DEMAND FORECASTING WITHIN MONTENEGRIN TOURISM USING BOX-JENKINS METHODOLOGY FOR SEASONAL ARIMA MODELS

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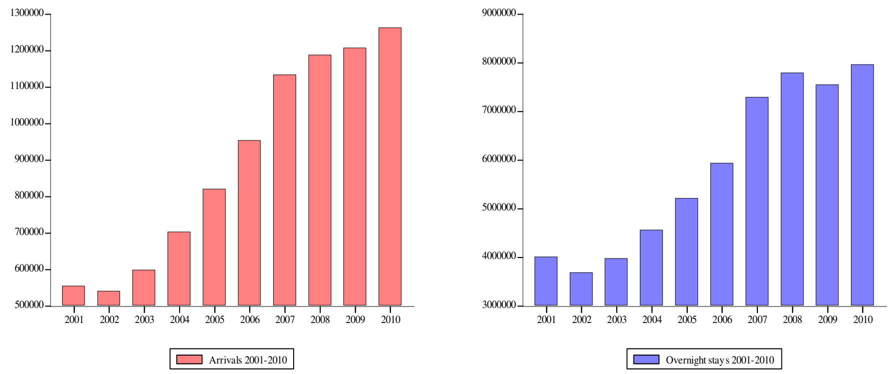
Abstract
The purpose of this paper is to construct adequate seasonal ARIMA models, using Box-Jenkins methodology, and to implement them in order to forecast short run flows of tourist arrivals and tourist overnight stays in Montenegro. Time scope covers ten years, from 2001/01 to 2010/12, while twelve months of 2011 are out-of-sample forecasts. Close inspection of related time series was applied which revealed no extreme and unusual specificities in the data. Therefore, only economic impacts have been affected the time series. This was important because econometric intervention analysis was excluded from models designing and building. As a result, our approach was based on time series modelling without need to take care of any structural breaks. Modified Box-Pierce and Jarque-Bera test statistics confirmed good quality of the models. Further, the results show excellent forecasting performances of specified models. According to forecasting output, Montenegro can expect upgrowth in terms of tourist arrivals as well as in terms of tourist overnight stays. The model has shown around 7,25% rise in arrivals, which is about 91 thousands tourists more in 2011 compared with the previous year. On the other hand, the calculated rise of overnight stays is around 8,42%, or about 670 thousands more than the year before.
Keywords Forecasting, Box-Jenkins methodology, Tourist arrivals, Tourist overnight stays

INTRODUCTION

Montenegro strongly bases its economy on tourism, which was officially proclaimed as developing priority. A destination's strategic goal is steady as possible product consuming among three main regions (coastal, central and northern) throughout the whole year. Therefore, a big challenge is time and spatial dispersion of demand (see Montenegro tourism development strategy to 2020, p. 36). However, prior to any demand management, a vital step is to predict the dynamics of demand, especially according to number of arrivals (NA) and number of overnight stays (NOS). This is the aim of this paper, to provide the data about demand flows in the near future, which can be used in managerial governance.

The NA and NOS in Montenegro have been growing in the last decade. From 2001 to 2010 they have enlarged 2,28 and 1,99 times, respectively. The most significant growth was recorded in 2007 when NA augmented 18,82% and NOS even more, 22,88%. That year can be used as a turning point in a new era of Montenegrin tourism. Nevertheless, in spite of that there are very vivid discussions on all levels about future local and global trends, which give specific importance for building a model that can cope with different opinions. Anyway, the assessment of the Government of Montenegro (Economic policy of Montenegro for 2011, p. 32-33) declares that positive tendency of overnight stays will continue in 2011.[1] This seems reasonable on the grounds of activities that have been undertaken in previous several years (new regulations, infrastructure improvements, promotional campaigns et cetera). Also, mostly positive tourism trends during the global economic crisis give an additional strength. Yearly movement of NA and NOS in the given period of time is shown in Figure 1.

Figure 1: **Number of arrivals and number of overnight stays (2001-2010)**



Source: Montenegro Statistical Office and Statistical yearbooks 2005-2010

Using this time period we first analyse the performances of related time series in order to describe and explain them. In this phase, we try to answer the questions such as stationarity, possible structural breaks and transformation issues. Then, we choose adequate models. At the end, we try to forecast future values of these two time series.

It is crucial to note that the number of tourist arrivals in Montenegro, just two years after Montenegrin independency (i.e., in the year 2008), exceeded the number of tourist arrivals recorded in year 1989, which was oftentimes mentioned as the golden age of Montenegrin tourism. Consequently, it is hard to expect a boost in tourist arrivals in the future. It is rather reasonable to mark some kind of limit or constant level for yearly number of tourist arrivals. Hence, the first *hypothesis* (H1) read: *NA will be approximately the same as a year earlier.*

Interestingly, it is quite different situation when we talk about the number of tourist overnight stays. Namely, during the golden age of Montenegrin tourism NOS was over 10 millions per year, which is more than 2 millions in comparison with the highest value of the last decade. This is a very interesting point, because nearly the same amount of tourists realized such a different number of tourist overnight stays. The difference is really colossal. Therefore, it is expected that number of overnight stays

[1] Documents (*Tourism strategy* and *Economic policy*) are available at: www.gov.me

will continue to rise in the future. Expectedly, the second *hypothesis* (H2) read: *NOS will continue to rise*.

