MODELLING INTERNATIONAL TOURISM DEMAND USING SEASONAL ARIMA MODELS

Original scientific paper

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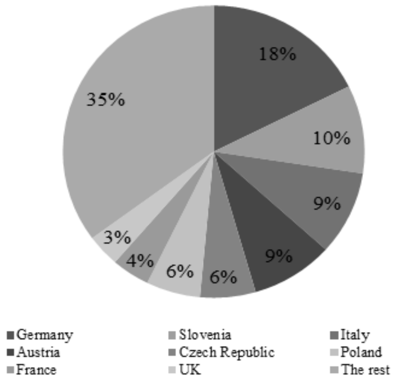
Abstract
Purpose – The purpose of this study is to establish a seasonal autoregressive integrated moving average model able to capture and explain the patterns and the determinants of German tourism demand in Croatia.
Design – The present study is based on the Box-Jenkins approach in building a seasonal autoregressive integrated moving average model intend to describe the behaviour of the German tourists' flows to Croatia.
Approach – The proposed model is a seasonal ARIMA$(0,0,0)(1,1,3)_4$ model.
Findings – The diagnostic checking and the performed tests showed that the estimated seasonal ARIMA$(0,0,0)(1,1,3)_4$ model is adequate in modelling and analysing the number of German tourists 'arrivals to Croatia.
Originality of the paper – This study provides a seasonal ARIMA model helpful to analyse, understand and forecast German tourists' flows to Croatia. Such, more detailed and systematic studies should be considered as starting points of future macroeconomic development strategies, pricing strategies and tourism sector routing strategies in Croatia, as a predominantly tourism oriented country.
Keywords international tourism demand, econometric modelling, seasonal ARIMA models, forecasting, forecasting accuracy

INTRODUCTION

Croatia is predominantly an internationally oriented tourist destination. In fact, international tourism represent a 87,61% of the total tourist arrivals. The structure of foreign tourist arrivals is shown in the figure below.

Figure 1: **Structure of international tourism arrivals in the Republic of Croatia in 2012**



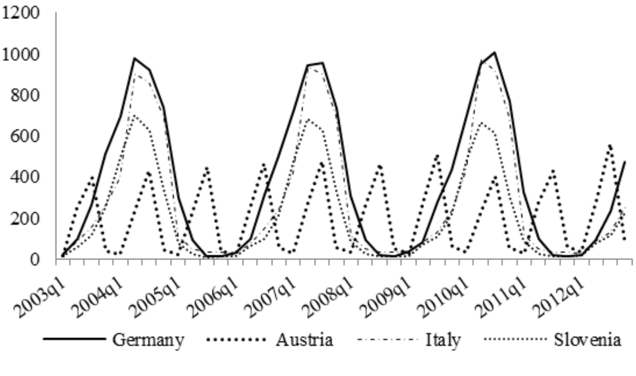
Source: http://www.dzs.hr

According to the figure 1, the highest number of foreign tourist arrivals in 2012 was realized by German tourists, followed by tourists from Italy, Slovenia and Austria.

The German tourist's flows to Croatia represent a significant source of profit for the tourism sector. Therefore, it is crucial to analyse the determinants and the core patterns of the German demand for tourism in Croatia. Germany has traditionally been one of the most important generators of tourist flows in Croatia. In 2012 most of the foreign tourists came from Germany and realized 13,9 million of nights, registering a growth rate of 7,8%. German tourists stayed in Croatia on average 7,5 days, and realized 24,2% of the total foreign tourist nights and 17,9% of the total foreign tourist arrivals. The German tourism flows to Croatia, obviously represent a significant income of tourism flows.

Besides internationality, seasonality is another core characteristic of tourism in Croatia, which is shown in the figure 2.

