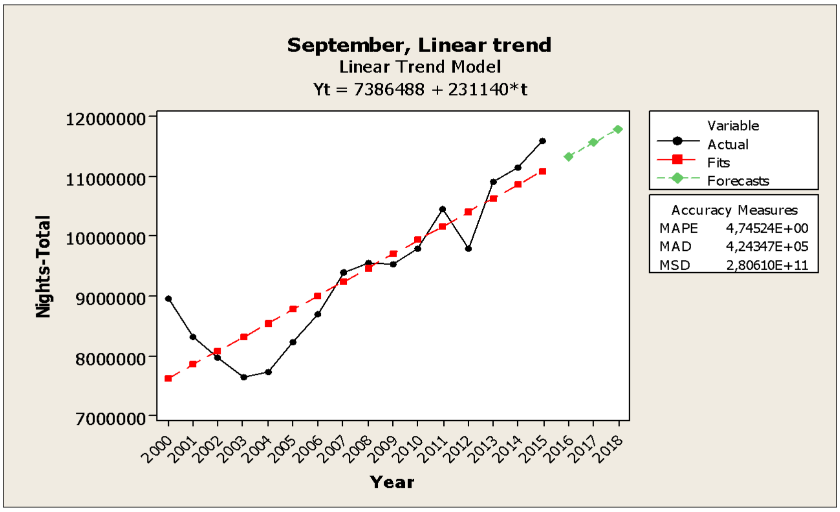


Figure II-50 September, Linear Trend for Nights-Total

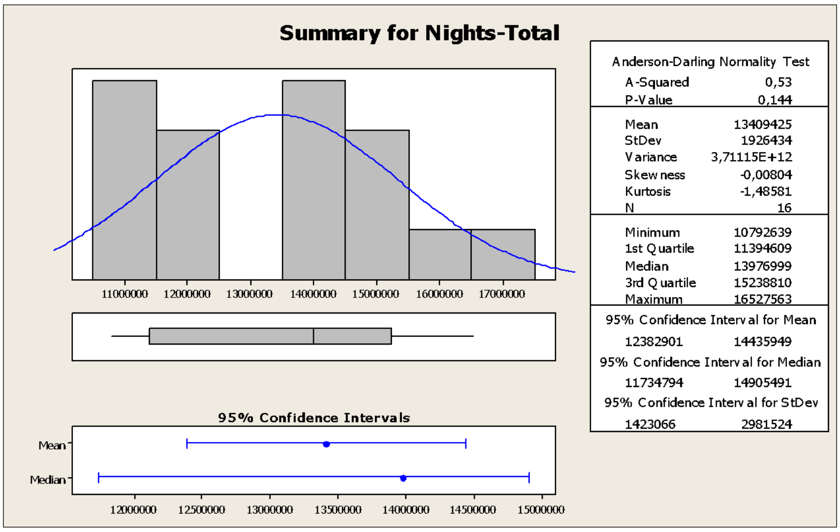


Figure II-51 September, Statistical Summary for Nights-Total

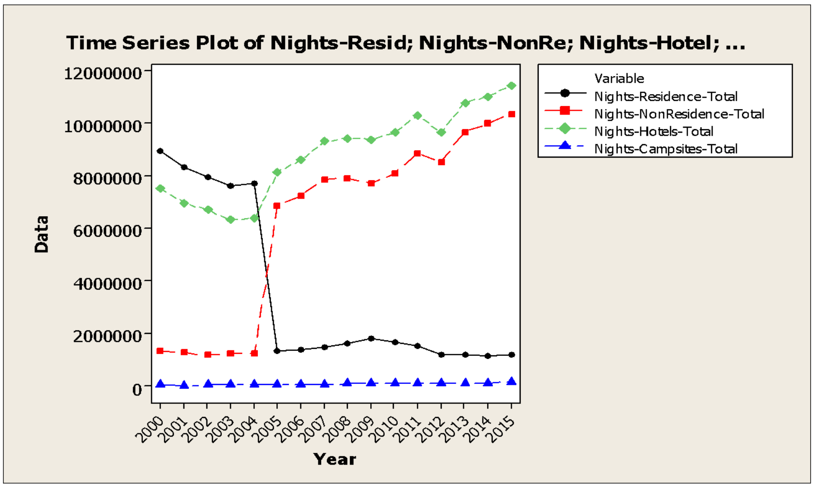


Figure II-52 September, break down time-series plot for Nights-Total

09 September, Arrivals

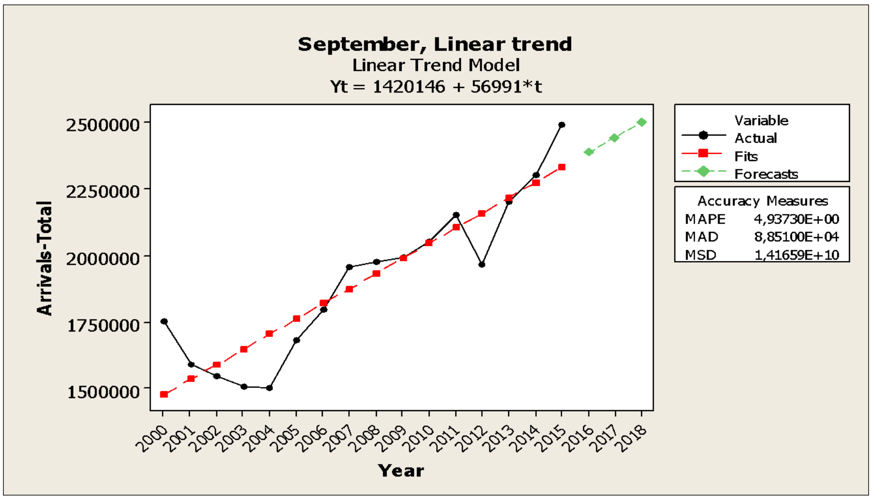


Figure II-53 September, Linear Trend for Arrivals-Total

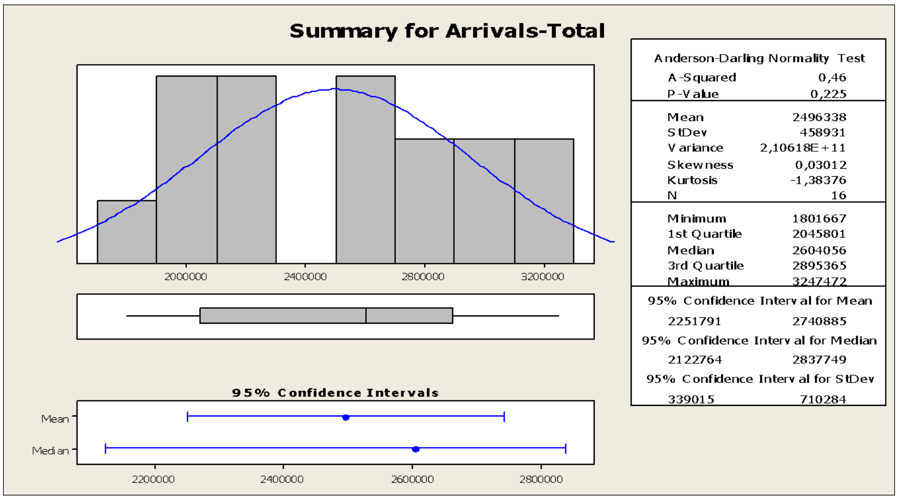


Figure II-54 September, Statistical Summary for Nights-Total

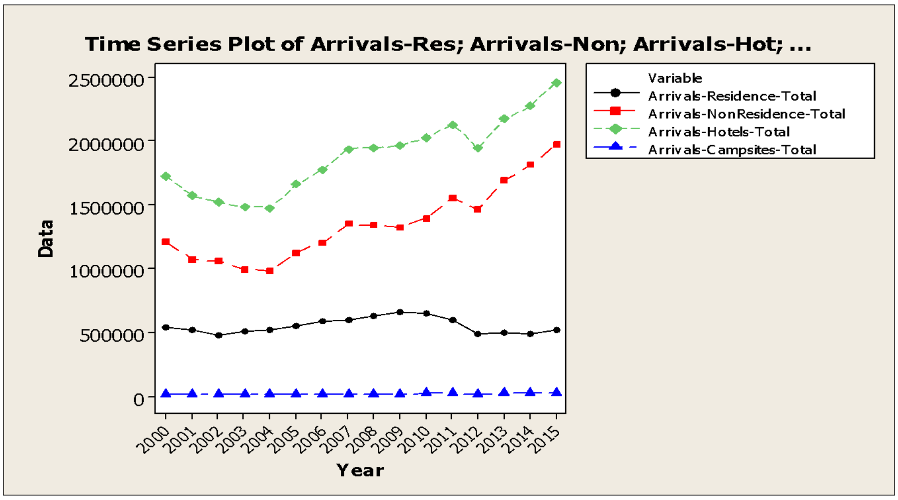


Figure II-55 September, break down time-series plot for Nights-Total

10 October, Nights

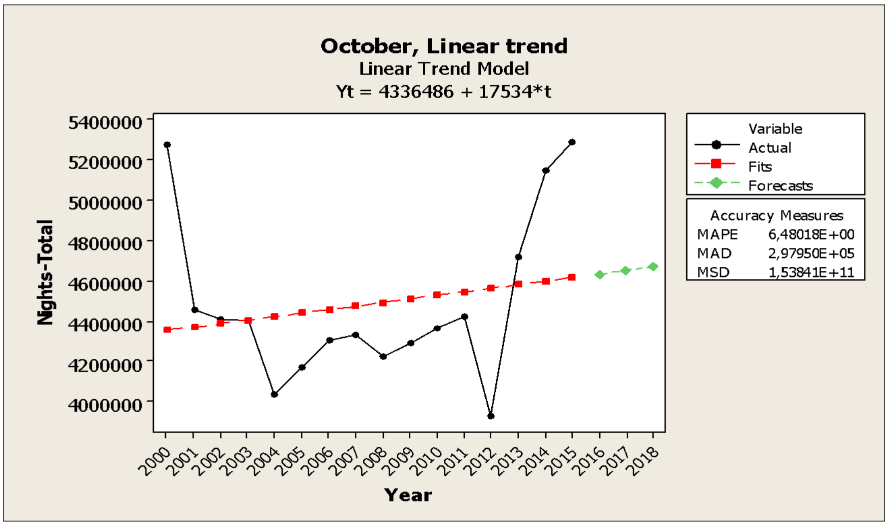


Figure II-56 October, Linear Trend for Nights-Total