The paper proceeds as follows. In the first chapter, we briefly outline a framework for understanding the role of tourism forecasting. Parallel, we emphasise the advantages of ARIMA forecasting. The subsequent chapter refers to the research context. This includes model identification, model estimation, model testing and forecasting – results presenting. Finally, a discussion and some concluding remarks are given in the last chapter.

FORECASTING AND TOURISM

Clements and Hendry (2004, p. 2) stated that anything can be forecasted, but we prefer to say nearly anything. It is the same in tourism industry, where almost anything can be forecasted, from lodging prices for the next year to number of guest complaints and volume of returning or satisfied tourists. But mostly, tourism forecasting encompasses only physical (NA and NOS) and financial (tourism spending) parameters (i.e., demand side of tourism market). Hence, forecasting of demand is the most important input in tourism business on macro as well as micro level. Without knowing the size of future demand it will be quite possible to take misleading steps about prices and quantities. Li et al. (2006, p. 219) accentuated that "estimates of expected future demand are critical in all planning activities and accurate forecasts are essential for efficient planning". Frechtling (2001, p. 5) stated that "tourism industries, and those interested in their success in contributing to the social and economic welfare of a citizenry, need to reduce the risk of decisions, that is, reduce the chances that a decision will fail to achieve desired objectives. One important way to reduce this risk is by discerning certain future events or environments more clearly. One of the most important events is the demand for a tourism product".

Then, the demand is a primary segment used for predicting tourism flows. It is quite reasonable, because there are sharp short and long run fluctuations in demand based on the changing economic and non-economic conditions. A term in usage, describing this instability in tourism demand, is a *roller coaster* (Biederman, 2008, p. 20). Exactly this makes tourism forecasting a very challenging activity, while numerous issues about heterogeneity and pronounced sensibility of tourism demand pave the way for permanent improvements in forecasting performances.

From the destination host's point of view, tourism forecasting is an essential element of destination planning system and „an integral part of the decision making activities of management" (Makridakis et al., 1998, p. 5). In addition, thinking strategically about efficient and effective destination management without quality projections is impossible. Thereby, tourism forecasting has become an important component in all kind of tourism destination research. However, because of the primary reliance on many human elements, variety of variables and unforeseen forces that may occur, forecasting at best is an imprecise science, more often wrong than right in projecting an accurate results (Biederman, 2008, p. 536). Consequently, more and more notable uncertainty calls for more and more accurate forecasts in tourism industry in order to take proper short, medium and long term actions.

Through time, forecasting has become increasingly complex, and different approaches have been used to generate forecasts. Following Makridakis et al. (1998, p. 6-13), Biederman (2008, p. 538-557), Clements and Hendry (2004, p. 3-5), Kovačić (1995, p. 6-9), Li et al. (2006, p. 220), Frechtling (2001, p. 19-21) and Gujarati and Porter (2009, p. 773-775) we can summarize some of the forecasting techniques that have been developed. All of tourism forecasting methods fall into two broad categories: qualitative (or judgemental) and quantitative. Qualitative forecasting techniques rely on intuition and subjective opinions that are neither scientific nor statistically based (Biederman, 2008, p. 538). ”Judgemental forecasting focuses on the incorporation of forecasters' opinions and experience into the prediction process“ (Önkal-Atay, 2004, p. 133). Some of them include guessing, “rules of thumb“, subjective probability assessment, jury of executive opinion, Delphi technique (expert judgement) and intention surveys. On the other side, quantitative forecasting techniques are objective and statistically based. They can be applied when information about the past are available, when this information can be quantified in the form of numerical data and when it can be assumed that some aspects of the past pattern will continue into the future (Makridakis et al., 1998, p. 9). Broadly speaking, there are several approaches to quantitative forecasting techniques ranging as follows: naive, moving (or rolling) averages, exponential smoothing, classical decomposition, autoregressive integrated moving average (technically known as the ARIMA methodology, but popularly known as the Box-Jenkins (BJ) methodology), vector autoregression (VAR), regression analysis and structural econometric methods.[2] Additionally, Wong et al. (2007) and Song et al. (2008) argued that forecast combination in tourism (combined forecasts) is significantly more accurate than average single model forecasts across all forecasting horizons. ”Empirical results demonstrate that no single forecasting method can generate the best forecasts in all situations and the relative accuracy of the different models varies with the origin-destination pairs and the lengths of the forecasting horizons“ (Wong, 2007). According to them, this provides a strong recommendation for forecast combination in tourism. However, there is one more very important indication that refers to the distinction between short and long run forecasting. ”It also appears that combining forecasts may be more beneficial for longer term forecasting“ (Song, 2008).

Since we focus on a short run forecasting, it is adequate to use a single forecasting method. For the purpose of this paper, we examine the framework and contents of the BJ methodology. Why? Unlike other forecasting techniques, the ARIMA methodology does not assume knowledge of any underlying economic model or structural relationships. It is assumed that past values of the series plus previous error terms contain information for forecasting purposes (Meyler et al., 1998). The emphasis of ARIMA method is on analyzing the probabilistic or stochastic properties of related time series on their own. For this reason, the ARIMA models are sometimes called atheoretic models because they are not derived from any economic theory (Gujarati and Porter, 2009, p. 774-775). Following Meyler et al. (1998), the main advantage of

[2] For the review of some published studies on this topics see: Song, H. and Li, G., (2008).

ARIMA forecasting is that it requires data on the time series in question only. This avoids a problem that sometimes occurs with multivariate models (e.g., it is possible that one series is only available for a shorter period of time than the other series, restricting the time period over which the model can be estimated).

