Advances in Management & Applied Economics, vol. 3, no.4, 2013, 119-132
ISSN: 1792-7544 (print version), 1792-7552(online)
Scienpress Ltd, 2013

Seasonal Adjustment versus Seasonality Modelling: Effect on Tourism Demand Forecasting

Amira Gasmi[1]

Abstract

In this study, we treat the seasonal variation in monthly time series in the context of the Western-European tourism demand for Tunisia, by presenting different techniques of detection of seasonality and the parametric and non-parametric approaches of seasonal adjustment. Then, we compare the forecasting performance of these methods. The empirical results militate in favour of the TRAMO-SEATS method. In fact, this approach provides the best forecast. In terms of forecasting efficiency, we note in addition, that the modelling of the seasonal variation using seasonal ARIMA model (SARIMA) may lead to better predictive results compared with other techniques of seasonal adjustment used in this research, namely: the X-12-ARIMA, regression on seasonal dummies and the ratio-to-moving average methods.

JEL Classification numbers: C22, C52, C53, L83.
Keywords: seasonality, tourism demand, forecasting performance, seasonal adjustment, seasonal modelling.

1 Introduction

Seasonality is a major characteristic of the tourism activity. It reveals the influence of the seasons on the tourism demand.

This phenomenon is related to weather changes as well as institutional factors (school holidays, professional vacation, public (Christmas or Easter), religious and commemorative festivals). The calendar can also generate a seasonal movement in monthly time series since the number of working days varies from one month to another. It is also related to certain socio-cultural characteristics (sport practices; social or religious habits).

---

[1]Laboratoire d'Economie et Finance Appliquées – IHEC Carthage, Tunisia.

Article Info: *Received :* February 23, 2013. *Revised :* March 28, 2013.
Published online : July 1, 2013

Taking that into account, the phenomenon of high and low seasons constitutes a problem of size which worries the actors of the tourism field.
Time series analysis aims to separate the short-term behaviour from that of long-term of an economic data series and to give reliable forecasts for these separate components and for the totality of the series.
The seasonal variations explain most of the variation in the growth rates of the majority of the economic time series. In order to draw conclusions on the nature of the business cycles and the long-term growth, the traditional approach is to remove the seasonal component of a series through the use of deterministic seasonal dummies, seasonal differentiation, or using the seasonal adjustment techniques such as the X-12-ARIMA method.
However, sometimes we show that it can be more appropriate to study the seasonal models themselves (Lee and Siklos (1993), Reimers (1997)) since they could give information on the behaviour of the economic agents which are exposed to changes of tendencies at the moment of planning and the formation of waitings. Thus, although seasonal variations-corrected data can be useful, it is typically recommended to use not adjusted data. Moreover, several recent empirical studies showed that many methods of seasonal adjustment lead to seriously denatured data, in the sense that the key properties such as the tendencies, the business cycles, the non-linearities are affected by the seasonal adjustment (Ghysels and Perron (1993), Ghysels, Granger and Siklos (1995), Hylleberg (1994), Miron (1996), Maravall (1995)).
In contrast, King and Kulendran (1997) evaluate several models, including the seasonal unit roots model, in the forecast of quarterly tourist arrivals in Australia coming from many countries. Their principal conclusion is that compared to time series models, the forecasting performance of the seasonal unit roots models is weak. This may be due to the lack of power of some unit roots tests. On the other hand, Paap, Franses and Hoek (1997) use empirical and simulation examples to demonstrate that the neglected seasonal average changes can destroy considerably the forecasting performance of the univariate autoregressive processes. Thus, appropriate treatment of seasonality is important to make reliable forecasts.
In this article, we propose firstly, to study the seasonal aspect strongly characterizing the tourism time series, by presenting different tests of seasonality detection and various methods of treatment of seasonality, in particular seasonal adjustment methods versus seasonality modelling. Then, secondly, we will compare the forecasting performance of these methods.

2 Analysis of Seasonality

2.1 Detection of Seasonality

During the analysis of a time series, it is necessary to identify the seasonal variation which can be probably observed. Various types of tests are set up to detect the presence of this component.

2.1.1 Autocorrelations

Seasonality can be detected graphically by examining autocorrelation (ACF) and partial autocorrelation functions (PACF) necessary for the identification of suitable ARIMA models. Indeed, the correlogram of a seasonal series often takes a sinusoidal form (see table 1).

2.1.2 Traditional tests of presence of seasonality

To test the presence of seasonal variation, a multiplicity of tests were suggested, namely: the stable seasonality and moving seasonality tests which are Fisher types tests based on models of analysis of the variance to one (the month or the quarter) and two factors (the month or the quarter and the year), respectively. Indeed, stable seasonality is a type of seasonality which is repeated at the same time each year, and this stable aspect facilitates the forecasts. While the moving seasonality is represented by a movement effect from one month to another.