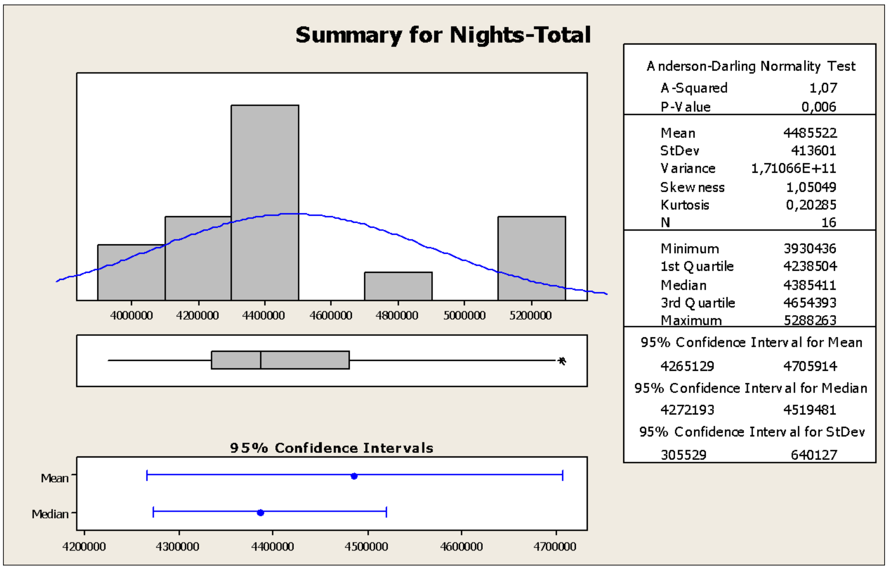


Figure II-57 October, Statistical Summary for Nights-Total

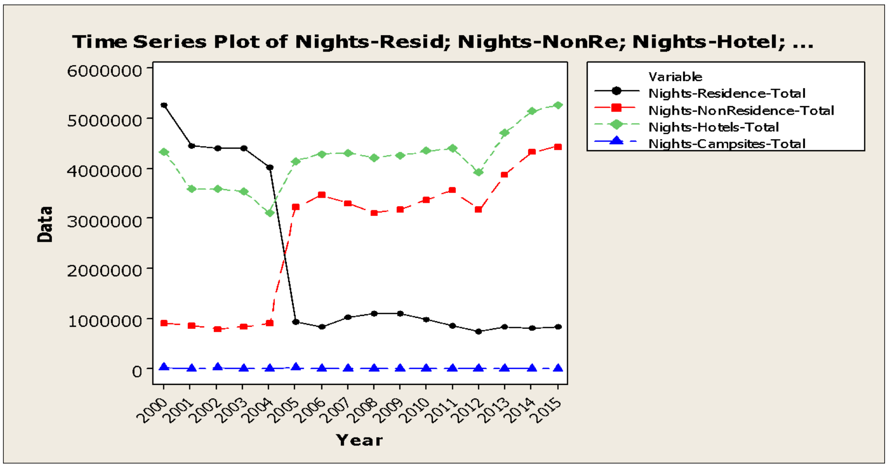


Figure II-58 October, break down time-series plot for Nights-Total

10 October, Nights

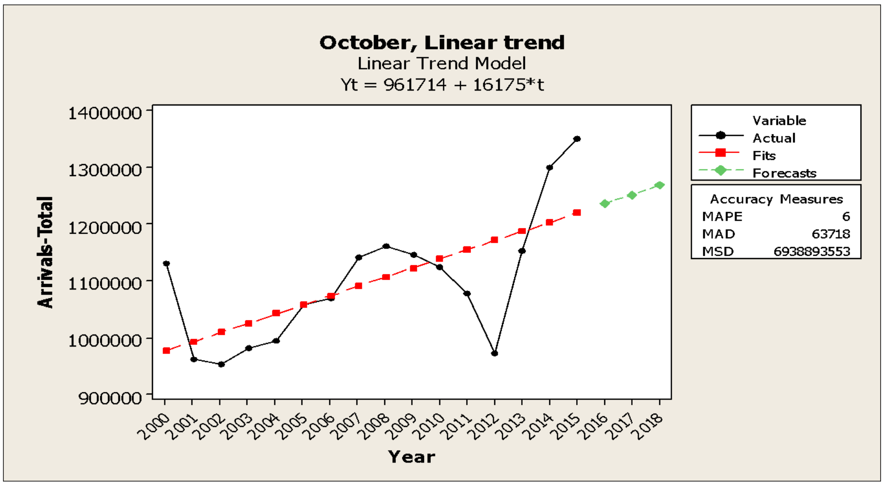


Figure II-59 October, Linear Trend for Arrivals-Total

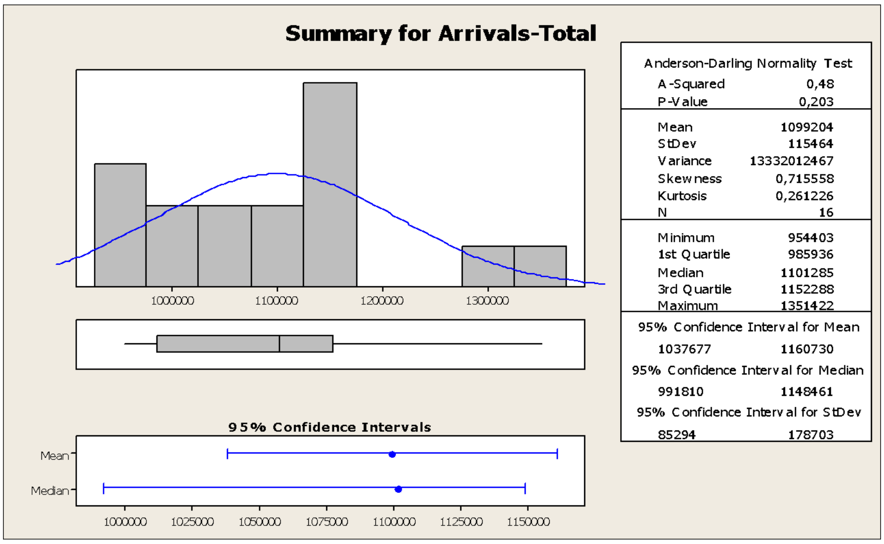


Figure II-60 October, Statistical Summary for Arrivals-Total

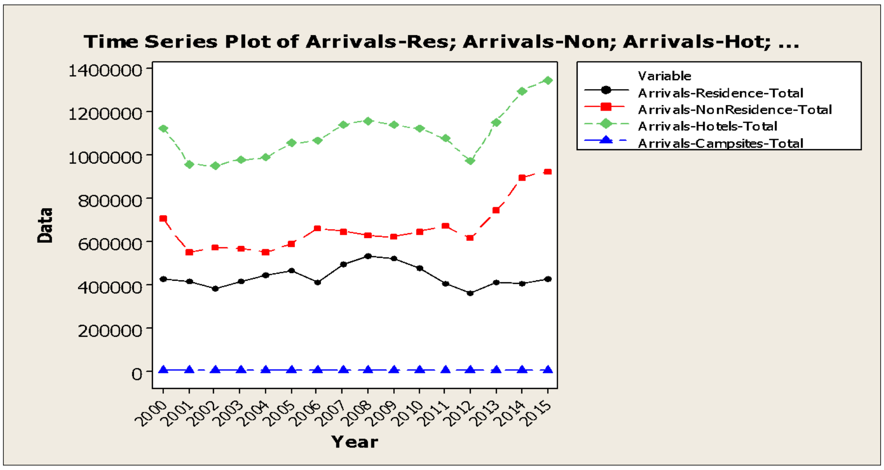


Figure II-61 October, break down time-series plot for Nights-Total

11 November, Nights

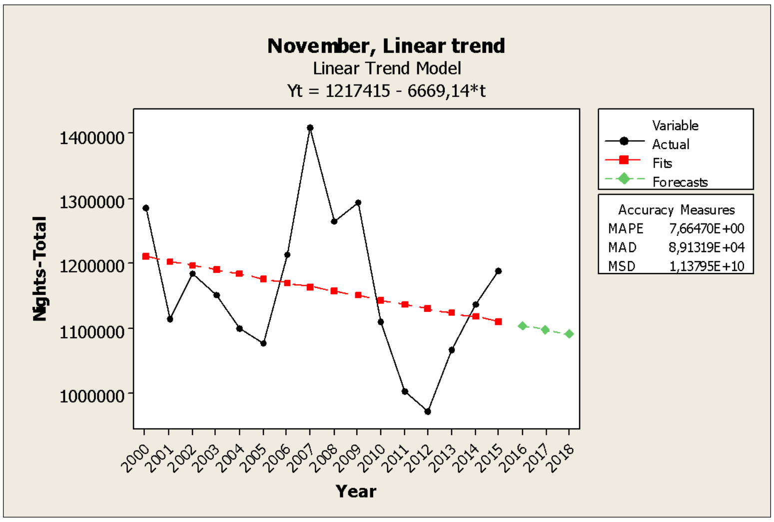


Figure II-62 November, Linear Trend for Nights-Total

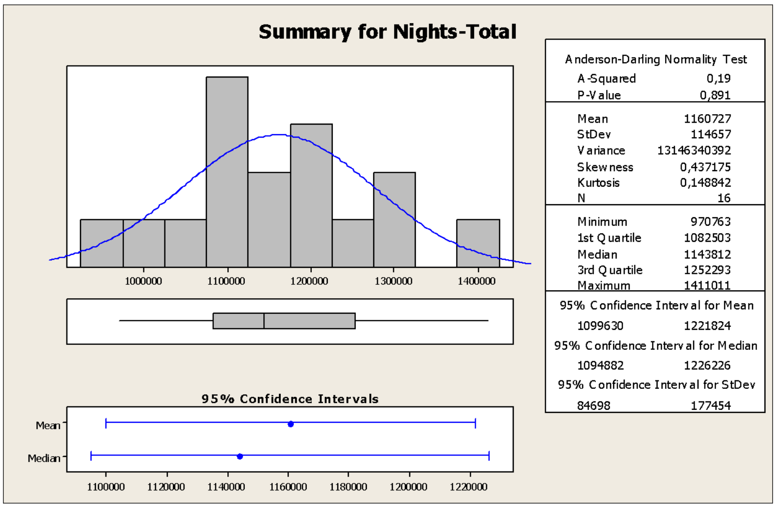


Figure II-63 November, Statistical Summary for Nights-Total

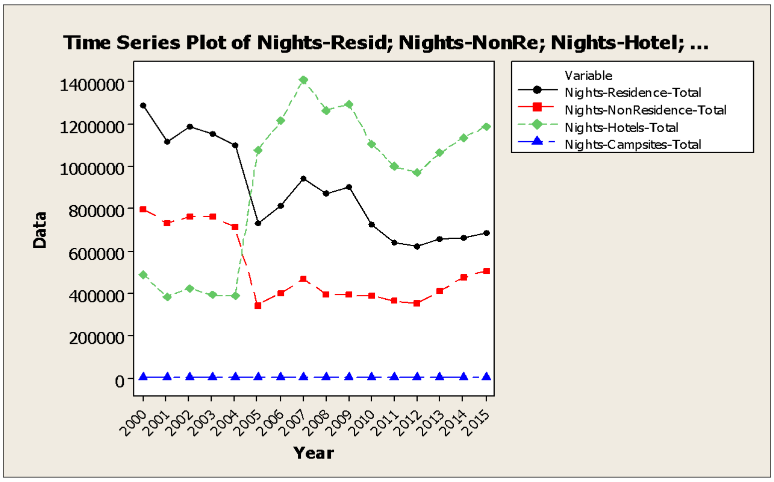