Figure 2: **Quarterly tourism arrivals in the Republic of Croatia from the main international tourism markets (in thousands)**



Source: http://www.dzs.hr

In spite of the great importance of tourism for the Croatian economy, there is an incomprehensible lack of systematic and exhaustive quantitative researches oriented on analysing the core determinants and patterns of the German tourism demand in Croatia. Therefore, it is crucial to analyse the determinants and the core patterns of the German demand for tourism in Croatia. Such, more comprehensive and detailed studies, could be used in formulation of future macroeconomic development strategies, pricing strategies and tourism sector routing strategies in Croatia, as a predominantly tourism oriented country.

LITERATURE REVIEW

With regard to time-series forecasting, ARIMA models have won great popularity in a large number of studies concerning the tourism demand modelling and forecasting. In a comprehensive study Song and Li (Song and Li, 2008) reviewed 121 papers on tourism demand modelling and forecasting published in the period between 2000 and 2007 and they found out that in 72 studies time-series models, e.g. different versions of ARIMA models proposed by Box and Jenkins, were used to model or forecast tourism demand. According to Song and Li different versions of ARIMA models have been applied in over two-thirds of the post-2000 studies that utilised the time-series forecasting techniques (Song and Li, 2008). These models have shown sound performance in a large number of tourism demand modelling and forecasting studies. In fact, in investigating the performance of combination forecasts of the UK outbound tourism demand Shen, Li and Song combined five econometric models and two time-series models. The empirical results shown that the time-series model were ranked second (the naive model) and third (the SARIMA model) (Shen, Li, Song, 2011). Lin, Chen and Lee demonstrate that the ARIMA models outperformed the Artificial Neural Networks models and the Multivariate Adaptive Regression Splines in forecasting tourism demand in Taiwan (Lin, Chen and Lee, 2011). Lim and McAleer (Lim, McAleer, 2002) used autoregressive integrated moving average models to estimate tourists arrivals to Australia, Hong Kong, Malaysia and Singapore. In an empirical study of from four European countries to Seychelles Preez and Witt (Preez, Witt, 2003) used an autoregressive integrated moving average model and prove that such model have better forecasting accuracy than multivariate and univariate state space modelling.

THEORETICAL AND METHODOLOGICAL ISSUES

In this study the Box-Jenkins approach is used to analyse German tourists' arrivals to Croatia for the period 2003-2012. The Box-Jenkins approach is a powerful method for determining mathematical models of a wide variety of stochastic-process phenomena. In fact it is a systematic multi-stage modelling methodology for identifying and estimating models that incorporate and combine autoregressive (AR) and moving average (MA) models in order to find the best fit of a time-series to past values and make forecasts. The advantages of the Box-Jenkins methodology involve extracting a great quantum of information from the analysed empirical time-series, using a small number of parameters. Furthermore, it can model both stationary and non-stationary time-series, with and without seasonal patterns.

Seasonality in economic time-series is a regular and quite common pattern of changes that repeats over S time period, where S is the number of time periods until the pattern repeats again. In this case $S=4$ (quarters per year) in the span of the periodic seasonal behaviour. In quarterly seasonal data high values tends always to occur in some particular months. As shown in Figure 3, the number of German tourist presences is at its maximum levels in the summer period till April to August. In order to deal with seasonality, ARIMA processes have been generalized and SARIMA models have then been formulated. Seasonal autoregressive integrated moving average (SARIMA) processes are designed to model time series with trends, seasonal patterns and short time correlation. They have developed from the standard model of Box and Jenkins (1970) and incorporate both seasonal autoregressive and moving average factors into the modelling process. The seasonal ARIMA (the SARIMA) models incorporate both non-seasonal and seasonal factors in a multiplicative model as follows:

$$ARIMA(p,d,q) \times (P,D,Q)_S \quad (1)$$

where:

- p – non-seasonal AR order
- d – non-seasonal differencing
- q – non-seasonal MA order
- P – seasonal AR order
- D – seasonal differencing
- Q – seasonal MA order
- S – time span of repeating seasonal pattern

The seasonal autoregressive integrated moving average model of Box and Jenkins (1970) is given by:

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D Y_t = \Theta_0 + \theta(B)\Theta(B^s)\varepsilon_t \quad (2)$$

where:

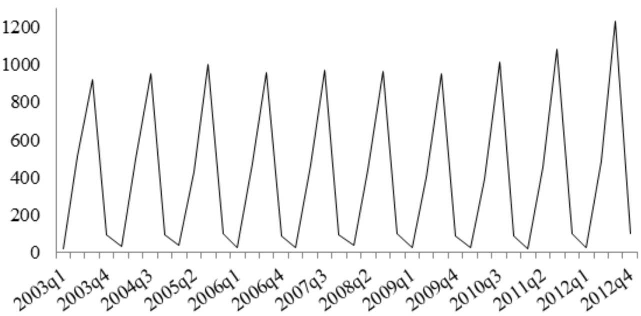
- $\phi(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p$ is the p-order non seasonal AR model
- $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ is the q-order non seasonal MA model
- $\Phi(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \cdots - \Phi_P B^{Ps}$ is the P-order seasonal AR model
- $\Theta(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - \cdots - \Phi_Q B^{Qs}$ is the Q-order seasonal MA model
- $(1-B)^d$ denotes the non-seasonal differencing of order d
- $(1-B^s)^D$ denotes the seasonal differencing of order D
- ε_t is the error term ~IID $(0,\sigma^2)$
- B is the backshift operator
- S is the seasonal order

The Box-Jenkins method is developed throughout three interactive steps, namely the model identification, the parameter estimation and the diagnostic checking stage. In the model identification stage the selection of the order of non-seasonal differencing (d), the order of seasonal differencing (D), the non-seasonal AR order (p) and the seasonal AR order (P), as well as the non-seasonal MA (q) and the seasonal MA (Q) order have to be determined. The model identification stage is based on the sample autocorrelations and the sample partial correlations functions. The estimation stage involves the selected model parameter estimation procedure. At least the diagnostic checking stage involves error terms testing procedures.

EMPIRICAL RESULTS AND DISCUSSION

The purpose of this section is to use the Box-Jenkins approach in order to determine the most appropriate seasonal autoregressive integrated moving average (SARIMA) model to describe the quarterly German tourists' arrivals time-series to Croatia from the period of 2003 to 2012. Data are quarterly and are taken from the Croatian Bureau of Statistics. The collected empirical data are plotted as shown in figure 3.

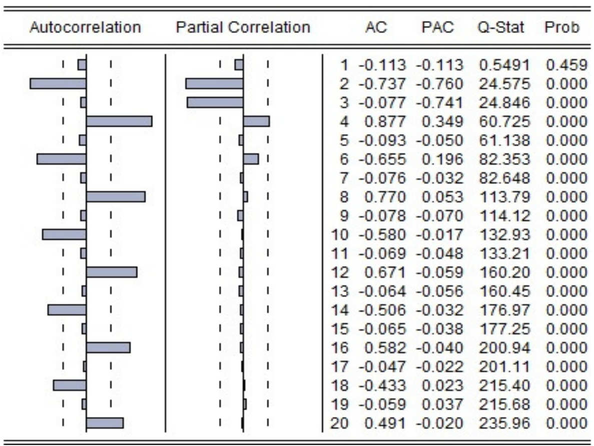
Figure 3: **Quarterly German tourists' arrivals in Croatia from 2003 to 2012**



Source: http://www.dzs.hr/

A first look at the figure reveals a high degree of seasonality and upward trend in time. Since the Box-Jenkins methodology requires the time-series to be stationary in its mean and variance; the empirical time-series need to be tested for stationarity. For this purpose, the autocorrelation function (ACF) and the partial correlation function (PACF) are analysed and the Augmented Dickey-Fuller (ADF) test is performed.

