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ЗДРУЖЕНИЕ ЗА ЕЛЕКТРОНИКА ТЕЛЕКОМУНИКАЦИИ АВТОМАТИКА И ИНФОРМАТИКА НА РЕПУБЛИКА МАКЕДОНИЈА

SOCIETY FOR ELECTRONIC TELECOMUNICATIONS AUTOMATICS AND INFORMATICS OF THE REPUBLIC OF MACEDONIA

Forecasting Dynamic Tourism Demand using Artificial Neural Networks

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***Abstract*—Planning tourism development means preparing the destination for coping with uncertainties as tourism is sensitive to many changes. This study tested two types of artificial neural networks in modeling international tourist arrivals recorded in Ohrid (North Macedonia) during 2010-2019. It argues that the MultiLayer Perceptron (MLP) network is more accurate than the Nonlinear AutoRegressive eXogenous (NARX) model when forecasting tourism demand. The research reveales that the bigger the number of neurons may not necessarily lead to further performance improvement of the model. The MLP network for its better performance in modelling series with unexpected challenges is highly recommended for forecasting dynamic tourism demand.**

Keywords— Time series, Tourism demand, Tourism planning, Modeling, COVID-19.

I. INTRODUCTION

Planning tourism development particularly in turbulent times during and after the COVID-19 (declared as a pandemic by the WHO, 12 March 2020), becomes not an easy task. Tourism as one of the most important contributors to the world's economy was found to be extremely fragile and vulnerable, facing enormous losses leading to a worldwide recession and depression. A severe drop in international tourist arrivals (estimations to -78%) and an enormous loss of US$ 1.2 trillion in export revenues from tourism, is the largest decline ever [1]. It may take a while before tourism will start again to generate a large financial portion in exports and job creation since COVID-19 provoked many transformations to global economic, socio-cultural, and political systems.

Tourism planners and policy-makers are already eager to continue the forecasting process as a way to furnish information for recovering exhausted economies. Creating solid tourism development plans based on accurate forecasted values envisages success and quick recovery. It is often a case, tourism development to be interrupted for various crises (e.g. terrorism, SARS, natural disasters, earthquakes, political conflicts, Ebola, regional instability, etc.), thus, provoking a structural change in the tourism time series. This disables smooth prediction of tourism values and modeling the series and makes it difficult to analyze expected tourism development. Currently, due to the many measures and strategies related to the COVID-19 (e.g. social distancing, national lockdowns, quarantine, mobility bans etc.), tourism has never experienced such a global collapse. Despite studies that argue the importance of managing the pandemic and finding another context for reimagining and transforming tourism to go a step beyond [2], [3], the inability to create a valid tourism forecasting model will continue long after the pandemic is gone. Structural changes interrupt the series, and the new trend rapidly differs from the previous one.

Many studies explore forecasting models, generally to assist in mitigating the potential negative impacts for the planning process. Although the classical linear models for the identification of time series, such as the ARIMA model [4], can be used in such cases, their application becomes quite complex due to the need to identify all individual structural changes and their influence on the series. Often, modeled series have poor performance in forecasting values [4],[5]. Classical models are linear and therefore unable to model the built-in nonlinear nature of certain time series [6]. On the other hand, models based on artificial neural networks (ANN) can be applied to both, linear and nonlinear time series.

In general, scholars apply the ANN and argue their suitability for forecasting in various fields, but with no focus on an in-depth identification of the cause that makes the model simple and more accurate. This study fills this gap by determining whether the greater number of neurons contributes to better results in modeling and forecasting. To this end, the research tests two types of ANN – the MultiLayer Perceptron network (MLP) and the Nonlinear AutoRegressive eXogenous model (NARX). The main research aim is to identify which model better describes and forecasts international tourism demand. The case of Ohrid is elaborated, as the most popular tourist destination in North Macedonia. Besides adding to the literature on forecasting methods, this study contributes to the scarce empirical academic work in North Macedonia, with some exceptions [7],[8],[9].