Figure II-64 November, break down time-series plot for Nights-Total

11 November, Arrivals

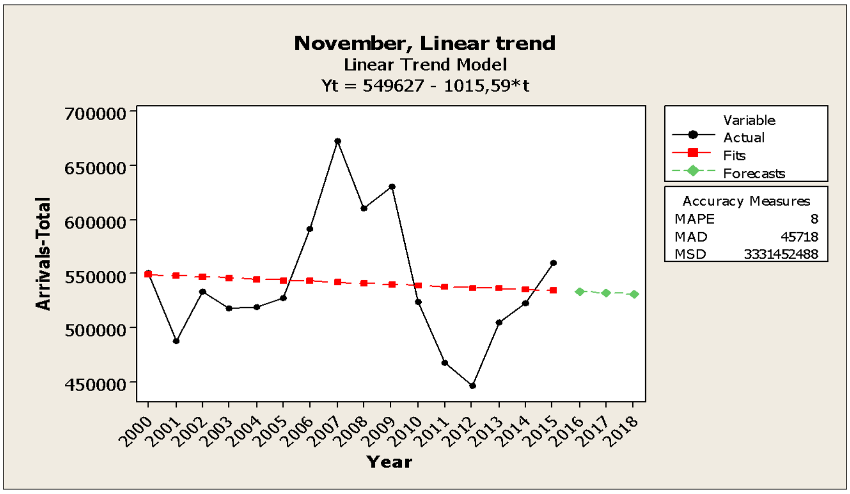


Figure II-65 November, Linear Trend for Arrivals-Total

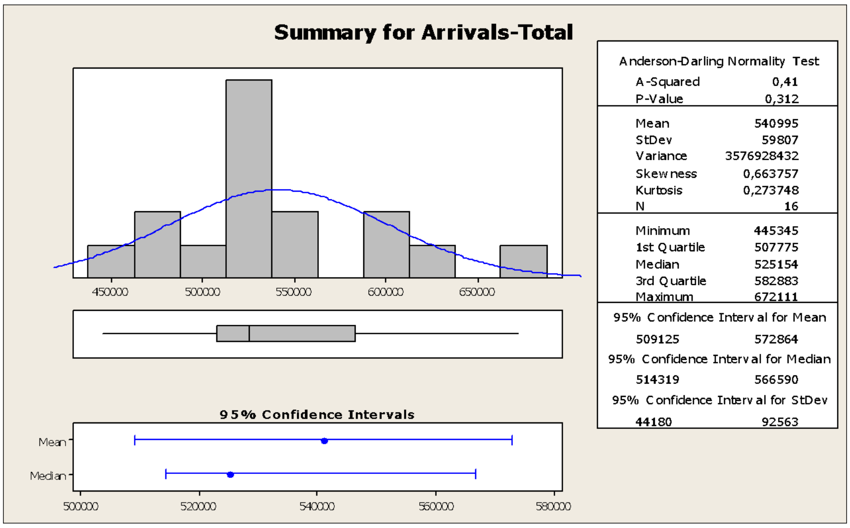


Figure II-66 November, Statistical Summary for Arrivals-Total

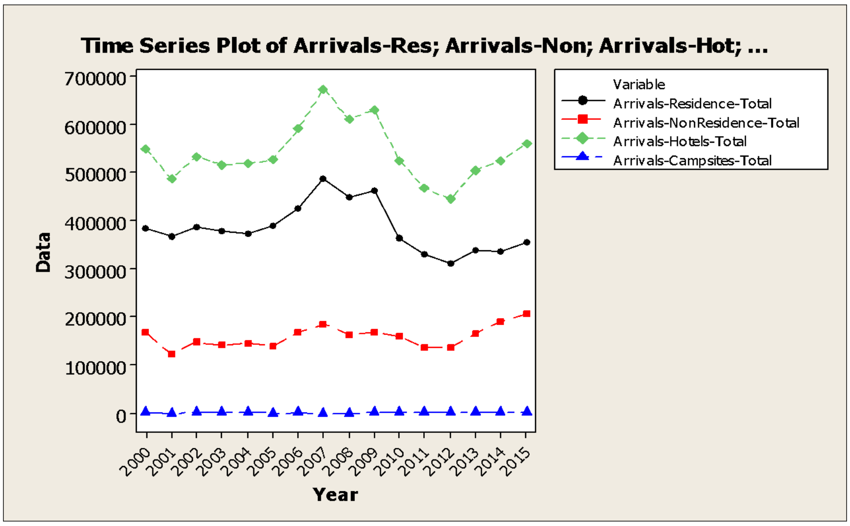


Figure II-67 November, break down time-series plot for Arrivals-Total

12 December, Nights

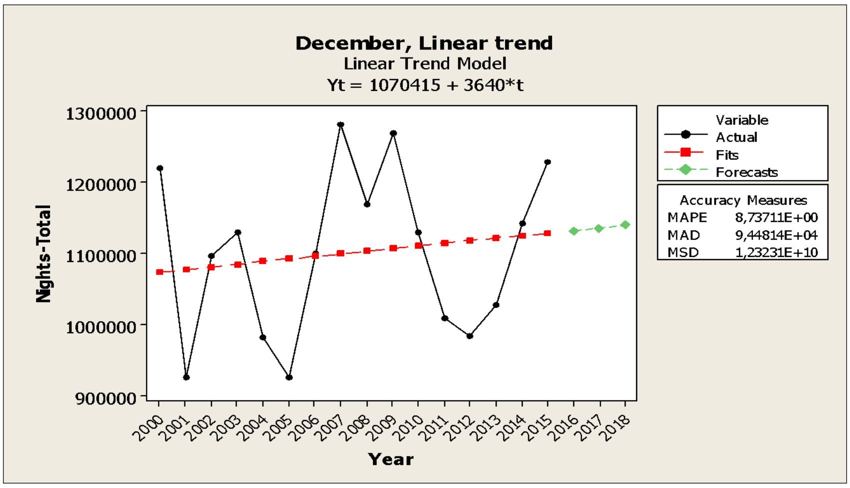


Figure II-68 December, Linear Trend for Nights-Total

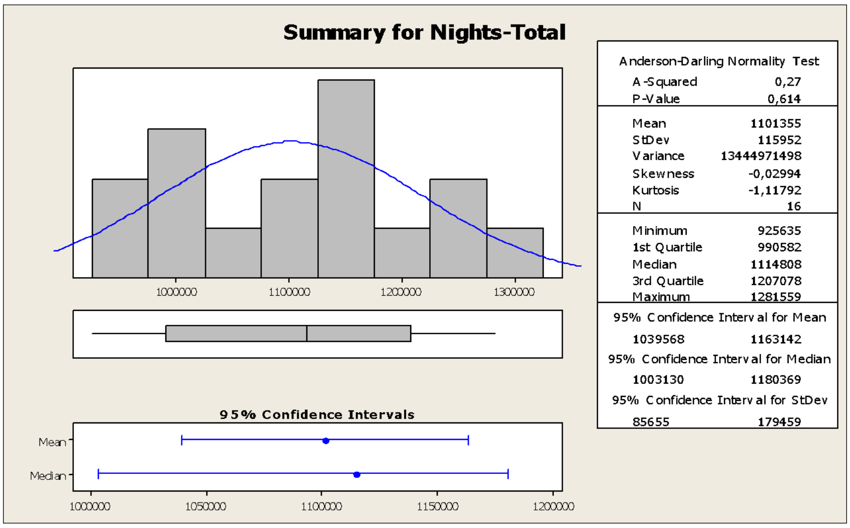


Figure II-69 December, Statistical Summary for Nights-Total

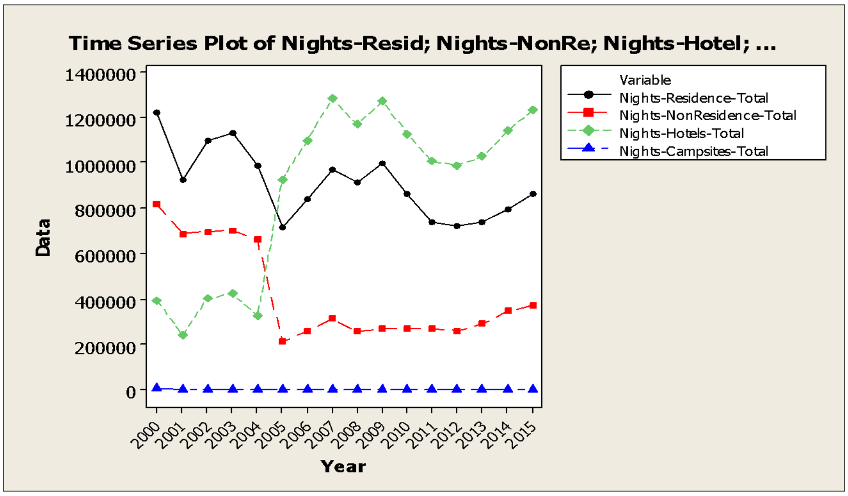


Figure II-70 December, break down time-series plot for Nights-Total

12 December, Arrivals