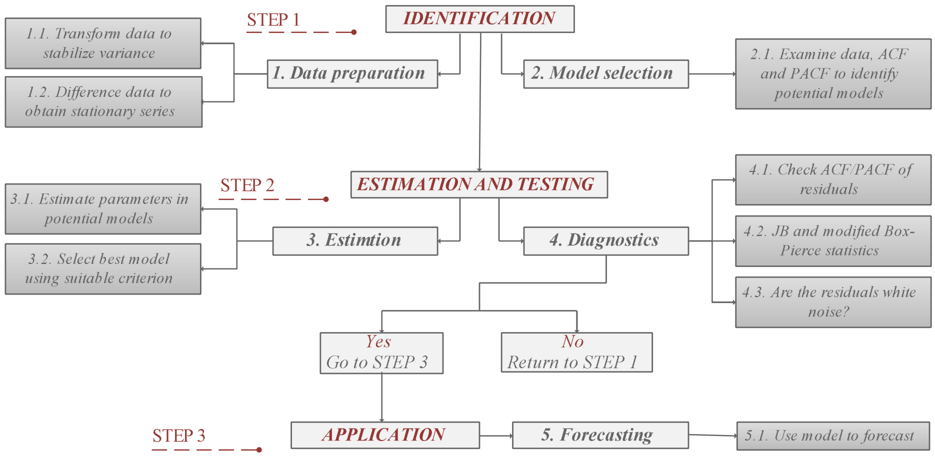
Forecasting using Box-Jenkins methodology

The aim of the BJ method is to find an adequate ARIMA[3] model that can properly describe the movement of data (Mladenović and Nojković, 2008, p. 69), in our case the movement of tourist arrivals and overnight stays. Consequently, we first expose an idea of the BJ methodology, which is applied in the next chapter. This method consists of three steps: *1. Identification*, *2. Estimation and testing and 3. Application*.

In the *first step,* it is necessary to find a class of ARIMA models. In other words, to find out the appropriate values of ARIMA $(p,d,q)(P,D,Q)_s$ terms (Gujarati and Porter, 2009, p. 777). Firstly, the choice depends on the answers about needfulness to transform the series in order to stabilize variance and to difference the data in order to obtain stationary series. When stationarity has been achieved, autocorrelation function (ACF) and partial autocorrelation function (PACF) are being used. ACF and PACF represent methodological frame for choosing the order of potential ARIMA model (Mladenović and Nojković, 2008, p. 69). The *next step* is to estimate the parameters of autoregressive and moving average terms included in the model, and to see whether the chosen model fits the data reasonably well – it is possible that another ARIMA model might do the job as well[4] (Gujarati and Porter, 2009, p. 777). Test of the chosen model comprises of checking ACF and PACF of residuals. The residuals left over after fitting the model should be white noise. In addition, Jarque-Bera (JB) and Box-Ljung Q (modified Box-Pierce) statistics reveal whether the residuals are normally distributed and whether autocorrelation in them exists. If the residuals are white noise, model is adequate and ready for the third step. If they are not, it is necessary to go back to the first step and repeat the procedure all over again. The final, *third step*, is application of the chosen model for forecasting. Schematic representation of the Box-Jenkins methodology discussed above is presented in Figure 2.

[3] When time series exhibits seasonal behaviour (i.e., regularities within one year), the ARIMA notation can be easily extended to handle seasonal aspects. In that case, we are dealing with seasonal ARIMA model.
[4] To determine the most economical model, information criterions are used (most frequently: Akaike – AIC, Schwarz – SC and Hannan-Quinn – HQC).

Figure 2: **Schematic representation of the Box-Jenkins methodology**



Source: Cfr., Makridakis, S. et al. (1998) and Gujarati and Porter (2009)

Kovačić (1995, p. 156-159) listed several principles, criterions, that characterise a good model. They are described as follows. *1. Parsimony*, means that chosen model should be the easiest possible among others. *2. Identifiability*, that allows model interpreting on satisfactory manner. *3. Consistency with data*, refers to good model fitting in relation to data. *4. Consistency with theory*, requests harmony with related economic theory or with common sense. *5. Data admissibility*, means that model must not predict values that do not satisfy some final (defined) restrictions.[5] *6. Forecasting success*, relates to forecast accuracy obtained by model. Taking into account the methodology discussed above, we move on to our empirical case.

RESEARCH CONTEXT

The research investigates two time series – number of tourist arrivals and number of tourist overnight stays, as the most important tourism figures in Montenegro. Time period includes total number of 120 monthly observations between January 2001 and December 2010. The source of data is Montenegrin Statistical Office (MSO) and different issues of Statistical Yearbook (from 2005 to 2010). The *hypotheses* that we formulated read: *NA will be approximately the same as a year earlier while NOS will continue to rise*.

Model identification

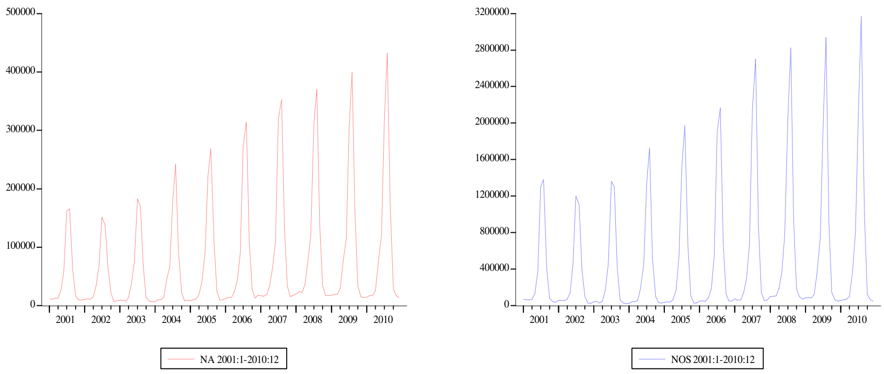
This is the first step in BJ modelling which includes data preparation and model selection. This is the critical point for the ultimate success of model building and also for proper methodology implementing.