The paper is structured as follows: after the introduction, Section 2 provides a brief overview of the literature on forecasting models. Section 3 presents background material on the case study selected for the analysis, i.e., Ohrid as a top tourist destination in North Macedonia. The description of the applied methodology in terms of data and models is presented in Section 4. Section 5 covers the modeling, main results, and discussion, while the conclusion and some future issues to be discussed are drawn in the final section

II. LITERATURE REVIEW

Forecasting tourism demand is vastly explored in academia. The forecasting methodology varies as scholars employ both the time series and econometric approaches in predicting tourism demand [21]. Often, a combined forecast is advocated for obtaining more accurate models [10],[11],[12].

On the other side, any change in the level or variance of the series is considered a structural change, and the analyzed series is not stationary in the entire analyzed period [5]. Nonlinear models can identify series that have a change in the level or variance of the series and are therefore suitable for modeling complex time series with structural changes [5],[12]. Neural network models are not limited to some specific type of series or some specific field of research. Yet, numerous studies use different types of neural networks to model tourism time series [13],[15],[5]. In [15] three types of neural networks are tested: multi-layer perceptron network, a radial basis function network and an Elman neural network to determine which one gives the best results in predicting future values of the series. The authors in [16] analyze the series on rural tourism by using the multi-layer perceptron network. [17] propose a Bayesian estimation and prediction procedure and assume that even in the period of forecasting future values, the possibility of structural changes should be considered.

Although indicators for describing tourism demand differ in academia, the most applicable one is the tourist arrivals. This is further decomposed into in-depth variables as holiday tourist arrivals, business tourist arrivals, as well as tourist arrivals for visiting friends and relatives [18],[19].

III. DATASET

Ohrid is the most famous tourist destination in North Macedonia. Due to favorable natural attractors (sun and lake) along with many additional factors (usage of vacations and ferries, personal preferences for summer season, etc.), Ohrid generally develops summer tourism simultaneously with other tourism forms (cultural, congress, etc.). The peak points for the international tourism demand are visible in the third quarter (summer months July-September) (Figure 2). So Ohrid is characterized by an unequal seasonal distribution of tourist arrivals and the presence of strong and powerful seasonality [20],[21].

For its exceptional natural values, first in 1979, and then in 1980 for its cultural and historical area, the Lake Ohrid region was inscribed as a transboundary mixed UNESCO property [22]. This adds value to this site in attracting tourists. In 2019, before the COVID-19, Ohrid accounted for a quarter of all tourist arrivals (322,573) and for almost one-third of all registered overnights in the country (1,101,563) [23]. 59.5% of all registered tourists in 2019 were foreigners, while in 2020 due to the total COVID-19 lockdown, this rapidly decreased to only 9.6% [24]. As such, Ohrid was experiencing a complete fiasco in its tourism development.

Figure 1 depicts the COVID-19 dramatic reshape in the international tourism demand as of March 2020 when a huge decrease of 66% was noted. The decrease was even more profound in April and May 2020 with less than 0.001%, and June with less than 0.1% of foreign tourists being registered compared to the same months in 2019. During July-December 2020, only 3-6% of foreigners were registered compared to 2019 [24]. This practically meant that Ohrid had no foreigners that season and no tourism development at all. So, COVID-19 has been so far the most significant crisis provoking unforeseen trajectories. This requires a redesign of tourism policy and building a new model since the 'old' exploratory models may be outdated.

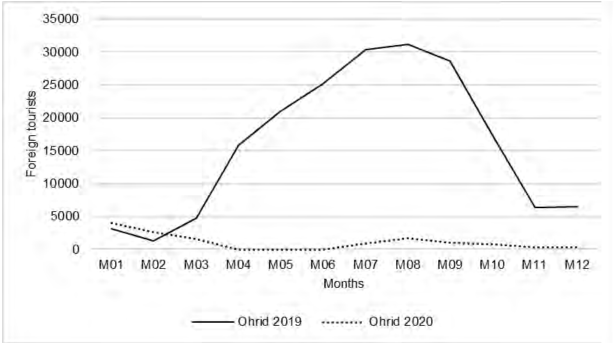

Fig 1. International Tourism Demand in Ohrid, 2019 vs. 2020

A good model of the series before 2020 and forecasting for 2020 and 2021 can give us information about loss of income in tourism sector if we compare forecasted and real data.