Figure 4: **Correlogram of the original time-series: The ACF and the PACF**



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.113	-0.113	0.5491	0.459
		2	-0.737	-0.760	24.575	0.000
		3	-0.077	-0.741	24.846	0.000
		4	0.877	0.349	60.725	0.000
		5	-0.093	-0.050	61.138	0.000
		6	-0.655	0.196	82.353	0.000
		7	-0.076	-0.032	82.648	0.000
		8	0.770	0.053	113.79	0.000
		9	-0.078	-0.070	114.12	0.000
		10	-0.580	-0.017	132.93	0.000
		11	-0.069	-0.048	133.21	0.000
		12	0.671	-0.059	160.20	0.000
		13	-0.064	-0.056	160.45	0.000
		14	-0.506	-0.032	176.97	0.000
		15	-0.065	-0.038	177.25	0.000
		16	0.582	-0.040	200.94	0.000
		17	-0.047	-0.022	201.11	0.000
		18	-0.433	0.023	215.40	0.000
		19	-0.059	0.037	215.68	0.000
		20	0.491	-0.020	235.96	0.000

Source: Research results

The autocorrelation (ACF) starts rather high and then decline slowly with accentuated seasonal peaks, which is a clear sign that the time-series is nonstationary. The analysis of the empirical functions in lags $k = 4,8,12,\ldots$ shows that the value of the autocorrelation function is significant for lag $k = 4$. It is therefore evident that the original time-series is seasonal nonstationary, and that a seasonal autoregressive model of order 4 should be appropriate.

In empirical analysis the testing of the presence of autocorrelation of higher order is performed by using, among others the Ljung–Box test Q-Statistics. It is a statistical test of whether any of a group of autocorrelations of a time series is different from zero. Instead of testing randomness at each distinct lag, it tests the "overall" randomness based on a number of lags, and is therefore a portmanteau test. It is evident that, even for higher time lags the corresponding Q-Statistics are high and the p-values small which is a clear sign of nonstationarity. Besides the correlogram, another formal test of stationarity is the Augmented Dickey-Fuller, the ADF test. The hypotheses of the Augmented Dicky-Fuller test are:

$$H_0: \gamma = 0, \text{ there is a unit root}$$
$$H_0: \gamma < 0, \text{ there is no unit root} \quad (3)$$

The testing results are shown in the next table.

Table 1: **Original time-series unit root testing results**

Null Hypothesis: ARRIVALS has a unit root			
Exogenous: Constant, Linear Trend			
Lag Length: 3 (Automatic–based on SIC, max lag=9)			
		t–Statistic	Prob.*
Augmented Dickey–Fuller test statistic		0,755704	0,9995
Test critical values:	1% level	–4,234972	
	5% level	–3,540328	
	10% level	–3,202445	
*MacKinnon (1996) one–sided p–values.			

Source: Research results

With the zero hypotheses is assumed the nonstaionarity, which is the presence of a unit root in the time-series. The ADF test statistics is 0,755704 and is greater than the critical values at 5% level. The hypothesis of nonstationarity can be therefore accepted. In order to eliminate the nonstationarity, the time-series variance should be stabilised. The original time-series is therefore seasonally differenced and the ADF test is performed again. The results of the ADF test, after transforming the original time-series with seasonally differencing, are shown in the table below.

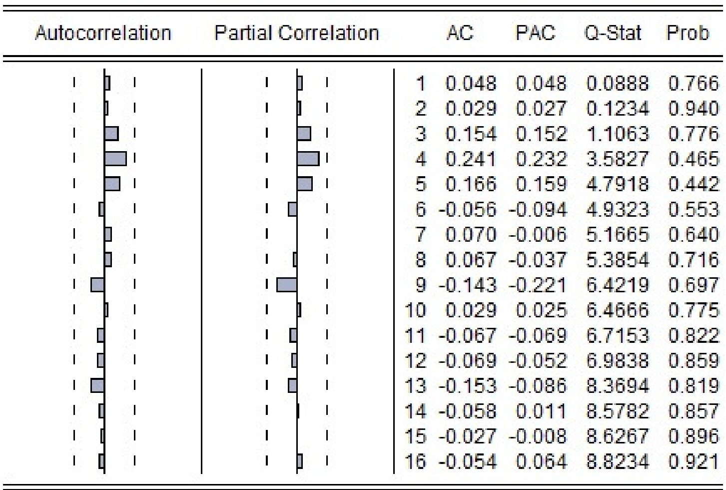
Table 2: **Seasonally differenced time-series unit root testing results**