[5] For instance, negative values or values over 100.

Data preparation and model selection

At this point, we want to emphasize the data characteristics and to see whether any transformation is needed. The original time series plots of NA and NOS are shown below in Figure 3.

Figure 3: **Original time series (NA and NOS), monthly data, 2001-2010**

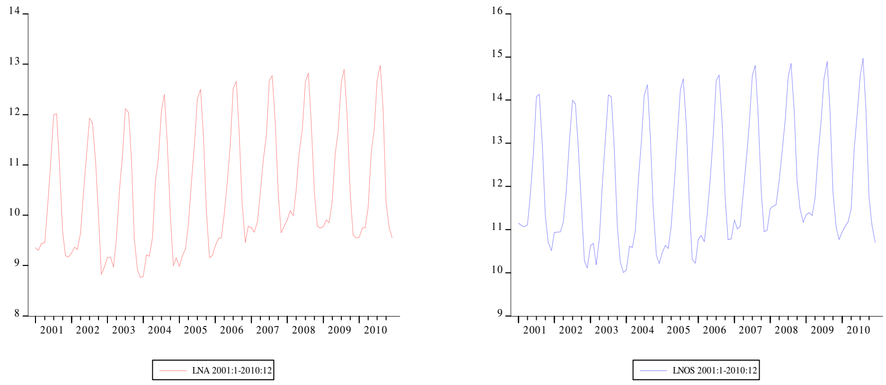


Source: Montenegro Statistical Office and Statistical yearbooks 2005-2010

The first thing we notice in both time series is general increasing trend and strong seasonal pattern, which implies a seasonal ARIMA model. Further, an inspection of plotted time series reveals that no extreme and unusual specificities are present in the data. Therefore, we conclude that only economic impacts have been affected the time series path. This is important because econometric intervention analysis is now excluded from models designing and building. As a result, our approach is based on time series modelling without need to take care of any structural breaks.

From the plotted data, it can be clearly seen that values increase over time, moving from left to right, which is referred to non-stationarity in the variance of the data. This must be corrected and stationary variance must be achieved prior to ARIMA model choosing. It is quite evident from the time series plots that the data in both time series need transforming in order to stabilize variance. For that purpose, we use the so-called Box-Cox transformation with zero value of λ (cfr., Mills, 1990, p. 119). By that, we get the logarithmic transformation of NA and NOS time series. Figure 4 shows the logarithm of the data. It is easily seen that magnitude of the fluctuations in both time series do not vary with time. Now, we can say that the Box-Cox transformations with zero λ value have achieved a time series that are stationary in its variances. Once this stationarity in variances is achieved, we can move on to analysis of related time series. The next thing we are interested in refers to the possible number of unit roots in the logged series.

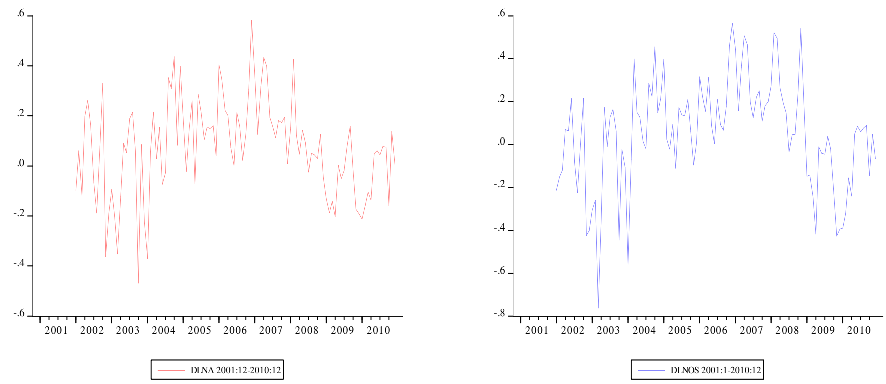
Figure 4: **Logarithms of NA and NOS - Box-Cox transformation (λ is zero)**



Source: Author's calculations using software

Augmented Dickey-Fuller (ADF) unit root test statistics (cfr., Brockwell and Davis, 2002, p. 194-195) have shown that LNA[6] (t-statistics | 0,74 |) and LNOS (t- statistics | 1,46 |) are also non-stationary in their means (i.e., have a unit roots) and require differencing (cfr., Brockwell and Davis, 2006, p. 19). In both cases, there is a strong seasonality and therefore we take a seasonal difference at lag 12 to try to obtain a stationary series. The logged and differenced series are shown in Figure 5.

Figure 5: **Differenced and logged NA and NOS series**



Source: Author's calculations using software

The once differenced series appear to be stationary. ADF unit root test statistics have shown that DLNA[7] (t-statistics | 2,96 |) and DLNOS (t-statistics | 4,78 |) are stationary in their means (i.e., do not have a unit roots) and do not require more differencing.[8]

[6] The letter L denotes natural logarithm.
[7] The letter D denotes differenced series.
[8] Furthermore, we performed a calculation of the variance of the series at different levels of differencing and saw that the lowest one is obtained by model that uses exactly one seasonal difference.