The research is based on available official statistical data further processed by the software E-views and Matlab. The original time series is the number of foreign tourists per month being registered in Ohrid in the period 2010-2019 (Figure 2). Data of 2020 are disregarded due to the long-standing structural change in the series provoked by the COVID-19. It is a common standpoint to omit structural breaks which do not allow good modeling of the series based on its previous values [13],[25].

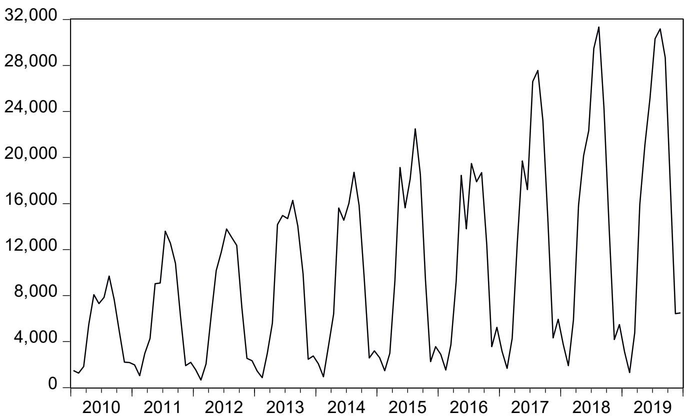

Fig 2. Monthly International Tourist Arrivals in Ohrid, 2010-2019

Based on Figure 2, several features of the series can be noticed: (i) The series is growing, i.e. there is a positive trend in almost the entire analyzed period; (ii) The series is heteroskedastic, the variance increases over time; (iii) The series has a seasonal character, i.e. every year the seasonality is expressed; and (iv) There is a change in the level in 2016 which indicates a possible structural change.

The first three features are visually evident from Figure 2, but the fourth assertion is tested by performing a Breakpoint Unit Root Test (Table 1). This test detects change of levels and trends that differ across a single break date. In combination with Dickey Fuller t-test we can detect significant change in the level or trend of the series at a certain point.

Table 1. Breakpoint Unit Root Test

Null Hypothesis: FOREIGN has a unit root
Trend Specification: Intercept only
Break Specification: Intercept only
Break Type: Innovational outlier

Break Date: 2011M02
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 0 (Automatic - based on Schwarz information criterion, maxlag=12)

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-3.429158	0.4250
Test critical values:	1% level	-4.949133	
	5% level	-4.443649	
	10% level	-4.193627	

The analysis of the structural change indicates a presence of a robust structural change in 2011 (Figure 3). After the World economic crisis in 2010, the government introduced a set of financial measures to support tourism development. The national Agency for Promotion and Support of Tourism introduced a new Rulebook to subsidize incoming tourism. So as of 2011, all tourism arrangements agreed between national incoming agencies and foreign tour operators were substantially subsidized, thus supporting tourism development in the country. This explains the structural change that occurred in 2011.

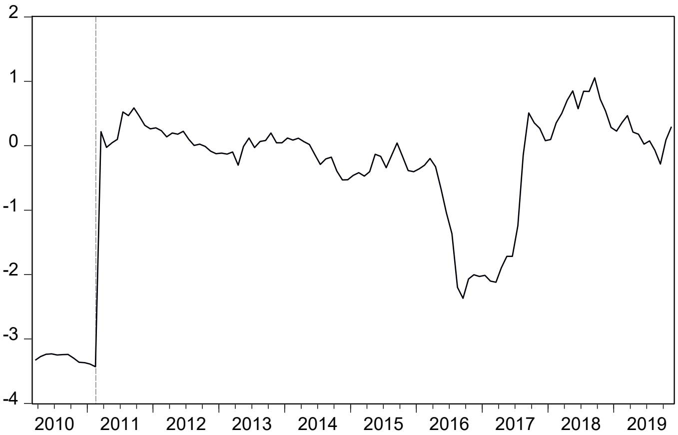

Fig 3. Dickey-Fuller t-statistics

A closer look at the period 2016-2017 (Figure 3), puts a shed-light for a second potential structural change. To check the presence of such, the series was shortened to 2012-2019 and the Breakpoint Unit Root Test was re-performed only to this segment of the series (Table 2).