This lack of stability makes its forecast difficult. Lastly, we distinguish the identifiable seasonality test completing the tests evoked above. It is built starting from the values of Fisher statistics of stable and moving seasonality tests (Lothian and Morry, 1978).

The test statistic, noted T, is expressed as follows:

$$T = \left(\frac{T_1 + T_2}{2}\right)^{1/2} \quad \text{with} \quad T_1 = \frac{7}{F_S} \quad \text{and} \quad T_2 = \frac{3F_M}{F_S}.$$

If statistic T is lower than 1 so we concludes the presence of identifiable seasonal component and the seasonal adjustment of the series is then necessary.

Table 1: Correlogram of Western-European tourist arrivals series

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.714	0.714	80.981	0.000
		2	0.371	-0.283	102.96	0.000
		3	-0.059	-0.435	103.52	0.000
		4	-0.393	-0.216	128.59	0.000
		5	-0.628	-0.268	193.01	0.000
		6	-0.615	0.009	255.23	0.000
		7	-0.595	-0.463	313.72	0.000
		8	-0.370	-0.076	336.54	0.000
		9	-0.071	0.045	337.39	0.000
		10	0.328	0.282	355.51	0.000
		11	0.630	0.272	423.04	0.000
		12	0.802	0.173	533.14	0.000
		13	0.565	-0.433	588.15	0.000
		14	0.288	0.100	602.53	0.000
		15	-0.061	0.261	603.18	0.000
		16	-0.319	0.172	621.05	0.000
		17	-0.507	-0.141	666.65	0.000
		18	-0.487	-0.017	709.02	0.000
		19	-0.476	0.132	749.77	0.000
		20	-0.302	0.087	766.34	0.000
		21	-0.071	-0.155	767.26	0.000
		22	0.245	-0.235	778.29	0.000
		23	0.485	0.197	821.89	0.000
		24	0.617	0.375	892.89	0.000

2.1.3 Seasonal unit roots tests

The detection of seasonal variation can be done using seasonal unit roots tests. For this purpose, a certain number of tests were implemented in the eighties and nineties, in particular to test the seasonal variation at order 4 and order 12.

Test DHF (Dickey, Hasza and Fuller, 1984): it allows to test the null assumption $\rho = 1$ in the model $x_t = \rho x_{t-s} + \varepsilon_t$. Under H_0 true, the series is seasonal and the filter $\Delta_s = (1 - L^s)$ suggested by Box & Jenkins (1970) is appropriate to adjust it (S being the period of seasonality).

Test HEGY (Hylleberg, Engle, Granger and Yoo, 1990): the literature on the concept of "units roots" (e.g., Dickey, Bell and Miller (1986)) shows that the assumption of existence of certain filters of differentiation amounts to emit the assumption of presence of a certain number of seasonal and non-seasonal units roots in a time series. This can be easily seen by writing: $\Delta_s = (1 - L^s)$, and by solving the equation: $(1 - z^s) = 0$.

The general solution to this equation is: $\{1, \cos(2\pi k/S) + i \sin(2\pi k/S)\}$; with the term $(2\pi k/s)$ for k = 1,2,…, represents the corresponding seasonal frequency, giving S different solutions which all of them are on the circle unit. The HEGY method, mainly conceived for the quarterly series, was adapted to the monthly case thanks to Franses (1990) and of Beaulieu and Miron (1993) works. In fact, if S = 12, solutions of the equation $(1 - z^{12}) = 0$ are: "1" for the non-seasonal unit root corresponding to frequency 0; and 11 seasonal unit roots $\left\{-1, \pm i, -\frac{1}{2}(1 \pm \sqrt{3}i), \frac{1}{2}(1 \pm \sqrt{3}i), -\frac{1}{2}(\sqrt{3} \pm i), \frac{1}{2}(\sqrt{3} \pm i)\right\}$ corresponding respectively to the following frequencies: $\left\{\pi, \pm\frac{\pi}{2}, \pm\frac{2\pi}{3}, \pm\frac{\pi}{3}, \pm\frac{5\pi}{6}, \pm\frac{\pi}{6}\right\}$ and to the operators of differentiation: (1+ L), (1+ L^2), (1+ L+ L^2), (1 – L+ L^2), (1+$\sqrt{3}$ L+ L^2) and (1 -$\sqrt{3}$ L+ L^2).

Thus, a filter of differentiation (Δ_s) can be written as: $\Delta_s = (1 - L)(1 + L + \ldots + L^{S-1})$, and can thus be decomposed into a part with non-seasonal unit root and a part with (S - 1) seasonal unit roots.