Therefore, we have identified the model – ARIMA $(p,0,q)(P,1,Q)_{12}$, where another values (i.e., *p*, *q*, *P*, *Q*) have been identified on the bases of time-consuming iterative process. Cho (2003) stated that identification methods are rough procedures applied to a set of data to indicate the kind of representational model that is worthy of further investigation. After checking more than 120 concurrent models with different combination of non-seasonal and seasonal parts (i.e., *p*, *q*, *P* and *Q*), we chose the following two models:

For NA: *DLNA = C + AR(1) + MA(1) + MA(2) + SMA(12)* Eq. (1)

For NOS: *DLNOS = C + MA(1) + MA(2) + MA(3) + MA(4) + SMA(12)* Eq. (2)

The values of the Box-Ljung Q statistic (i.e., hypothesis of no autocorrelation in the residuals), the values of the Jarque-Bera test statistic (i.e., hypothesis that the residuals are normally distributed) and the values of the outliers in the residuals (i.e., a smaller or greater standardized values than | 3 |) were used to arrive at the parameters of the BJ models. Thus, ARIMA model building is always very difficult because of the fact that there are no strictly theoretical directions for parameters identification. “This is why BJ ARIMA modelling is more an art than a science; considerable skill is required to choose the right ARIMA model“ (Gujarati and Porter, 2009, p. 777). But, how good are the chosen models? We will check this immediately after estimation and testing (diagnostics) procedure.

Model estimation and testing

This is the second step in BJ modelling which includes model estimation and model testing (i.e., diagnostics of models properties). Once the identified models are estimated, it is crucial to check their adequacy. Only adequate models can be applied and used in the forecasting process.

Estimation and diagnostics

The method of least squares (cfr., Pindyck and Rubinfeld, 1998, p. 5-10) is used for parameters estimation. In the tables and figures that follow, we are presenting the estimation outputs for the previously selected models in Eq. (1) and Eq. (2).

Table 1 shows that all of the identified parameters are highly significant (i.e., all *p*-values are very small) showing that each of the terms used in the model is required.[9] Standard error is 0,1333. The value of the Box-Ljung Q statistic is 24,88 and *p*-value is 0,21, thus we accept null hypothesis of no autocorrelation in the residuals. Further, the JB test statistic is very small, about 0,36 and *p*-value is about 0,84, so we do not reject null hypothesis and we can conclude that the residuals are normally distributed.[10] We

[9] In case that these parameters had not been significant, we may have been able to improve the estimated model just by dropping insignificant term or even terms from the corresponding model.

[10] For this model, we also calculated the ***Anderson-Darling*** normality test (A^2 statistic). The computed A^2 statistic is 0,575 and *p*-value of obtaining such a value is 0,132, which is reasonably high. Therefore, we do not reject null hypothesis that the residuals are normally distributed.

also checked that there are no outliers in the residuals, which means that there are no smaller or greater standardized values than ǀ 3 ǀ.

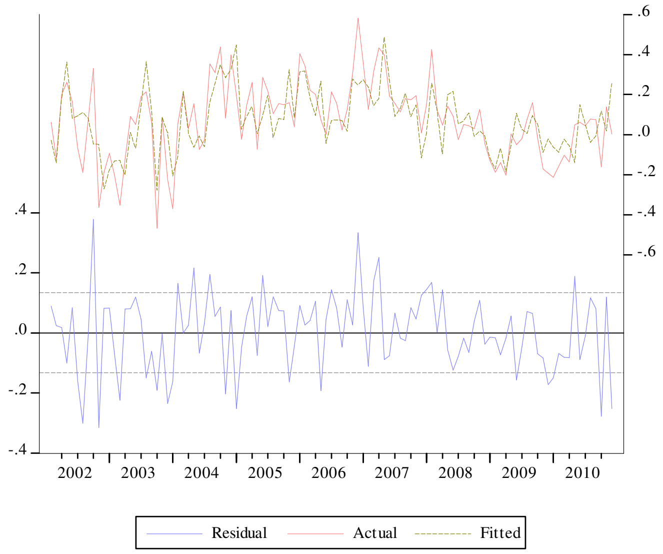
Table 1: **Estimation output for Eq. (1)**

Variable	***Coefficient***	***Std. Error***	***t-Statistic***	***Prob.***
C	0.109868	0.026244	4.186358	0.0001
AR(1)	0.932279	0.048821	19.09603	0.0000
MA(1)	-0.420336	0.117942	-3.563915	0.0006
MA(2)	-0.214446	0.094365	-2.272515	0.0252
SMA(12)	-0.895865	0.022628	-39.59109	0.0000
S.E. = 0,1333	**Q(24)** = 24,88(0,21)		**JB** = 0,36(0,84)	**SC** = -1,02

Source: Author's calculations using software

Figure 6 shows the actual and fitted values as well as the residuals for the first model (DLNA). As we can see, this model approximates the movement of NA time series fairly good. The residuals are normally distributed and uncorrelated.

Figure 6: **Actual and fitted values with residuals – DLNA**



Source: Author's calculations using software

On the other hand, Table 2 shows that all of the identified parameters in the model 2 are highly significant (*p*-values are very small), so each of the terms used in the second model are required. Standard error is 0,1664. The value of the Q statistic is 18,00 and *p*-value is 0,52, thus we accept null hypothesis of no autocorrelation in the residuals. The JB test statistic is about 1,31 and *p*-value is about 0,52, therefore we do not reject null hypothesis and we can conclude that the residuals are normally distributed.[11] We also checked that there are no outliers in the residuals – smaller or greater than | 3 |.