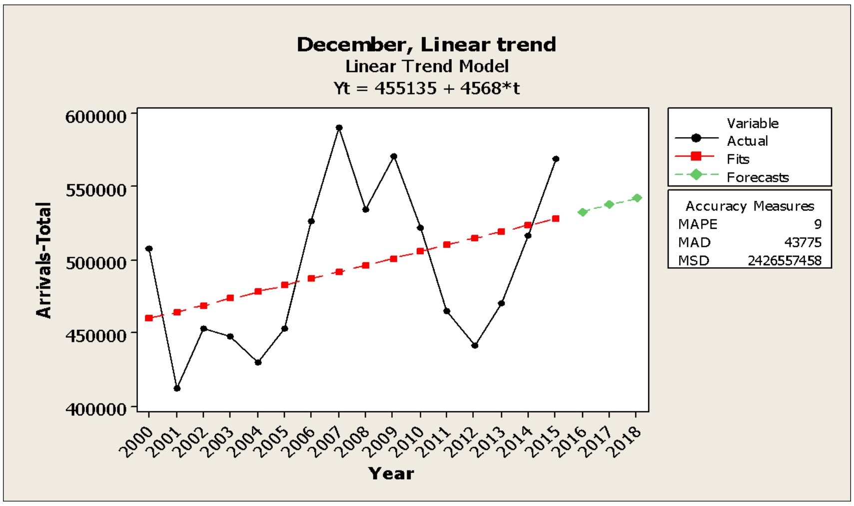


Figure II-71 December, Linear Trend for Arrivals-Total

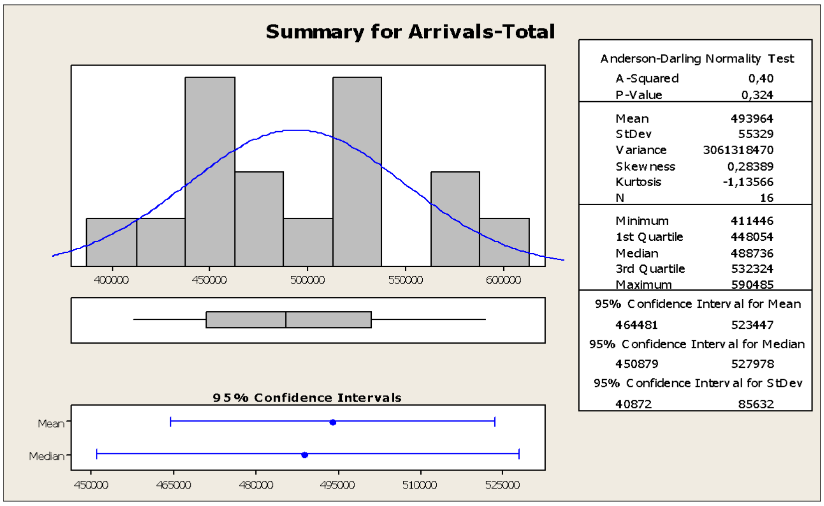


Figure II-72 December, Statistical Summary for Arrivals-Total

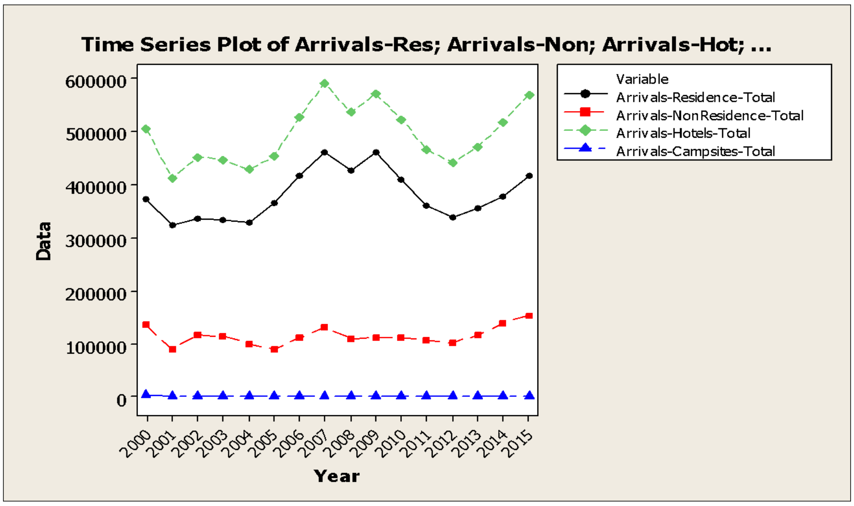


Figure II-73 December, break down time-series plot for Arrivals-Total

Appendix III. Mean and ANOVA tests for Seasons

Mean and Anova tests

Mean Tests

One-Sample Test

	Test Value = 0					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference Lower	Upper
Arrivals-Campsites-Total	8.970	191	.000	27812.219	21696.24	33928.20
Arrivals-Hotels-Total	23.114	191	.000	1223552.307	1119139.38	1327965.24
Nights-Hotels-Total	16.116	191	.000	5185974.151	4551265.62	5820682.68
Nights-Campsites-Total	7.667	191	.000	95511.755	70938.68	120084.83