In this test, we resort to the decomposition of the polynomial (1-L^{12}), with 12 roots units and we consider the following form:

$$\Theta(L) z_{8t} = \mu_t + \pi_1 z_{1,t-1} + \pi_2 z_{2,t-1} + \pi_3 z_{3,t-1} + \pi_4 z_{3,t-2} + \pi_5 z_{4,t-1} + \pi_6 z_{4,t-2} + \pi_7 z_{5,t-1} + \pi_8 z_{5,t-2} + \pi_9 z_{6,t-1} + \pi_{10} z_{6,t-2} + \pi_{11} z_{7,t-1} + \pi_{12} z_{7,t-2} + \varepsilon_t \quad (1)$$

The variables z_{it} are in such a way that: $z_{it} = P_i(L) y_t$, where polynomials P_i are defined as follows[2] :

[2]Arthur Carpenter (2003).

$$\begin{cases} P_1(L) = (1+L)(1+L^2)(1+L^4+L^8) \\ P_2(L) = -(1-L)(1+L^2)(1+L^4+L^8) \\ P_3(L) = -(1-L^2)(1+L^4+L^8) \\ P_4(L) = -(1-L^4)(1-\sqrt{3}L+L^2)(1+L^2+L^4) \\ P_5(L) = -(1-L^4)(1+\sqrt{3}L+L^2)(1+L^2+L^4) \\ P_6(L) = -(1-L^4)(1-L^2+L^4)(1-L+L^2) \\ P_7(L) = -(1-L^4)(1-L^2+L^4)(1+L+L^2) \\ P_8(L) = (1-L^{12}) \end{cases}$$

With also: $\Theta(L)$ is an autoregressive polynomial in L, and μ_t may contain a constant, 11 seasonal dummies and/or a trend.

The variables z_{it} are then associated to the different roots of the polynomial. The equation (1) is estimated using least squares ordinary method.

We may carry out "t" tests for the parameters π_1 and π_2, and "F" tests associated to the couples $(\pi_3,\pi_4),(\pi_5,\pi_6),(\pi_7,\pi_8),(\pi_9,\pi_{10})$ and (π_{11},π_{12}): it is a question of testing the joined significance of the coefficients. This amounts to test the assumption of existence of unit roots at the different frequencies. For this purpose, we must compare the test statistics related to the estimated parameters with the critical values provided by Franses (1990) and Beaulieu and Miron (1993).

To check the existence of the roots "1" and "-1" corresponding to frequencies 0 and π respectively, we carry out two individual tests on parameters π_1 and π_2. As for the other seasonal unit roots, we can perform either joined tests whose null assumption takes the form $\pi_k = \pi_{k-1} = 0$ and this for the even values of k, from 4 to 12; or quite simply, individual tests, suggested in Franses (1990), allowing to verify the non-stationarity of the time series at all the seasonal frequencies and this by testing the null assumption according to which there is a seasonal unit root ($\pi_k = 0, k \in [3,12]$). However, it should be noted that the application of the OLS to the regression (1) is made where the order of $\Theta(L)$ is given in such a way that the errors are roughly white noises, or at least, non-autocorrelated residuals. For this purpose, Hylleberg and al. (1990) and Engle and al. (1993) propose to introduce additional lags of the variable until we obtain non-autocorrelated residuals.

2.2 Seasonal Adjustment Methods

Seasonal adjustment methods can be classified in two categories, namely: parametric approach and nonparametric approach[3].

---

[3]Bourbonnais and Terraza (2008) propose another classification according to the nature of the seasonal variation which can be is flexible (stochastic: random in amplitude and/or period), that is to say rigid (determinist: marked well and repetitive).

2.2.1 Non-parametric approaches

The X-12-ARIMA method: when the seasonal variation is very apparent in the time series, a first approach consists in removing such seasonal fluctuations by using a seasonal adjustment programs. They are techniques allowing the identification of the different components of the initial series (trend-cycle, seasonality, irregular) by applying linear filters, which cancels or preserves a well defined component (tendency-cycle or seasonal variation). The irregular one is represented thereafter by the residual of the decomposition.

These linear filters are moving averages which constitute the principal tool of Census X-11 method built from successive iterations of moving averages of different natures for better estimating the series components.

However, this technique leads to a loss of information in the final end of the series. This gap is filled by the forecast of future values of the time series before its seasonal adjustment, and this using ARIMA models. It is what made it possible to extend the X-11 technique (Census Bureau, 1967) to X-11-ARIMA (Dagum, 1988) and then to X-12-ARIMA (Findlay and Al, 1998). The latter contains the RegARIMA module which allows to detect and to remove any undesirable effect of the series (outliers, calendar effects…).

The ratio to moving average method: Monthly values of the studied series (X_t) are divided by the moving average figure corresponding for each month (MA_t), and expressed in % to generate the ratio-to-moving average:

$$M_{ratio} = \left(\frac{X_t}{MA_t} \right) \times 100$$

The moving average is calculated as follows:

$$M_m = \frac{1}{2m}\left[X_{t-p} + 2X_{t-p+1} + ... + 2X_{t-1} + 2X_t + 2X_{t+1} + ... + 2X_{t+p-1} + X_{t+p} \right], m = 2 \times p$$

$$MA_t = M_{12}(X_t) = \frac{1}{24}\left[X_{t-6} + 2X_{t-5} + 2X_{t-4} + ... + 2X_{t+5} + X_{t+6} \right]$$

A. Carpenter (2003) reveals that this moving average eliminates seasonal variations from monthly series, preserves linear trends and reduces of more than 90% the variance of a white noise.