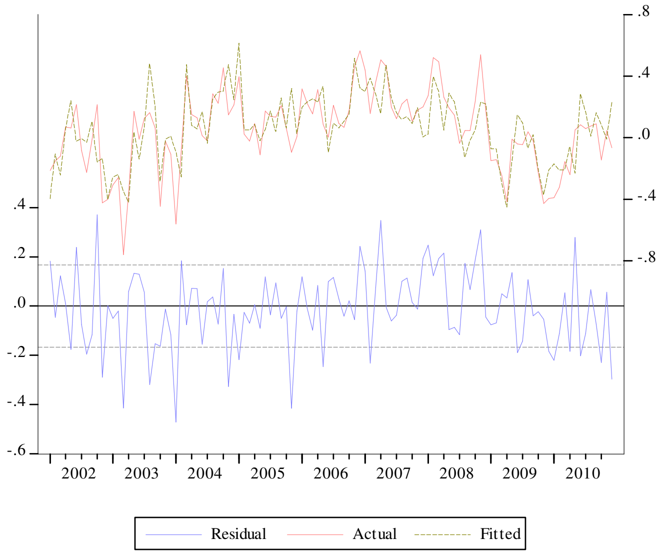
Table 2: **Estimation output for Eq. (2)**

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	0.102944	0.017279	5.957826	0.0000
MA(1)	0.662184	0.096185	6.884469	0.0000
MA(2)	0.370936	0.099369	3.732902	0.0003
MA(3)	0.472168	0.102871	4.589890	0.0000
MA(4)	0.335901	0.083221	4.036271	0.0001
SMA(12)	-0.892877	0.021647	-41.24696	0.0000
S.E. = 0,1664	**Q(24)** = 18,00(0,52)		**JB** = 1,31(0,52)	**SC** = -0,55

Source: Author's calculations using software

Figure 7 shows the actual and fitted values as well as the residuals for the second model (DLNOS). This model is a good approximation of the movement of related time series. Moreover, the residuals are normally distributed and uncorrelated.

Figure 7: **Actual and fitted values with residuals – DLNOS**



Source: Author's calculations using software

[11] The computed A² statistic is 0,558 (*p*-value 0,146). We do not reject null hypothesis.

Application – Forecasting

Now, we turn to the application (i.e., forecasting). Our objective is to predict the 12 future values of time series (out-of-sample monthly forecasts for both time series). Table 3 shows monthly forecasted results with confidence limits for NA time series. As expected, May, June, July, August and September are the months with the most prominent values, thus expressing the extension of strong seasonal movement in the number of arrivals in Montenegro.

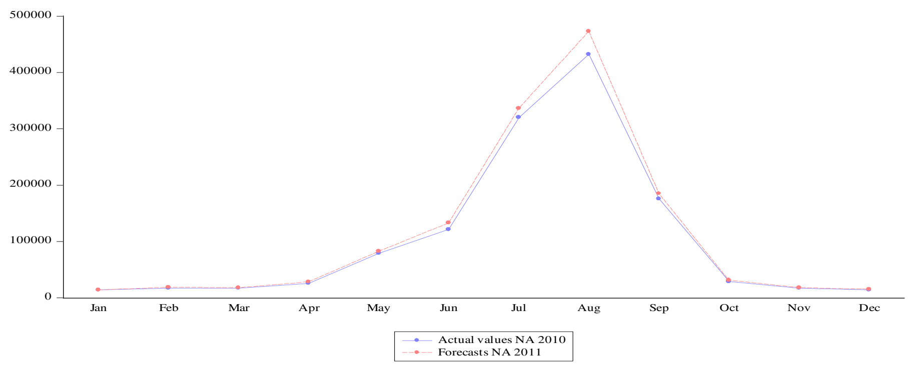
Table 3: **Out-of-sample forecasts with 95% confidence limits for NA time series**

Period	*Forecasts*	*Lower 95% limit*	*Upper 95% limit*
January 2011	**13805**	9846	19355
February 2011	**18943**	13146	27296
March 2011	**17901**	12420	25802
April 2011	**28613**	19849	41246
May 2011	**82768**	57406	119336
June 2011	**133319**	92448	192240
July 2011	**336347**	233235	485095
August 2011	**473071**	328010	682351
September 2011	**185109**	128322	267026
October 2011	**31320**	21709	45180
November 2011	**18093**	12542	26103
December 2011	**15332**	10626	22119

Source: Author's calculations using software

Comparing with the previous year and according to the model output, Montenegro can expect a rise in the number of tourist arrivals. The model has shown around 7,25% rise in arrivals (about 91 thousands tourists more in 2011). A greater number of arrivals can be expected, mostly during August, as we can see in Figure 8.

Figure 8: **Actual values NA 2010 and Forecasts NA 2011**



Source: Author's calculations using software

Table 4 shows monthly forecasted results with 95% confidence limits for the model 2. It is not unusual that the number of tourist overnight stays is dominant between May and September with its peak in August, again expressing the extension of strong seasonal movement in the series.