One-way ANOVA: Nights-Total versus Season

```
Source   DF           SS           MS       F      P
Season    2  3,16183E+15  1,58092E+15  352,73  0,000
Error   189  8,47097E+14  4,48199E+12
Total   191  4,00893E+15

S = 2117072   R-Sq = 78,87%   R-Sq(adj) = 78,65%


                             Individual 95% CIs For Mean Based on
                             Pooled StDev
Level   N     Mean    StDev  --------+---------+---------+---------+-
1      80  9638758  3172561                                      (-*)
2      32  3235670  1128468          (--*--)
3      80   904806   397362  (-*)
                             --------+---------+---------+---------+-
                               2500000   5000000   7500000  10000000

Pooled StDev = 2117072


Grouping Information Using Tukey Method

Season   N     Mean  Grouping
1       80  9638758  A
2       32  3235670    B
3       80   904806      C

Means that do not share a letter are significantly different.


Tukey 95% Simultaneous Confidence Intervals
All Pairwise Comparisons among Levels of Season

Individual confidence level = 98,08%
```

```
Season = 1 subtracted from:

Season                   Lower               Center                   Upper
-------+---------+---------+---------+--
2       -7448906  -6403088  -5357270        (--*--)
3       -9524516  -8733952  -7943388  (-*-)

-------+---------+---------+---------+--
                                      -7000000  -3500000         0   3500000


Season = 2 subtracted from:

Season                   Lower               Center                   Upper
-------+---------+---------+---------+--
3       -3376683  -2330865  -1285047                   (--*--)

-------+---------+---------+---------+--
                                      -7000000  -3500000         0   3500000
```

One-way ANOVA: Arrivals-Total versus Season

```
Source   DF           SS           MS       F      P
Season    2  9,34028E+13  4,67014E+13  448,90  0,000
Error   189  1,96625E+13  1,04034E+11
Total   191  1,13065E+14

S = 322543   R-Sq = 82,61%   R-Sq(adj) = 82,43%


                                 Individual 95% CIs For Mean Based on Pooled
StDev
Level   N     Mean   StDev      -+---------+---------+---------+--------
1      80  2050593  485580                                     (*)
2      32  1040318  118331                (-*-)
3      80   536555   87233      (-*)
                                -+---------+---------+---------+--------
                            500000   1000000   1500000   2000000

Pooled StDev = 322543


Grouping Information Using Tukey Method

Season   N     Mean  Grouping
1       80  2050593  A
2       32  1040318    B
3       80   536555      C

Means that do not share a letter are significantly different.


Tukey 95% Simultaneous Confidence Intervals
All Pairwise Comparisons among Levels of Season

Individual confidence level = 98,08%


Season = 1 subtracted from:

Season                   Lower               Center                   Upper
-------+---------+---------+---------+--
2       -1169609  -1010275   -850941          (-*--)
3       -1634483  -1514038  -1393593  (-*-)

-------+---------+---------+---------+--
```

```
                                    -1200000   -600000         0    600000


Season = 2 subtracted from:

Season    Lower   Center    Upper  -------+---------+---------+---------+--
3       -663097  -503763  -344429                 (--*-)
                                   -------+---------+---------+---------+--
                                   -1200000   -600000         0    600000
```

Appendix IV. Literature Review – Tourism Forecasting

Table 1. Publications based on ARIMA models

Reference	Model type	Dependent variable(s)	Independent variable(s)	Data	Comparison with	Outcome
Kim & Uysal(1998)	ARMAX	Hotels in Seoul,Korea -number of nights	Price of hotel rooms, number of events (e.g. international conventions, seminars and exhibitions), and total trade volume of the destination country	Monthly - 1/1991 -12/1995	-	Price, number of events and trade volume directly affected demand
Cho (2001)	ARIMAX (adjusted ARIMA)	Hong Kong tourist arrivals	ARIMA residuals of GDP/GNP, unemployment rate, money supply, Consumer Price Index (CPI), imports, exports, and discount rate	Quarterly - 1/1975 -4/1997	(univariate) ARIMA, Exponential Smoothing	ARIMAX is the best forecasting method for Japan, while univariate ARIMA is the best predictor for the US and UK
Akal (2004)	AR(I)MAX	Tourism revenues for Turkey	Tourist arrivals	Annual - 1963 - 2001	Static Regression	AR(I)MAX outperformed the simple econometric cause–effect technique
Gounopoulos, Petmezas, & Santamaria (2012) (*)	ARIMA (1, 1, 1)	Tourist numbers to Greece	Unemployment levels, Consumer Price Indices (CPI), and Consumer Confidence Indicators of the country of origin	Monthly - 1/1977-12/2009	Exponential smoothing models	ARIMA(1,1,1) performs better

ShuiKi, ShinHuei, & ChiKeung (2013)	SARIMA	Tourist arrivals to Hong Kong		Monthly	Seasonal moving average model & Holt-Winter model.	SARIMA pefroms better
Baldigara and Mamula (2015)	SARIMA	German tourist flows to Croatia		Quartlerly - 2003 - 2012	No comparison	ARIMA(0,0,0)(1,1,3) is adequate
Hassani, Silva, Antonakakis, Filis, & Gupta (2017)	Univariate approach / Parametric and nonparametric forecasting techniques, including ARIMA	international tourist arrivals to European countries			ETS, NN, TBATS, ARFIMA, MA, WMA, SSA-R and SSA-V	No single model outperforms others in all cases. Neural Networks and ARFIMA have the worst performance

(*) Gounopoulos, Petmezas, & Santamaria (2012) use of unemployment and consumer confidence as alternative proxies for the state of the economy in the country of origin. Although no studies have yet to document the impact of macroeconomic shocks on future tourists' arrivals, reviewing the wider literature on the impact of unemployment, changes in the tourists' cost of living, and consumer confidence could provide useful inferences on potential effects to international tourism flows.

Causal forecasting

A number of authors put forward causal forecasting approaches with the aim of predicting tourism demand. Their studies are based on the selection of a set of factors they consider as most influential. Those factors are fed into pertinent models and generate forecasts. As discussed in the ensuing literature review, the most widely used models are the ADLM, the VAR and the ECM. The performance of each technique is assessed by means of comparison with alternative and benchmark models.

Witt & Witt (1992) employ the ADLM approach for the case of tourist arrivals. The explanatory variables under consideration include income in origin country, prices, exchange rate, travel cost (airfare), travel cost to substitute destinations, currency restrictions, and dummy variables. In addition they apply univariate forecasting methods, such as AR, ARIMA, and Exponential Smoothing. Syriopoulos (1995) adopt an ECM approach to estimate tourism expenditure. The explanatory variable of this model include income in origin country, relative tourism price, exchange rate, and dummy variables.

Song, Romilly, and Liu (2000) measure the outbound tourism - total or per capita tourism visits (expenditure) from the origin country. For this purpose they employ an ECM framework and incorporate the income in origin country, the relative price, the substitute price, and the preference index which reflects psychological, social, and cultural influences on tourists' decisions. The comparison with a naïve model, as well as with AR(1), ARMA, and VAR demonstrates the superiority of the proposed approach. Shan & Wilson (2001) feed similar variables (tourist arrivals, income in origin country, relative price, exports, imports, and exchange rate) into a VAR model, but this time to estimate tourist arrivals.

Rosselló-Nadal (2001) forecasts tourist arrivals using ADLM with leading indicators, including exchange rates and economic indicators, and then compares its performance with an ARIMA model.