These ratios are weighted by the month and thereafter will separate the seasonal and cyclic components.

2.2.2 Parametric approaches

The regression method: this approach is based on the Buys-Ballot model (1847) which consists in carrying out the regression below, using seasonal dummies ($S_{t,i}$) in such a way that $S_{t,i}$ takes value 1 if T corresponds to the seasonal period, and 0 if not. The model is written as follows: $X_t = \beta_0 + \beta_1 t + \sum_{i=1}^{T-1} \gamma_i S_{t,i} + \varepsilon_t$.

With: T being the period of seasonality (T = 4 for a quarterly series, T = 12 for monthly data). The use of only (T - 1) dummies makes it possible to avoid the problem of colinearity which could exist with the vector unit relating to the constant[4]. We estimate thus (T - 1) seasonal coefficients and we check the T^{th} using the principle of conservation of the surfaces[5]: $\sum_{i=1}^{T}\gamma_i = 0$.

Seasonal adjustment by method TRAMO-SEATS: TRAMO-SEATS program (Gomez & Maravall, 1996) belongs to the parametric seasonal adjustment methods based on the signal extraction. It is composed of two independent subroutines but which are complementary since they are generally used together:

- TRAMO program (**T**ime series **R**egression with **A**RIMA noise, **M**issing observations and **O**utliers) falls under the same optic as ARIMA modelling, or more exactly, it is about an extension to these models. Its principle is in fact to model the initial series using the univariate approach of Box & Jenkins via ARIMA or seasonal ARIMA (SARIMA) models, while detecting, estimating and correcting as a preliminary the outliers, the missing values, the calendar effects (holidays, public holidays…) as well as structural changes, likely to disturb the estimation of the model coefficients.
- SEATS program (**S**ignal **E**xtraction **A**RIMA **T**ime **S**eries) comes to complete TRAMO procedure by decomposing the initial series thus modelled in its components (trend, cycle, irregular and seasonality) by signal extraction, using the spectral analysis of the initial series.

2.3 Seasonal Differentiation and Seasonality Modelling

The verification of the existence of seasonal unit roots using specific tests such as DHF (1984) and HEGY (1990) requires special treatment of seasonality.

The use of the filter $(1 - L^s)$, suggested by Box and Jenkins (1970), to differentiate the seasonal series, depends on the fact that the variable is non-stationary at frequency 0 and at all the seasonal frequencies (Pichery and Ouerfelli, 1998).

The existence of seasonal unit roots leads to model the seasonal variation instead of correcting or removing it using seasonal adjustment methods. The most largely used seasonal model is the multiplicative seasonal ARIMA model or SARIMA(p,d,q)(P,D,Q)S proposed by Box & Jenkins (1970) as a generalization of ARIMA(p,d,q) models containing a seasonal part and which is written in this form:

$$\phi_p(L)\Phi_P(L^s)\Delta^d\Delta_s^D y_t = \theta_q(L)\Theta_Q(L^s)\varepsilon_t \qquad (2)$$

Where: S is the period of seasonality (S = 12 for monthly data, S = 4 for quarterly data); $\Delta = 1 - L$, $\Delta_s = 1 - L^s$, $\phi_p, \Phi_P, \theta_q, \Theta_Q$ are polynomials of degrees: p, P, q, Q and the roots are of module higher than 1; (ε_t) is a white noise ; d and D are respectively the orders of non seasonal and seasonal differentiation.

---

[4]We can also consider *T* dichotomist variables in the model and remove the constant.
[5]R. Bourbonnais & Mr. Terraza (2008).

3 The Data

The Western-European market being the principal market transmitting tourists towards Tunisia, the empirical application is carried out based on the series of the Western-European tourist arrivals in Tunisia transformed to logarithm and subsequently noted LTOEU. The sample covers the period from January 1997 to December 2009. For the estimation, we use the data between January 1997 and June 2009, the six remaining observations are used for the ex-post forecast and for the predictive performance evaluation of the various methods.
Data are provided by the National office of Tunisian Tourism relating to the ministry of tourism and trade.