NullHypothesis: D(ARRIVALS, 0, 4) has a unitroot			
Exogenous: Constant, Linear Trend			
LagLength: 0 (Automatic–based on SIC, maxlag=9)			
		t–Statistic	Prob.*
AugmentedDickey–Fuller test statistic		–6,257595	0,0000
Test criticalvalues:	1% level	–4,243644	
	5% level	–3,544284	
	10% level	–3,204699	
*MacKinnon (1996) one–sided p–values.			

Source: Research results

By applying the ADF test for the seasonally differenced time-series it can be observed that the series become stationary. The ADF test statistics is –6,257595 and is smaller than the critical values at 5% level. The ACF and the PACF are show in the figure below.

Figure 5: **Correlogram of the seasonally differenced time-series: the ACF and the PACF**



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.048	0.048	0.0888	0.766
		2	0.029	0.027	0.1234	0.940
		3	0.154	0.152	1.1063	0.776
		4	0.241	0.232	3.5827	0.465
		5	0.166	0.159	4.7918	0.442
		6	-0.056	-0.094	4.9323	0.553
		7	0.070	-0.006	5.1665	0.640
		8	0.067	-0.037	5.3854	0.716
		9	-0.143	-0.221	6.4219	0.697
		10	0.029	0.025	6.4666	0.775
		11	-0.067	-0.069	6.7153	0.822
		12	-0.069	-0.052	6.9838	0.859
		13	-0.153	-0.086	8.3694	0.819
		14	-0.058	0.011	8.5782	0.857
		15	-0.027	-0.008	8.6267	0.896
		16	-0.054	0.064	8.8234	0.921

Source: Research results

The figure reveals that seasonal differencing has removed quite all significant autocorrelations. After removing seasonality and achieving stationarity, the most appropriate seasonal autoregressive integrated moving average model (SARIMA) should be identified in order to describe and forecast the empirical data. Several models were computed and only models with statistically significant (5%) coefficient were selected, ensuring the normality and the non-autocorrelation of residuals at 5%. Among the analysed models the seasonal $\mathrm{ARIMA}(0,0,0)(1,1,3)_4$ model was identified as the most adequate because it presented the smallest AIC, SBC and HQ Information criterion and the smallest mean absolute percentage error (MAPE). The selected model can be written as follows:

$$(1-\Phi_1 B^4)(1-B^4)Y_t = (1-\Theta_1 B^4 - \Theta_2 B^8 - \Theta_3 B^{12})\varepsilon_t \quad (4)$$

where:
Y_t – represents the tourists' arrivals
B – is the backshift operator
ε_t – is the a random noise

The model in (4) is estimated and the results are reported in the following table.

Table 3: **The seasonal ARIMA$(0,0,0)(1,1,3)_4$ model estimation results**

DependentVariable: D(ARRIVALS,0,4)
Method: LeastSquares
Sample (adjusted): 2005Q1 2012Q4
Included observations: 32 after adjustments
Convergence achieved after 24 iterations
MA Back cast: 2002Q1 2004Q4