Song, Witt & Jensen (2003) embark on causal forecasting of the expenditure-weighted number of nights spent by tourists using two ECMs - one based on the WB approach and another one on the JML. The set of explanatory variables consists of the real private consumption expenditure per capita in origin country, the real cost of living for tourists (adjusted by the exchange rate), the prices in substitute destinations, the travel cost (airfare), and a number of dummy variables (oil crisis, Gulf War, German unification, and Chernobyl/U.S. bombing of Libya). The alternative models include static regression, ADLM, unrestricted VAR, TVP, and two univariate models (ARIMA and no-change model). The best performing models are found to be the TVP (for 1-year-ahead and 2—year-ahead forecasts) and the static model (2-, 3 – and 4- years-ahead forecasting horizons). The inferior performance of the VAR model may be attributed to the absence of any distinction between endogenous and exogenous variables. Witt, Song, and Louvieris (2003) use the same variables, but adds more data. The expanded dataset enhances the reliability of forecast error measurements. According to the new results, the VAR model outperforms its counterparts for 2- and 3-years-ahead forecasts, while the TVP and the ADLM are more robust for 1-year-ahead forecasts. Another contribution of this study is the statistical testing of directional change forecasting performance and unbiasedness. Song, Witt & Li (2003) base their analysis on a similar set of explanatory variables (they also consider trade volume and habit persistence). Those variables are fed into the following causal models: Reduced ADLM, Wickens–Breusch ECM, and Johansen maximum likelihood ECM. The alternative approaches include a Naïve model, ARIMA, and TVP. ARIMA seems to generate the most modest forecasts and the JML-ECM the most optimistic ones. In addition, habit persistence is found to be the most critical factor.

Nadal, Font, & Rossello (2004) develop an ECM model to describe the intra-year variation in tourist arrivals through the Gini-coefficient. The explanatory variables comprise income in origin country and exchange rates. The study of Dritsakis (2004) is based on a VAR framework and confirms that there is significant causality between domestic economic growth and tourism earnings.

Wong, Song, & Chon (2006) demonstrate that Bayesian VAR (BVAR) models overcome the weaknesses of VAR models for the prediction of tourism demand. The explanatory variables used include the income level in origin countries, the relative cost of living and a weighted average of the consumer price index of the major substitute destinations.

Kasimati (2011) employs a trivariate model consisting of exchange rates, the GDP and tourist arrivals. The ultimate goal is to explore the causal relationship between economic growth and demand for tourism in the context of VAR/VECM models. Unlike similar studies, the results do not support the existence of such a relationship.

Georgantopoulos (2012) adopts a similar modelling framework, but with different variables. In this case the underlying variables involve tourism expenditure, tourism growth and real output (RGDP) with real effective exchange rate (REER). In parallel, he develops another model which considers the following inputs: Leisure travel and tourism spending (LTS), business travel and tourism spending (BTS), RGDP and REER. Overall, the results show that all variables are co-integrated.

Chatziantoniou, Degiannakis, Eeckels, & Filis (2016) develop a SARMAX model incorporating the following macroeconomic indicators: Industrial production, CPI, CC index, BC index, Economic PUI, and the consumer price differentials (CPDs). The comparison with a SARIMA model show that the addition of exogenous variables improves the forecasting ability of this framework. However, none of these variables appears to be critical for all origin and destination combinations of this study.

Zhu, Lim, Xie, & Wu (2016) adopt a different approach to forecast tourist flows. They use a Frank copula model which draws on linkages between tourist flows and a set of variables (i.e. Income, relative price, and transportation cost). This model is compared with product copula and ARDL-ECM; The results demonstrate its superiority.

Table 2 lists the reviewed publications on causal forecasting models, presenting the model types used, the dependent and independent variables, the time period on which the forecasting is made, the models compared and the main outcome. For selected references, their contribution is also given at the end of Table 2.

Table 2. Publications based on causal forecasting models

Reference	Model type	Dependent variable(s)	Independent variable(s)	Data	Comparison with	Outcome
Witt & Witt (1992)	ADLM	France, Germany, UK, and US tourist arrivals	Income in origin country, prices, exchange rate, travel cost (airfare), travel cost to substitute destinations, currency restrictions, dummy variables	Annual - 1965 - 1980	Naive 1,2 AR, Exponential Smoothing, ARIMA Trends	
Syriopoulos (1995)	CI/ECM	Mediterranean countries tourism receipts/expenditure	Y/P C RC ER D DT(ST) income in origin country, relative tourism price, exchange rate, dummy variable, deterministic (linear) trend (stochastic trend)	Annual - 1962 - 1987	-	
Song, Romilly, and Liu (2000)	ECM	UK outbound tourism - total or per capita tourism visits (expenditure) from the origin country	Income in origin country, relative price, substitute price, the preference index (incorporates social, cultural and psychological influences on tourists' decisions), dummy variable	Annual - 1965 - 1994	Naive, AR(1), ARMA, VAR	ECM model has the best overall forecasting performance
Shan & Wilson (2001)	VAR	China tourist arrivals	Tourist arrivals, income in origin country, relative price, exports, imports, exchange rate	Montlhy - 1/1987 - 1/1998	-	
Rosselló-Nadal (2001)	ADLM (Leading indicator)	Balearic Islands tourist arrivals	Exchange rate, Other economic indicators	Monthly - 1/1975 - 12/1999	Naïve ARIMA	

Song, Witt & Jensen (2003)	ECM - Two ECMs, one based on the WB approach and the other on the JML approach	Denmark expenditure-weighted number of nights spent by tourists	Real private consumption expenditure per capita in origin country, the real cost of living for tourists (adjusted by the exchange rate), prices in substitute destinations, travel cost (airfare), dummy variables (oil crisis, Gulf War, German unification, Chernobyl/U.S. bombing of Libya	Annual - 1969 - 1997	Static regression, ADLM, unrestricted VAR, TVP, and two univariate time-series models (ARIMA and no-change model)	The TVP model generates the most accurate 1-year-ahead forecasts. The TVP and static models generate the most accurate 2-years-ahead forecasts. For 3- and 4-years-ahead forecasts the static model is ranked first.
Witt, Song, and Louvieris (2003)	CI/ECM	Denmark expenditure-weighted number of nights spent by tourists	Real private consumption expenditure per capita, the real cost of living for tourists (adjusted by the exchange rate), prices in substitute destinations, travel cost (airfare), dummy variables (oil crisis, Gulf War, German unification, Chernobyl/U.S. bombing of Libya)	Annual - 1969 - 1999	Static Regression, ADLM,Unrestricted VAR, the Time-Varying Parameter (TVP) approach - The univariate timeseries models comprise an ARIMA model and the no-change model	For both 2- and 3-years-ahead forecasting horizons,the VAR model generates the most accurate,unbiased forecasts. For a 1-year-ahead forecasting horizon,the TVP model and the reduced ADLM generate the most accurate,clearly unbiased forecasts
Song, Witt & Li (2003) (1)	Reduced ADLM, Wickens–Breusch ECM, and Johansen maximum likelihood ECM	Thailand tourist arrivals	Income in origin country, relative tourism price, substitute tourism price, trade volume, habit persistence, and dummy variables (two oil crises, Visit Thailand Year' campaign, Asian financial crisis, Seoul Olympics, and student demonstrations in Korea in 1980)	Annual 1963/1968 - 2000	ARIMA, Naive, TVP	ARIMA produces the most modest prediction (with the exception of Singapore), while the JML-ECM generates the most optimistic forecasts. Habit persistence is the most important factor.

Nadal, Font, & Rossello (2004) (2)	ECM	Intra-year variation in arrivals to the Balearic Islands	Y/P ER RC income in origin country, exchange rate	Monthly/Annual - 1982 - 2001	-	
Dritsakis (2004)	VAR	Long-run economic growth of Greece (real gross domestic product & real effective exchange rate)	International tourism earnings	1960-2000	-	Significant causality
Wong, Song, & Chon (2006) (3)	Bayesian VAR (BVAR)	Demand for Hong Kong tourism by residents from six major origin countries	Income level of origin country, the relative cost of living, the Substitute Price variable	Annual - 1973 - 1996	unrestricted VAR models	Univariate Bayesian VAR (BVAR) the best performing model
Kasimati (2011)	VAR/VECM - Trivariate model - Granger causality	Economic growth of Greece (GDP, employment)	International tourist arrivals	Annual data - 1960-2010	-	No direct causality
Georgantopoulos (2012)	VAR/VECM - Trivariate model	Tourism expenditure and growth in Greece	Total tourism expenditure (TE) and real output (RGDP) with real effective exchange rate (REER)	Annual data - 1988-2012	A second model treated leisure travel and tourism spending (LTS), business travel and tourism spending (BTS), RGDP and REER as separate inputs	All variables return to their long-term equilibrium

Chatziantoniou, Degiannakis, Eeckels, & Filis (2016)	SARMAX (with exogenous macroeconomic variables)	Tourist arrivals to Greece from seven key origin countries(Aggregate data) - Disaggregated data by origin country	Macroeconomic indicators: Industrial production, consumer price index (CPI), CC index, BC index, Economic PUI, and the consumer price differentials (CPDs) between Greece and the origin countries (estimated using the Greek CPI) -	Monthly data	SARIMA	SARMAX outperforms SARIMA - No single variable improves the forecasting accuracy for all cases - The CC index is critical for Canada and the UK - The price level for France and Germany - Income for Italy and Spain - Economic policy uncertainty for the USA.
Zhu, Lim, Xie, & Wu (2016) (4)	Frank copula-based model	Tourist flows to Singapore from 6 countries	Income, relative price, and transportation cost - Exponential smoothing is used to predict them	Monthly data - 1995 - 2013	Product copula, ARDL-ECM	Frank model performs better

Song, Witt & Li (2003) (1) The relatively poor forecasting performance of the VAR model for all forecasting horizons other than 4 years ahead may have arisen because it is the only causal model included in the forecasting comparison which generates ex ante forecasts. Alternatively, however, the low ranking may suggest that the distinction between endogenous and exogenous variables in tourism demand forecasting models is fairly clear, or at least that allowing for the distinction not to be clear does not result in more accurate forecasts except perhaps in the longer term.