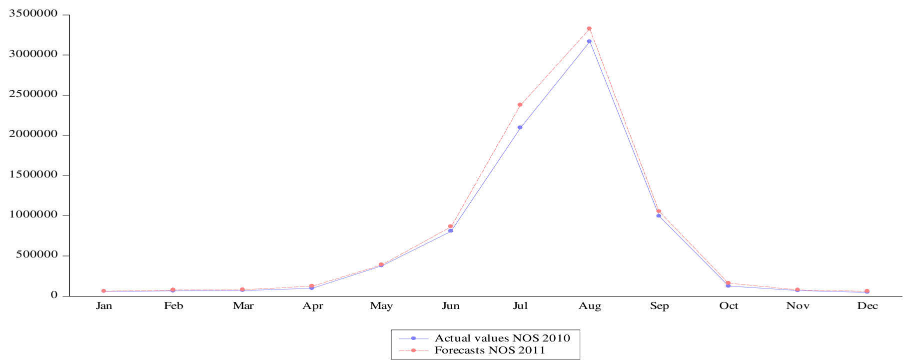
Table 4: **Out-of-sample forecasts with 95% confidence limits for NOS time series**

Period	*Forecasts*	*Lower 95% limit*	*Upper 95% limit*
January 2011	**59113**	41752	83692
February 2011	**73666**	47491	114256
March 2011	**78065**	49267	123698
April 2011	**121322**	73976	198968
May 2011	**388753**	232606	649722
June 2011	**864494**	517311	1444827
July 2011	**2376882**	1422178	3972475
August 2011	**3326396**	1990308	5559396
September 2011	**1052628**	629890	1759253
October 2011	**161490**	96626	269898
November 2011	**75705**	45297	126526
December 2011	**57417**	34355	95961

Source: Author’s calculations using software

According to the model output and comparing with the last year, Montenegro can expect an upgrowth in terms of tourist overnight stays. The figures are showing that the expected rise is around 8,42%, or about 670 thousands more than the year before. The flow of NOS for 2010 and forecasted values of NOS for 2011 are depicted in Figure 9. It is evident that the forecasted rise is present in each month, the most prominently in July.

Figure 9: **Actual values NOS 2010 and Forecasts NOS 2011**



Source: Author’s calculations using software

But, how good are these forecasts? The best way to evaluate this is by comparing them with the actual values. Table 5 shows the forecasted number of arrivals, the actual number of arrivals as well as their differences. At the annual level, the total difference between the two is only about 19 thousands, which is negligible. The monthly differences are also very small. All these values are close to each other, and thus we can conclude that the model is adequate for forecasting.

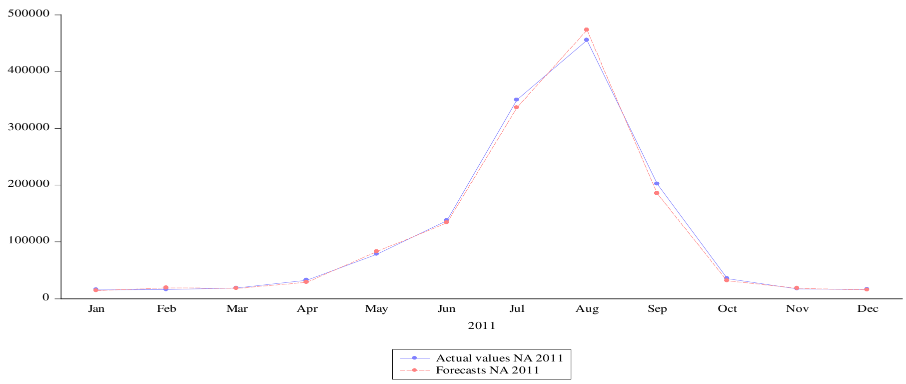
Table 5: **Forecasts, Actual values and Differences for NA time series**

Period	*Forecasts*	*Actual values*	*Differences*
January 2011	13805	15374	**-1569**
February 2011	18943	15840	**3103**
March 2011	17901	18516	**-615**
April 2011	28613	32380	**-3767**
May 2011	82768	77967	**4801**
June 2011	133319	137576	**-4257**
July 2011	336347	349801	**-13454**
August 2011	473071	455185	**17886**
September 2011	185109	201871	**-16762**
October 2011	31320	35221	**-3901**
November 2011	18093	17354	**739**
December 2011	15332	16369	**-1037**
Total NA 2011	1354621	1373454	**-18833**

Source: Author's calculations using software

A comparison between actual and forecasted values is also visually shown in Figure 10. There is only small difference between the actual and forecasted data, which confirms the quality of our model.

Figure 10: **Actual values and Forecasts NA 2011**



Source: Author's calculations using software

On the other side, Table 6 shows the forecasted number of overnight stays, the actual number of overnight stays and their differences. Monthly discrepancies between them are very small. At the annual level, the total difference between the data is about 139 thousands, which is also negligible. All these values are close to each other thus confirming the model adequacy.