Variable	Coefficient	Std. Error	t–Statistic	Prob.
AR(4)	0,909841	0,200988	4,526848	0,0001
MA(4)	–0,364834	0,149076	–2,447308	0,0209
MA(8)	0,443710	0,128667	3,448515	0,0018
MA(12)	–0,863647	0,058170	–14,84704	0,0000
R–squared	0,575880	Mean dependent var		8515,219
Adjusted R–squared	0,530439	S.D. dependent var		39670,01
S.E. of regression	27183,69	Akaike info criterion		23,37509
Sum squared resid	2,07E+10	Schwarz criterion		23,55831
Log likelihood	–370,0014	Hannan–Quinncriter.		23,43582
Durbin–Watson stat	2,055818			
Inverted AR Roots	,98	–,00+,98i	–,00–,98i	–,98
Inverted MA Roots	,98	,89–,44i	,89+,44i	,44+,89i
	,44–,89i	,00+,98i	–,00–,98i	–,44+,89i
	–,44–,89i	–,89–,44i	–,89+,44i	–,98

Source: Research results

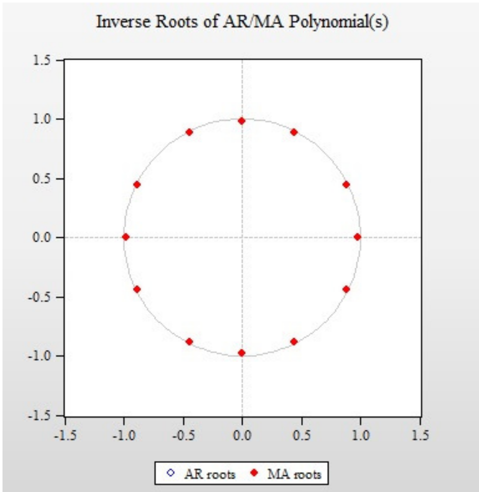
The estimated seasonal ARIMA$(0,0,0)(1,1,3)_4$ can be written as:

$$(1-0{,}909841B^4)(1-B^4)Y_t = (1+0{,}364834B^4 - 0{,}443710B^8 + 0{,}863647B^{12})\varepsilon_t \quad (5)$$

The adjusted R^2 of the model is $0{,}530439$ and shows a quite good model fitting. According to Baggio and Klobas (2011:151) a MAPE value of 9,329873 indicates a high model forecasting accuracy.

After parameter estimation the usual diagnostic tests are computed. The model is first tested for stationarity and invertibility using the inverted AR and MA roots. As reported in table 3 and in figure 6 all the absolute values of the inverted AR and MA roots are smaller than one, the estimated model is therefore stationary and invertible.

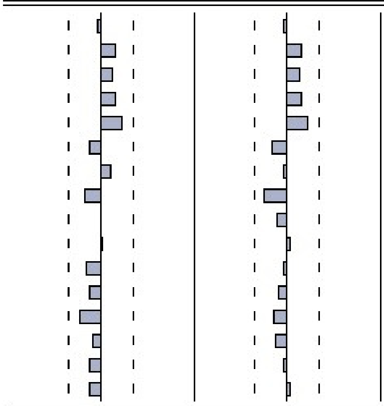
Figure 6: **Inverse roots of ARIMA polynomials**



Source: Research results

The estimated model is tested also for residuals autocorrelation. The presence of autocorrelation is investigated using the ACF, the PACF and the correlogram reported in the next figure.

Figure 7: **The ACF and the PAC of the estimated seasonal ARIMA $(0,0,0)(1,1,3)_4$ model**



	AC	PAC	Q-Stat	Prob
1	-0.029	-0.029	0.0296	
2	0.157	0.156	0.9257	
3	0.130	0.142	1.5598	
4	0.170	0.163	2.6873	
5	0.246	0.238	5.1196	0.024
6	-0.117	-0.164	5.6945	0.058
7	0.100	-0.033	6.1278	0.106
8	-0.172	-0.261	7.4723	0.113
9	0.006	-0.104	7.4741	0.188
10	0.010	0.041	7.4788	0.279
11	-0.166	-0.048	8.9002	0.260
12	-0.118	-0.089	9.6608	0.290
13	-0.245	-0.149	13.091	0.159
14	-0.083	-0.135	13.512	0.196
15	-0.123	-0.040	14.486	0.207
16	-0.115	0.026	15.383	0.221