Table 2 : Results of Seasonality tests

	F_S	F_M	T
Value	304,959	9,797	0,2439
Decision	Presence of stable seasonality	Absence of moving seasonality	Presence of identifiable seasonality

Table 3 : Result of test DHF (1984)
Western-European tourist arrivals in Tunisia

Test statistic	Level 5%	Decision	Filter
1,166	-5,84	Accepte H_0	$(1- L^{12})$

Table 4 : Result of test HEGY (1990)
Western-European tourist arrivals in Tunisia

Frequency	Test statistic	Level 5%	Decision	Filter
0	-0,795	-2,76	Accepte H_0	$(1- L)$
Π / 6	3,187	-1,85	Accepte H_0	$(1- \sqrt{3}L + L^2)$
Π / 3	3,21	-3,25	Accepte H_0	$(1- L + L^2)$
Π / 2	6,080	-3,25	Accepte H_0	$(1+ L^2)$
2Π / 3	-1,783	-1,85	Accepte H_0	$(1+ L + L^2)$
5Π / 6	1,61	-1,85	Accepte H_0	$(1+ \sqrt{3}L + L^2)$
Π	-4,027	-2,76	Rejet de H_0	-

4 Empirical Results

Detection of the seasonality: The presence of seasonal variation noted graphically in table 1 is confirmed thanks to the results of the combined test which indicates the presence of an identifiable seasonal variation, since the test statistic provides a value lower than 1 (see table 2). This is marked thanks to the results of test HEGY presented in table 4.
In fact, by using the comparison of the T-statistic calculated in the table with the critical values provided in Beaulieu and Miron (1993), this test reveals the presence of the non-seasonal unit root “1” corresponding to the zero frequency. This allows us to conclude of

the non-stationarity of the variable. Hence, its differentiation with the filter (1 - L) is required.
Furthermore, the test leads to the acceptance of the assumption H_0 of presence of unit roots at all the seasonal frequencies, except for the frequency π. Consequently, the product of the filters indicated in table 4 must be applied to eliminate the seasonal and non-seasonal unit roots, that is to say: $(1-L)(1+L^2+L^4+L^6+L^8+L^{10})$.
Taking that into account, we can conclude that the suitability of the application of the filter $(1-L^{12})$ to a seasonal series, as it is recommended by Box & Jenkins (1970), depends on the fact that the series is integrated at the seasonal frequency zero and at all frequencies.
This being, these results imply that the automatic application of the filter of seasonal differentiation is likely to produce a specification error.
The proof presented here indicates that the unit roots are sometimes missing at certain seasonal frequencies, then their presence have to be checked by using the test HEGY, rather than to impose them a priori at all the frequencies.
However, and by contrariety of simplification, and taking into account the existence of only one seasonal frequency where the assumption H_0 is rejected, we have preferred the application of the filter of seasonal differentiation $(1-L^{12})$ suggested by Box & Jenkins (1970) and recommended by the test of Dikey, Hasza and Fuller (1984) whose result arises in table 3.

Comparison of the seasonal adjustment methods: Figures 1, 2 and 3 present the series of the Western-European tourist arrivals adjusted by the different seasonal adjustment methods considered in this study. We propose to compare the forecasting performance. For this purpose, we followed the forecast process of Box & Jenkins (1970) and the steps of identifications, estimation and validation enabled us to retain the following forecasting models: ARIMA (2,1,2), SARMA (1,1) $(1,1,1)_{12}$, ARMED (1,1), ARIMA (2,1,2), ARIMA (2,1,1) and ARMA(1,1) for each one of these methods of treatment of the seasonal variation, respectively: the filter of seasonal differentiation $(1\text{-}L^{12})$ suggested by test DHF (forecasts 1), the X-12-ARIMA method (forecasts 2), the ratio-to-moving average technique (forecasts 3), the regression on seasonal dummies (forecasts 4) and the TRAMO-SEATS program (forecasts 5). To compare the forecasting efficiency of these models, we retained various criteria of evaluation of the predictive precision, namely: the MAPE, the RMSE, the RMSPE and the U-Theil inequality coefficient. The reading of table 5 makes it possible to conclude that overall (six-months-ahead horizon), the TRAMO-SEATS seasonal adjustment method allows to obtain the most precise forecasts since they admit the weakest evaluation criteria, followed by the seasonal model "SARIMA" (second rank) and the X-12-ARIMA method (third rank).
Therefore, modelling seasonality by the recourse to the SARIMA model (application of the filter of seasonal differentiation $(1\text{-}L^{12})$) is more advised in terms of forecasting efficiency than the seasonal adjustment by the X-12-ARIMA, the ratio-to-moving average and the regression on seasonal dummies methods.