Nadal, Font, & Rossello (2004) (2) The rigorous statistical testing of directional change forecasting performance and unbiasedness presented in the current study is new to the tourism forecasting literature

Wong, Song, & Chon (2006) (3) The reason why Bayesian approach tend to improve the forecasting performance of the unrestricted VAR model may be attributed to the introduction of the Bayesian priors. These priors serve to improve the estimation efficiency through increasing the degrees of freedom and controlling for over-parameterization associated with the unrestricted VAR models.

Zhu, Lim, Xie, & Wu (2016) (4) Unlike prior tourism research, we take into account the dependence relations among the different tourist flows via copula.

Machine Learning

Techniques based on Machine Learning and Artificial Neural Networks have gained traction over the past few years and constitute a relatively new trend in tourism forecasting.

Atsalakis, Chnarogiannaki, and Zopounidis (2014) forecast tourist arrivals using Adaptive Neuro-Fuzzy Inference System (ANFIS). They also fit Autoregressive (AR) & autoregressive moving average (ARMA) models. The comparison shows that the ANFIS outperform the alternative approaches.

Claveria, Monte, and Torra (2015) compares the performance between Radial basis function neural networks and multi-layer perceptron and Elman recursive neural networks. According to the results, the first approach forecasts tourist arrivals more accurately. In addition, Claveria, Monte, & Torra (2016) forecast tourist arrivals through an extension of the Gaussian process regression (GPR) model to a multiple-input and multiple-output framework that take account of the cross-interactions. The authors show that the proposed model outperforms the standard neural network, which is use as a benchmark.

Kummong and Supratid (2016) uses Discrete Wavelet Decomposition (DWD)-NARX - Combination of DWD and nonlinear autoregressive neural network with exogenous input (NARX). This methodology appears to generate better predictions of tourist arrivals in the short-run than alternative neural network approaches, such as GRNN, Elman's RNN and BPNN.

Yu, Wang, Gao, and Tang (2017) adopt seasonal trend autoregressive integrated moving averages with Dendritic Neural Network (SA-D model) with the aim of forecasting the number of inbound tourists. The results suggest that this model performs better that the combined SARIMA and DNN.

Table 3 lists the reviewed publications on Machine Learning and Artificial Neural Networks models, presenting the model types used, the dependent and independent variables, the time period on which the forecasting is made, the models compared and the main outcome. For selected references, their contribution is also given at the end of the Table 3.

Table 3. Publications based on Machine Learning and Artificial Neural Networks

Reference	Model type	Dependent variable(s)	Independent variable(s)	Data	Comparison with	Outcome
Atsalakis, Chnarogiannaki, & Zopounidis (2014)	Adaptive Neuro-Fuzzy Inference System (ANFIS)	Tourist arrivals to Greece by air, sea, and land transport		Monthly – 1/1996 – 11/2011	Autoregressive (AR) & autoregressive moving average (ARMA)	The ANFIS outperformed the other models
Claveria, Monte, & Torra (2015) (1)	Radial basis function neural networks	Tourist arrivals to Catalonia	Correlations in the evolution of inbound international tourism demand	Monthly - 1/2001 - 7/2012	Multi-layer perceptron and Elman recursive neural networks	Radial basis function neural networks performs better
Claveria, Torra, & Monte (2016) (2)	Machine learning techniques - Support Vector Regression (SVR)	International tourist arrivals to key Spanish regions		Monthly - 1/1999 to 3/2014	Neural Network (NN), ARMA	SVR with a Gaussian radial basis function kernel performs better than the other models

Claveria, Monte, & Torra (2016) (3)	Extension of the Gaussian process regression model for multiple-input multiple-output forecasting	Tourist arrivals to all Spanish regions	Cross-correlations in tourist arrivals to all markets	Monthly data - 1/1999 - 3/2014	Standard neural network	Extension of Gaussian outperforms the benchmark
Kummong & Supratid (2016) (4)	Discrete Wavelet Decomposition (DWD)-NARX - Combination of DWD and nonlinear autoregressive neural network with exogenous input (NARX)	Thailand tourist arrivals		Relative price with respect to 6 top-ranked tourist countries (exogenous)	NARX and other neural network approaches (GRNN, Elman's RNN and BPNN)	DWD-NARX more suitable for short-term projections
Yu, Wang, Gao, Tang (2017) (5)	Seasonal trend autoregressive integrated moving averages with Dendritic Neural Network (SA-D model) - Combined SARIMA and DNN	Inbound tourists - Japan		1/2009 - 12/2015	Dendritic Neural Network (DNN)	SA-D performs better

Claveria, Monte, & Torra (2015) (1) A way of using the common trends in tourist arrivals from different visitor markets and assessing its performance.

Claveria, Torra, & Monte (2016) (3) The main contribution of this study to the previous literature on tourism demand forecasting is the evaluation of the performance of several ML techniques by means of an iterated multi-step ahead forecasting comparison.

Claveria, Monte, & Torra (2016) (3) Incorporating the connections between different markets in the modelling process may prove to be useful in refining predictions at a regional level.

Kummong & Supratid (2016) (4) (DWD)-NARX deals with non-stationarity and overcomes overfitting.

Yu, Wang, Gao, Tang (2017) (5) The study is based on neuron model with dendritic nonlinearity model and it theoretically strengthens the assumption that a neural network model performs better than linear models when forecasting nonlinear variables. This study mixed linear and nonlinear models and opens the door for further combinations.

Miscellaneous/ Alternative modelling approaches

Data limitations are a common barrier to the robust performance of most tourist forecasting techniques. This has compelled some researches to seek new sources of data. Thus, some of them have based their analysis on web search data. For example, Peng, G., Liu, Y., Wang, J., and Gu, J. (2016) estimate the number of visitors fitting web search query data into a HE-TDC screening model. The comparison with classical regression analysis reveals that this new methodology can improve the forecasting accuracy. Li, Pan, Law, and Huang (2017) use large search trend data and construct a Composite search index on the basis of a Generalized Dynamic Factor Model (GDFM) to forecast tourism demand (including tourist numbers and hotel occupancy). This model outperforms both a time-series model and a model based on Principal Component Analysis (PCA).

Some other authors have taken a different path towards forecasting tourist arrivals. They have departed from the typical techniques in the tourism forecasting literature and test novel approaches. For example, Chinnakum and Boonyasana (2016) develop a Kink AR-GARCH models to predict tourist arrivals. This model appears to improve the forecasting ability, considering that the AR(m)- GARCH(p,q) which is used for comparison purposes performs worse. In another study Wan, Song, and Ko (2016) embark on density forecasting to predict the growth rate of tourist arrivals. The explanatory variables include the GDP and the exchange rate-adjusted consumer price index.

Table 4 lists the reviewed publications on alternative methodologies than those mentioned before. It has the same structure with Tables 1,2 and 3.