Source: Research results

All the autocorrelation coefficients do not differ significantly from zero and they are within the 2–sigma limits ($\pm 2 \cdot \frac{1}{\sqrt{n}}$). The Ljung–Box test for lag $k = 16$ is performed. The hypotheses for the test are:

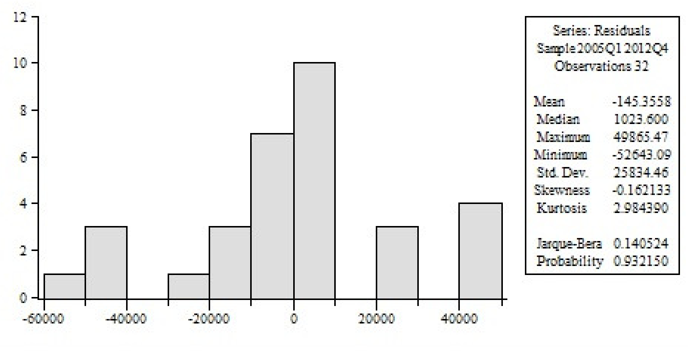
$$H_0:\ \rho(1) = \rho(2) = \cdots = \rho(16) = 0 \qquad (6)$$
$$H_0:\ \exists \rho(j) \neq 0, \quad j = 1, 2, \ldots, 16$$

The empirical value of the Ljung-Box test statistics is $Q = 15{,}383$, and is smaller than the critical value $\chi^2_{0,05}$with $(k - p - q)$ degrees of freedom, $\chi^2_{0,05;12} = 21{,}02607$, and the associated probability value is $0{,}221$. It therefore evident that, at the $\alpha = 0{,}05$ significance level, the zero hypotheses can be accepted: there is no evidence of autocorrelation of the residuals for lags $k \leq 16$. The normality of the residuals is tested using the Jarque-Bera test. The hypotheses of the JB test are:

$$H_0:\ \textit{the residuals are normally distributed} \qquad (7)$$
$$H_1:\ \textit{the residuals are not normally distributed}$$

The testing results are reported in the next figure.

Figure 8: **The Jarque-Bera testing results**



Source: Research results

As the value of the JB statistic ($0{,}140524$) is smaller than the critical value of $\chi^2_{0,05;\,2} = 5{,}991$, the zero hypothesis of normally distributed residuals can be accepted. To test the model for the presence of heteroscedasticity the White test is used. The White test for heteroscedasticity is the LM statistic for testing that all of the δ_j coefficients, except for the intercept, are zero. The hypotheses are:

$$H_0: \delta_1 = \delta_2 = \cdots = \delta_5 = 0 \qquad (8)$$
$$H_1: \delta_j \neq 0, \qquad j = 1, \ldots 5$$

The results are shown in the next table.

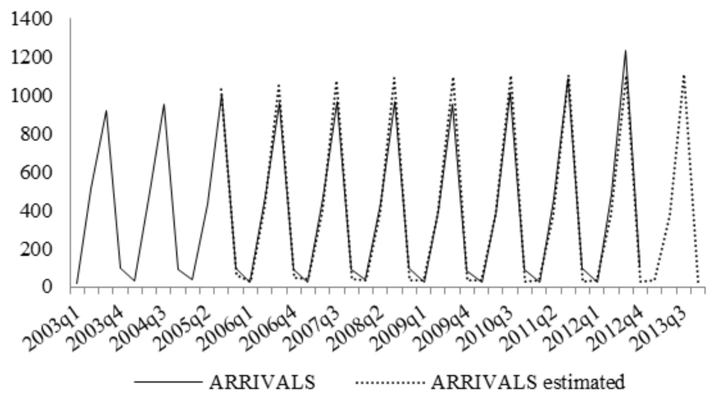
Table 4: **The White test results for the seasonal $ARIMA(0,0,0)(1,1,3)_4$ model**

Heteroskedasticity Test: White			
F–statistic	0,744731	Prob. F(4,27)	0,5700
Obs*R–squared	3,179752	Prob. Chi–Square(4)	0,5282
Scaledexplained SS	2,420010	Prob. Chi–Square(4)	0,6590

Source: Research results

The White statistics is $3{,}179752$ and is smaller than the critical value $\chi^2_{(0{,}05;4)} = 9{,}48773$. The zero hypothesis of the homoscedasticity of the variance can be accepted.