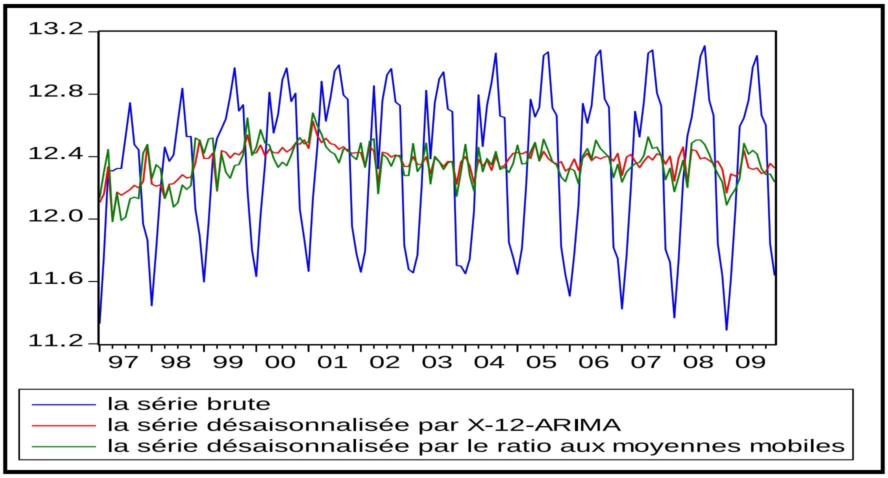

Figure 1: Non-parametric seasonal adjustment approaches

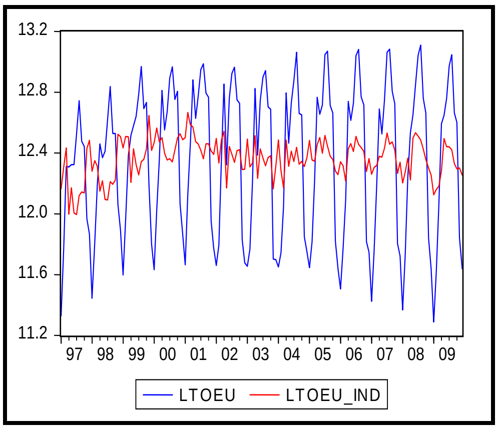

Figure 2: Seasonal adjustment with seasonal dummies

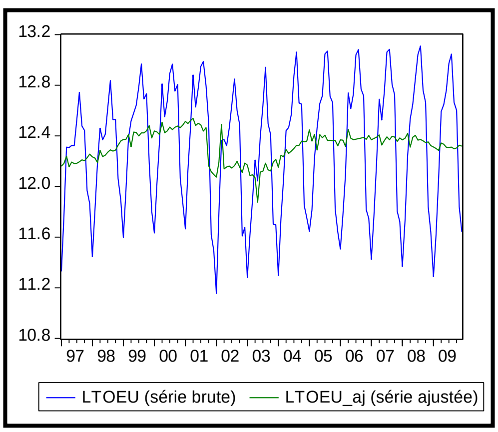

Figure 3: Seasonal adjustment with the TRAMO-SEATS method

This order is maintained for one-month and two-month-ahead horizons. On the contrary, for the three-month-ahead horizon, the forecasts resulting from the X-12-ARIMA method become better than those obtained using the SARIMA model. In consequence, the forecasting performance of the various methods can vary according to the horizon of forecast, which corroborates with the results found in preceding studies (Wong and al., 2007; Shen and al., 2009; Shen and al., 2011).

By elsewhere, the empirical evidence suggests that the techniques of treatment of the seasonal variation affect the forecasting performance of the models, and that differs according to stochastic or deterministic nature of the seasonal variation. In effect, the results obtained in this empirical exercise reveal that the best forecasts result from the TRAMO-SEATS and the X-12-ARIMA methods and also from the seasonal ARIMA model which consider the stochastic seasonal variation (Bourbonnais and Terraza, 2008).

Table 5: Forecasting performance of seasonal adjustment

Methods	Horizons*	MAPE	RMSE	RMSPE	U-Theil
		$\frac{\sum_{t=1}^{h}\left\|\hat{X}_t - X_t\right\|/X_t}{h}$	$\sqrt{\frac{\sum_{t=1}^{h}(\hat{X}_t - X_t)^2}{h}}$	$\sqrt{\frac{\sum_{t=1}^{h}((\hat{X}_t - X_t)/X_t)^2}{h}}$	$\frac{\sqrt{\sum_{t=1}^{h}(\hat{X}_t - X_t)^2/h}}{\sqrt{\sum_{t=1}^{h}\hat{X}_t^2/h}+\sqrt{\sum_{t=1}^{h}X_t^2/h}}$
Forecasts 1 (filter ($1-L^{12}$))	one month (2)	0,7226	819,4837	0,7226	0,3626%
	2 months (2)	2,4325	3772,6082	2,7568	1,5085%
	3 months (3)	2,7088	5130,5156	2,7411	1,2751%
	6 months (2)	2,1184	9516,7616	3,0800	1,4653%
Forecasts 2 (X-12-ARIMA)	one month (3)	0,7527	853,5948	0,7527	0,3749%
	2 months (3)	2,4037	3797,8214	2,7680	1,5184%
	3 months (2)	1,6840	3501,5787	2,0260	0,8725%
	6 months (3)	4,0014	15139,9351	4,5367	2,3034%
Forecasts 3 (ratio-to-moving average)	one month (4)	2,4143	2738	2,4143	1,1928%
	2 months (4)	3,6977	4593,102	3,7609	1,7802%
	3 months (4)	8,2109	15714,649	8,2483	3,7769%
	6 months (5)	12,8957	32761,35	14,8750	4,9032%
Forecasts 4 (regression on seasonal dummies methods)	one month (5)	4,6037	5220,842	4,6037	2,2500%
	2 months (5)	4,2033	5371,418	4,5867	2,0788%
	3 months (5)	9,2562	18323,210	9,3456	4,3768%
	6 months (4)	11,6240	28989,436	13,418	4,3701%
Forecasts 5 (TRAMO-SEATS)	one month (1)	0,05674	64,3498	0,05674	0,0284%
	2 months (1)	1,6191	2219,9875	1,6724	0,8833%
	3 months (1)	1,0769	1777,527	1,3353	0,4448%
	6 months (1)	1,2054	4719,821	1,4008	0,7291%