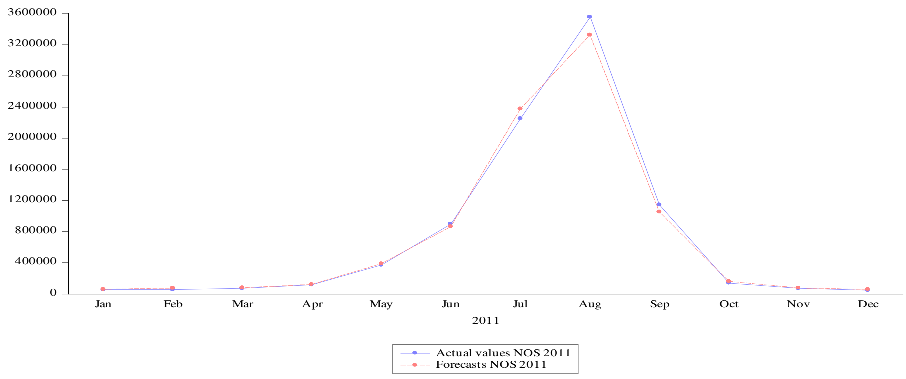
Table 6: **Forecasts, Actual values and Differences for NOS time series**

Period	*Forecasts*	*Actual values*	*Differences*
January 2011	59113	56006	**3107**
February 2011	73666	55751	**17915**
March 2011	78065	70336	**7729**
April 2011	121322	117721	**3601**
May 2011	388753	371486	**17267**
June 2011	864494	897516	**-33022**
July 2011	2376882	2250493	**126389**
August 2011	3326396	3556078	**-229682**
September 2011	1052628	1143745	**-91117**
October 2011	161490	138516	**22974**
November 2011	75705	71170	**4535**
December 2011	57417	46353	**11064**
Total NOS 2011	8635931	8775171	**-139240**

Source: Author's calculations using software

The actual and forecasted values of NOS are also visually shown in Figure 11. A comparison between them confirms the validity of the model.

Figure 11: **Actual values and Forecasts NOS 2011**



Source: Author's calculations using software

It is easy to notice that both models did a rather good job in forecasting the number of arrivals and number of overnight stays in Montenegro. Now, the question is how the obtained results correspond to the formulated hypotheses and what are the implications of such results?

DISCUSSION AND CONCLUSION

In this paper, we considered two forecasting models in order to determine the size of the flows of tourism demand in Montenegro according to the number of arrivals and overnight stays, which are some of the key variables in tourism analysis. Theoretical framework that we used was the Box-Jenkins methodology for seasonal ARIMA models. After constructing the appropriate models, we utilized them to generate the forecasts of demand within Montenegrin tourism. The obtained results (i.e., forecasted values) can provide important information needed for an adequate destination management.

The models showed that a rise in NA and NOS could be expected in 2011. Unfortunately, the first hypothesis (i.e., NA will be approximately the same as a year earlier) is rejected. On the other hand, the second hypothesis (i.e., NOS will continue to rise) is accepted. Two models offered us the values of the potential future movements for both time series (+7,25% for NA and +8,42% for NOS for the entire year). In our opinion, the first outcome is surprising while the second one is not.

First of all, the number of tourist arrivals in Montenegro is expected to stabilize on some level, especially when there is a strong seasonal pressure. As we stated as at the beginning, the number of tourist arrivals in Montenegro, just two years after Montenegrin independency, exceeded the number of arrivals recorded in the year 1989, which was oftentimes mentioned as the golden age of Montenegrin tourism. Consequently, it is reasonable to define some kind of limit or constant level for yearly number of arrivals. Based on the past volume, our suggestion for that margin is around 1,2 millions of tourists per year. Now, the question poses itself: why the actual values exceeded this level? We believe that this is a direct consequence of non-economic influence. Concretely, political instability in the Arab world positively affected Montenegrin tourism in 2011. From safety concerns, a certain number of tourists have decided not to go to North Africa. This is the reason why there was an increase in the number of tourist arrivals in Montenegro. However, we believe that in the current year there will be no increase in that number. On the contrary, we believe that the number of tourist arrivals in Montenegro will be decreasing in the future.

It is quite different situation when we talk about the number of tourist overnight stays. As previously stated, during the golden age of Montenegrin tourism NOS was over 10 millions per year, which is more than 2 millions in comparison with the highest value of the last decade. This is a very interesting point, because nearly the same amount of tourists realized such a different number of tourist overnight stays. Therefore, it is expected that the number of overnight stays will continue to rise in the future. When NOS reaches some critical level, which is, in our opinion, about 11 millions overnight stays per year, it will be reasonable to expect a stabilization of the volume of this indicator. Our results are congruent with this premise.

Furthermore, the simple analyses of all monthly forecasts provide some more serious information. Even a snap view of the monthly forecasted values shows a “chronic illness“ of Montenegrin tourism. It is evident that a huge pressure is still present in several months during the summer season. Only in July and August, according to the model's output, about 59,7% of the total number of tourist arrivals in 2011 is expected to be realized. In 2010 the actual number of arrivals for these two months was 59,6% while in 2009 it was 58,5%. On the other hand, the figures for the overnight stays are pretty similar. According to our forecasts, only during July and August, we can expect about 66,0% of the total number of overnight stays in Montenegro to be realized. The actual values for 2010 and 2009 were 66,1% and 65,0%, respectively. There is no doubt that these unfavourable proportions will continue to replicate in the future flows of the number of arrivals and overnight stays. The results are congruent with the above premise.

Finally, it would be noteworthy to have an opportunity to compare our results with some other measurements made by another authors using different models. Unfortunately, there are no available forecasts that can be used for comparison. Only one available data, related to the number of tourist overnight stays, is presented in "Economic policy of Montenegro for 2011". According to that document, the expected growth of NOS is 3%, which is more than 5% smaller than our forecasted value. It is a rather cautious figure and it would be very interesting to see which model was used to generate such a relatively small value. In addition, there are no separate forecasts for each month pointed out in that document as well as no forecasts for the number of tourist arrivals. Therefore, the results of the present study are expected to be useful for all destination management organizations.

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