Figure 9: **Quarterly German tourist arrivals in Croatia — fitted versus actual (in thousands, time bounds: 2003-2013)**



Source: Research results

All the performed diagnostic statistics show that the model passes all the tests. As shown in Figure 9 the model fits the data reasonably well throughout the sample period, both for the in sample and out of sample. The forecasts follow quite well the overall trend of the time-series and show good correspondence with empirical data; the in sample MAPE and out of sample MAPE are 9,32987 and 3,800651 respectively.

CONCLUSION

In this paper the SARIMA based models and its usefulness was investigated in modelling and forecasting tourism demand. The aim of the paper is to discuss the development of international tourism demand in Croatia, in particular the behaviour of the German tourists' flows in Croatia in the period 2003-2012. Using the Box-Jenkins methodology a seasonal autoregressive integrated moving average model was built to model the empirical data. According to the Box-Jenkins approach the model building was conceived following the model identification, the parameter estimation and the diagnostic checking stage. As the most adequate model the seasonal $ARIMA(0,0,0)(1,1,3)_4$ model was chosen to model empirical data. The chosen model passed all the diagnostic checking and showed high accuracy performance in modelling the data. As showed the used SARIMA model presents an in sample MAPE of 9,329873 and an out of sample MAPE of 3,800651. According to Klobas (2011:151) a MAPE less than 10% shows a highly accurate forecasting performance of the model.

Starting from the importance of international tourist' flows, especially German, for the Croatian tourism sector, in their previous researches, the authors used different quantitative methods, both extrapolative and causal, in analysing the empirical series of German tourists' arrivals to Croatia, beside the seasonal autoregressive integrated moving average model presented in this study.

As the research results showed, the basic extrapolative methods, i.e. the seasonal naive and the Holt-Winters triple exponential smoothing showed also quite reasonable good modelling performances. In fact, according to Mamula (2015:110) in modelling the German tourists' flows to Croatia in the period from 2003-2012 the seasonal naive model showed an in sample MAPE of 20,217, and out of sample MAPE of 23,912 and the Holt-Winters triple exponential smoothing model (α=0,3, β=0,4, and γ=0,5) showed an in sample MAPE of 19,280 and an out of sample MAPE of 7,603. Furthermore, according to Baldigara and Mamula (2015:7) in modelling the German tourists' flows using multiple regression, the results showed a reasonable modelling accuracy. In fact the conceived model fitted well the general movement of the analysed series during the entire sample period. The forecast results were reasonably good; the predicted values were quite close to the actual ones and the MAPE of the fit was 1,689.

The aim of those researches was to compare the accuracy of different forecasting algorithms, on the same empirical time-series and for the same modelling period, in order to create quantitative models which are able to represent a valuable dataset for further detailed and systematic tourism sector analysis and create theoretical and practical starting points for future tourism development strategies.

Finally, the study wants to emphasize that, starting from the importance of tourism for Croatia's economic development, there is a lack of quantitative approaches in tourism demand modelling and forecasting. Considering the seasonality of the Croatian tourism, as well as the large number of negative consequences that arise from it (tourist traffic density in a specific destination, a lower rate of return on tourism investment, large fluctuations in the demand for labour in tourism and a significant load on the physical environment and natural resources in particular destinations), more detailed and systematic studies should be considered as starting points of future macroeconomic development strategies, pricing strategies and tourism sector routing strategies in Croatia, as a predominantly tourism oriented country.

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