MAPE: Mean Absolute Percentage Error; RMSE: Root Mean Square Error; RMSPE: Root Mean Square Percentage Error.

(*): Figures in brackets represent the forecasts order by horizon.

5 Conclusion

In this paper, we applied four seasonal adjustment methods: two parametric methods (TRAMO-SEATS and regression on seasonal dummies) and two non-parametric ones (the X-12-ARIMA and the ratio-to-moving average), to a monthly series representing the Western-European tourist arrivals in Tunisia.

We compared the forecasting performance of these methods in particular, seasonal adjustment versus seasonality modelling.

The obtained results militate in favour of the TRAMO-SEATS method. In fact, this approach provides the best forecast at all the forecast horizons.

Always in terms of forecasting performance, we have been able to note that the seasonality modelling using seasonal ARIMA (SARIMA) models may lead to better predictive results compared with the other techniques of seasonal adjustment, namely: the X-12-ARIMA, the regression on seasonal dummies and the ratio-to-moving average.

Consequently, it could be sometimes more appropriate to model the seasonal variation rather than to resort to its correction or suppression by the means of seasonal adjustment methods.

Another conclusion that we could draw from the results is that the forecasting performance is influenced by the manner with which the seasonal variation is treated in the series, i.e. it differs according to stochastic or deterministic nature of seasonality. Indeed, the empirical results reveal that the best predictive performance rises from the TRAMO-SEATS program, the X-12-ARIMA method and of the SARIMA model which consider the stochastic seasonality (Bourbonnais and Terraza, 2008). This is on line with other researches which suggest the stochastic treatment of the seasonal variation (for example, Shen and Al, 2009).

ACKNOWLEDGEMENTS: I would like to thank Mr. Regis Bourbonnais (Paris-Dauphine University) for his constructive comments and helpful suggestions throughout this work.

References

[1] Beaulieu, J.J. and Miron, J.A., The seasonal cycle in U.S. manufacturing, Economics Letters, **37**, (1991), 115–118.

[2] Beaulieu, J.J. and Miron, J.A., Seasonal unit roots in aggregate U.S. data, Journal of Econometrics, **55**, (1993), 305–328.

[3] Bell, W.R. and Hillmer, S.C., Issues Involved with the seasonal adjustment of economic time series. Journal of Business and Economic Statistics, **2**, (1984), 291–320.

[4] Bourbonnais, R. and Terraza, M., Analyse des séries temporelles, Dunod, 2008.

[5] Box, G.E.P. and Jenkins, G.M., Time Series Analysis, Forecasting and Control, San Francisco: Holden-Day, 1976.

[6] Charpentier, A., Introduction à la théorie des processus en temps discret. Modèles ARIMA et Méthode Box-Jenkins, Université Paris Dauphine, 2003.

[7] Clements, M.P. and Hendry, D.F., An empirical study of unit roots in forecasting. International Journal of Forecasting, **13**, (1997), 341–355.

[8] Dagum, E.B., The X11ARIMA/88 Seasonal Adjustment Method - Foundations and User's Manual, Time Series Research and Analysis Division, Statistics Canada technical report, (1988).

[9] Darné, O. and Terraza, M., La désaisonnalisation des séries temporelles viticoles, Version préliminaire, Colloque d'oenométrie, (2002).

[10] Darné, O., Litago, J. and Terraza, M., Tests de racines unitaires saisonnières pour des données journalières, Revue de Statistique appliquée, **50**, (2002), 71–91.

[11] Dickey, D.A., D.P. Hasza, and Fuller, W.A., Testing for unit roots in seasonal time series, Journal of the American Statistical Association, **79**, (1984), 355–367.

[12] Dickey, D.A., Bell, W.R. and Miller, R.B., Unit Roots in Time Series Models: Tests and Implications, The American Statistician, **40**, (1986), 12–26.

[13] Engle, R.F., Granger, C.W.J. and Hallman, J.J., Merging short- and long-run forecast. An application of seasonal cointegration to monthly electricity sales forecasting, Journal of Econometrics, **40**, (1989), 45–62.