Table 4. Publications based on Miscellaneous/ Alternative modelling approaches

Reference	Model type	Dependent variable(s)	Independent variable (s)	Data	Comparison with	Outcome
Peng, G., Liu, Y., Wang, J., & Gu, J. (2016)	HE-TDC screening method (A new method that combines Hurst Exponent (HE) and Time Difference Correlation (TDC) analysis)	Volume of tourism visitors in Jiuzhai Valley		Web search query data	Regression analysis	The HE-TDC method improves the predictive ability.
Li, Pan, Law, & Huang (2017)	Composite search index in the framework of a Generalized Dynamic Factor Model (GDFM)	Tourism demand in Beijing, including tourist numbers and hotel occupancy		Large search trend data	A traditional time-series model and a model with an index created by Principal Component Analysis (PCA)	GDFM improves the forecasting accuracy
Chinnakum & Boonyasana (2016)	Kink AR-GARCH	Tourist arrivals to Thailand from East Asia	-	Monthly data - 1/1991 - 2/2016	AR(m)-GARCH(p,q)	Kink AR(1)-GARCH(1,1) performs better

Wan, Song & Ko (2016) (1)	Density forecasting - ARDL (p,q,r)	Y-O-Y growth rate of tourist arrivals to Hong Kong	GDP (growth) and Exchange rate-adjusted consumer price index (infl)	Quarterly data - 1996Q1 - 2015Q1	-	

Wan, Song & Ko (2016) (1) This research attempts to alleviate this risk by introducing density forecast for tourism demand that accommodates both mean forecast and its uncertainty in the analysis. Interval forecast is an immediate response to the above criticism on point forecast as it specifies the probability that the actual outcome will fall within a stated interval.

Areas of focus

Most of the previously mentioned studies focus on Asian and European countries. Specifically, Shan and Wilson (2001), Wong et al. (2006), Cho (2001), ShuiKi et al. (2013), Wan et al. (2016), Wan et al. (2016), Peng et al. (2016), Li et al. (2017) concentrate on Hong Kong and China, while Song and Witt (2003), Kim and Uysal(1998) on Korea. Furthermore, Song et al. (2003), Zhu et al. (2016), Kummong and Supratid (2016), Chinnakum and Boonyasana (2016), Yu et al. (2017) consider other Asian destinations.

Several other studies refer to Mediterranean and European countries - especially Spain Witt and Witt (1992), Syriopoulos (1995), Song et al. (2000), Rosselló & Nadal (2001), Song et al., (2003), Witt et al. (2003), Nadal et al. (2004), Akal (2004), Baldigara and Mamula (2015), Claveria et al., (2015), Claveria et al. (2016), Claveria et al.(2016), and Hassani et al. (2017).

Finally, there is another growing strand in the literature that focuses on Greece and the prediction of tourism demand there Dritsakis (2004), Kasimati (2011), Gounopoulos et al., (2012), Georgantopoulos (2012), Atsalakis et al., (2014), and Chatziantoniou et al., (2016). This is consistent with the objectives of the present study, which pertain to the specification of suitable forecasting models for Greek tourism.

Table 5 presents the selected papers for review in terms of the region/country they examine.

Table 5. Publications presented by region / country

Region / Country		**References**
Europe	Greece	Dritsakis (2004), Kasimati (2011), Gounopoulos et al., (2012), Georgantopoulos (2012), Atsalakis et al., (2014), and Chatziantoniou et al., (2016).
	Spain	Witt and Witt (1992), Syriopoulos (1995), Song et al.(2000), Rosselló & Nadal (2001), Song et al., (2003), Witt et al. (2003), Nadal et al. (2004), Akal (2004), Baldigara and Mamula (2015), Claveria et al., (2015), Claveria et al. (2016), Claveria et al. (2016), and Hassani et al. (2017).
Asia	China, Hong Kong	Shan and Wilson (2001), Wong et al. (2006), Cho (2001), ShuiKi et al. (2013), Wan et al. (2016), Wan et al. (2016), Peng et al. (2016), Li et al. (2017)
	Korea	Song and Witt (2003), Kim and Uysal (1998)

	Other	Song et al. (2003), Zhu et al. (2016), Kummong and Supratid (2016), Chinnakum and Boonyasana (2016), Yu et al. (2017)

References

Akal, M. (2004). Forecasting Turkey's tourism revenues by ARMAX model. Tourism Management, 25(5), 565-580.

Atsalakis, G., Chnarogiannaki, E., & Zopounidis, C. (2014). Tourism demand forecasting based on a neuro-fuzzy model. Hospitality, Travel, and Tourism: Concepts, Methodologies, Tools, and Applications: Concepts, Methodologies, Tools, and Applications, 106.

Baldigara, T., & Mamula, M. (2015). Modelling international tourism demand using seasonal ARIMA Models. Tourism and Hospitality Management, 21(1), 19-31

Chatziantoniou, I., Degiannakis, S., Eeckels, B., & Filis, G. (2016). Forecasting tourist arrivals using origin country macroeconomics. Applied Economics, 48(27), 2571-2585.

Chinnakum, W., & Boonyasana, P. (2016). Forecasting International Tourism Demand in Thailand. Thai Journal of Mathematics, 231-244.

Cho, V. (2001). Tourism forecasting and its relationship with leading economic indicators. Journal of Hospitality & Tourism Research, 25(4), 399-420.

Claveria, O., Monte, E., & Torra, S. (2015). Common trends in international tourism demand: Are they useful to improve tourism predictions?. Tourism Management Perspectives, 16, 116-122.

Claveria, O., Monte, E., & Torra, S. (2016). Combination forecasts of tourism demand with machine learning models. Applied Economics Letters, 23(6), 428-431.

Claveria, O., Monte, E., & Torra, S. (2016). Modelling cross-dependencies between Spain’s regional tourism markets with an extension of the Gaussian process regression model. SERIEs, 7(3), 341-357.

Dritsakis, N. (2004). Cointegration analysis of German and British tourism demand for Greece. Tourism management, 25(1), 111-119.

Georgantopoulos, A. G. (2012). Forecasting tourism expenditure and growth: A VAR/VECM analysis for Greece at both aggregated and disaggregated levels. International Research Journal of Finance and Economics, 96(105), 155-167.

Gounopoulos, D., Petmezas, D., & Santamaria, D. (2012). Forecasting tourist arrivals in Greece and the impact of macroeconomic shocks from the countries of tourists’ origin. Annals of Tourism Research, 39(2), 641-666.

Hassani, H., Silva, E. S., Antonakakis, N., Filis, G., & Gupta, R. (2017). Forecasting accuracy evaluation of tourist arrivals. Annals of Tourism Research, 63, 112-127.

Kasimati, E. (2011). Economic impact of tourism on Greece’s economy: Cointegration and causality analysis. International research journal of Finance and Economics, 79(5), 79-85.

Kummong, R., & Supratid, S. (2016). Thailand tourism forecasting based on a hybrid of discrete wavelet decomposition and NARX neural network. Industrial Management & Data Systems, 116(6), 1242-1258.

Kim, Y., & Uysal, M. (1998). Time-dependent analysis for international hotel demand in Seoul. Tourism Economics, 4(3), 253-263

Li, X., Pan, B., Law, R., & Huang, X. (2017). Forecasting tourism demand with composite search index. Tourism Management, 59, 57-66.

Nadal, J. R., Font, A. R., & Rossello, A. S. (2004). The economic determinants of seasonal patterns. Annals of Tourism Research, 31(3), 697-711

Peng, G., Liu, Y., Wang, J., & Gu, J. (2016). Analysis of the prediction capability of web search data based on the HE-TDC method–prediction of the volume of daily tourism visitors. Journal of Systems Science and Systems Engineering, 1-20.

Rosselló-Nadal, J. (2001). Forecasting turning points in international visitor arrivals in the Balearic Islands. Tourism Economics, 7(4), 365-380.

Shan, J., & Wilson, K. (2001). Causality between trade and tourism: empirical evidence from China. Applied Economics Letters, 8(4), 279-283.

ShuiKi, W., ShinHuei, W., & ChiKeung, W. (2013). Aggregate vs. disaggregate forecast: case of Hong Kong. Annals of Tourism Research, 42, 434-438.

Song, H., Romilly, P., & Liu, X. (2000). An empirical study of outbound tourism demand in the UK. Applied economics, 32(5), 611-624.

Song, H., Witt, S. F., & Jensen, T. C. (2003). Tourism forecasting: accuracy of alternative econometric models. International Journal of Forecasting, 19(1), 123-141.
Song, H., Witt, S. F., & Li, G. (2003). Modelling and forecasting the demand for Thai tourism. Tourism Economics, 9(4), 363-387.

Syriopoulos, T. C. (1995). A dynamic model of demand for Mediterranean tourism. International review of applied economics, 9(3), 318-336.

Wan, S. K., Song, H., & Ko, D. (2016). Density forecasting for tourism demand. Annals of Tourism Research, 60, 27-30.

Witt, S. F., Song, H., & Louvieris, P. (2003). Statistical testing in forecasting model selection. Journal of Travel Research, 42(2), 151-158.

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

Wong, K. K., Song, H., & Chon, K. S. (2006). Bayesian models for tourism demand forecasting. Tourism Management, 27(5), 773-780.

Yu, Y., Wang, Y., Gao, S., & Tang, Z. (2017). Statistical Modeling and Prediction for Tourism Economy Using Dendritic Neural Network. Computational intelligence and neuroscience, 2017.

Zhu, L., Lim, C., Xie, W., & Wu, Y. (2016). Modelling tourist flow association for tourism demand forecasting. Current Issues in Tourism, 1-15.