[14] Engle, R.F., Granger, C.W.J., Hylleberg, S. and Lee, H.S., Seasonal cointegration: the Japanese consumption function, Journal of Econometrics, **55**, (1993), 275–298.
[15] Findley, D.F., B.C. Monsell, W.R. Bell, Otto, M.C. and Chen, B.C., New Capabilities of the X-12-ARIMA Seasonal Adjustment Program (with Discussion), Journal of Business and Economic Statistics, **16**, (1998), 127–177.
[16] Franses, P.H., Seasonality, nonstationarity and the forecasting of monthly time series, International Journal of Forecasting, **7**, (1991), 199–208.
[17] Franses, P.H., Recent advances in modelling seasonality, Journal of Economic Surveys, **10**, (1996), 299–345.
[18] Franses, P.H. and Hobijn, B., Critical values for unit root tests in seasonal time series, Journal of Applied Statistics, **24**, (1997), 25–47.
[19] Ghysels, E., On the economics and econometrics of seasonality. In: Sims, C.A. (Ed.), Advances in Econometrics, Sixth World Congress of the Econometric Society, Cambridge University Press, Cambridge, (1994).
[20] Ghysels, E., L'analyse économétrique et la saisonnalité, L'actualité économique, **70**, (1994), 43–62.
[21] Ghysels, E., Lee, H.S. and Noh, J., Testing for unit roots in seasonal time series, Journal of Econometrics, **62**, (1994), 415–442.
[22] Gomez, V. and Maravall. A., Programs TRAMO (Time Series Regression with Arima Noise, Missing Observations, and Outliers) and SEATS (Signal Extraction in Arima Time Series). Instructions for the User, Document de travail **9628** du Département de recherche de la Banque d'Espagne, (1996).
[23] Gooijer, J.G. and Franses, P.H., Forecasting and seasonality, International Journal of Forecasting, **13**, (1997), 303–305.
[24] Hasza, D.P. and Fuller, W. A., Testing for non-stationary parameter specifications in seasonal time series models, Annals of Statistics, **10**, (1982), 1209–1216.
[25] Herwartz, H., Performance of periodic error correction models in forecasting consumption data, International Journal of Forecasting, **13**, (1997), 421–431.
[26] Hylleberg, S., Engle, R.F., Granger, C.W.J. and Yoo, B.S., Seasonal integration and cointegration, Journal of Econometrics, **44**, (1990), 215–238.
[27] Hylleberg, S., Modelling seasonal variation. In: Hargreaves, C.P. (Ed.), Nonstationary Time Series Analysis and Cointegration, Oxford University Press, Oxford, 1994.
[28] Hylleberg, S. and Pagan, A.R., Seasonal integration and the evolving seasonal model, International Journal of Forecasting, **13**, (1997), 329–340.
[29] Lee, H.S., Maximum likelihood inference on cointegration and seasonal cointegration, Journal of Econometrics, **54**, (1992), 351–365.
[30] Lee, H.S. and Siklos, P.L., The influence of seasonal adjustment on the Canadian consumption function, 1947 – 1991, Journal of Economics, **26**, (1993), 575–589.
[31] Lothian, J. and Morry, M., A test for the presence of identifiable seasonality when using the X-11 program, Research paper **78-10-002E**, Seasonal Adjustment and Time Series Staff, Statistics Canada, (1978).
[32] Miron, J.A., The Economics of Seasonal Cycles, MIT Press, Cambridge USA, 1996.
[33] Novales, A. and Flores, R., Forecasting with periodic models. A comparison with time invariant coefficient models, International Journal of Forecasting, **13**, (1997), 393–405.
[34] Paap, R., Franses, P.H. and Hoek, H., Mean Shifts, Unit Roots, and Forecasting Seasonal Time Series, International Journal of Forecasting, **13**, (1997), 357–368.

[35] Pichery, M.C. and Ouerfelli, C., Juillet, La non stationnarité dans les séries saisonnières. Application au tourisme tunisien, Université de Bourgogne, Dijon, (July, 1998).
[36] Reimers, H.E., Forecasting of seasonal cointegrated processes, International Journal of Forecasting, **13**, (1997), 369–380.
[37] Shen, S., Li, G., and Song, H., Effect of seasonality treatment on the forecasting performance of tourism demand models, Tourism Economics, **15**(4), (2009), 693–708.
[38] Shen, S., Li, G., and Song, H., Combination forecasts of international tourism demand, Annals of Tourism Research, **38**(1), (2011), 72–89.
[39] Shiskin, J., Young, A.H. and Musgrave, J.C., The X-11 variant of the census method II seasonal adjustment, Technical Paper **No. 15**, Bureau of the Census, U.S. Department of Commerce, (1967).
[40] Wong, K. K. F., Song, H., Witt, S.F., and Wu, D. C., Tourism forecasting: to combine or not to combine?, Tourism Management, 28, (2007), 1068–1078.