Results in Table 2, and the visual presentation in Figure 4, point to a conclusion for the presence of another structural change, this time in the first quarter of 2017. There isn't any known causal event that we can mention for this structural break. There can be several different events that should cause such a break like: canceled flights, bad weather conditions, reduced number of airlines, change in the interest of tourists from important countries, etc.

Table 2. Breakpoint Unit Root Test, Cropped Time Series

Null Hypothesis: FOREIGN has a unit root
Trend Specification: Intercept only
Break Specification: Intercept only
Break Type: Innovational outlier

Break Date: 2017M03
Break Selection: Minimize Dickey-Fuller t-statistic
Lag Length: 11 (Automatic - based on Schwarz information criterion, maxlag=11)

		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-2.492220	0.9049
Test critical values:	1% level	-4.949133	
	5% level	-4.443649	
	10% level	-4.193627	

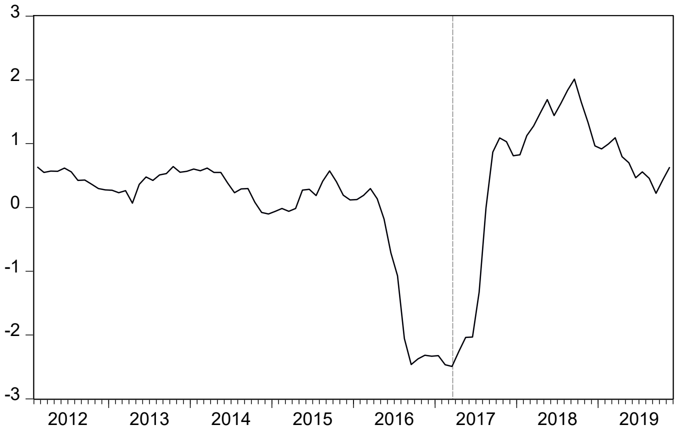

Fig 4. Dickey-Fuller t-statistics

Concluding that the analyzed time series has a presence of seasonality and two structural changes, the built-in character makes the time series unsuitable for linear analysis with the ARIMA model [26][27][28]. The complex nature of the series itself indicates to model with nonlinear models that can detect all confirmed features of the series without having to do preprocessing of batch data.

In order to detect valid inputs, we made an correlogram of the lags. Results are given in table 3. From the values given in the table, we can conclude that there is a serial correlation pattern in the lags of the correlogram, and the 12th lag is significant, and it should be part of the inputs. These results are expected according to the emphasized seasonality of the analyzed series.

Table 3. Corrrelogram of the analyzed series

Sample: 2010M01 2019M12
Included observations: 119

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.253	0.253	7.8245	0.005
		2	0.004	-0.064	7.8268	0.020
		3	0.089	0.111	8.7993	0.032
		4	-0.168	-0.239	12.320	0.015
		5	-0.355	-0.270	28.253	0.000
		6	-0.574	-0.553	70.291	0.000
		7	-0.361	-0.303	87.079	0.000
		8	-0.183	-0.376	91.413	0.000
		9	0.094	0.090	92.561	0.000
		10	0.006	-0.508	92.565	0.000
		11	0.265	-0.160	101.94	0.000
		12	0.857	0.546	200.77	0.000
		13	0.237	-0.109	208.39	0.000
		14	0.022	-0.104	208.45	0.000
		15	0.085	-0.062	209.44	0.000
		16	-0.151	-0.122	212.65	0.000
		17	-0.328	0.005	227.84	0.000
		18	-0.511	0.057	265.03	0.000

IV. ANN MODELS

So the research applied two types of ANN models, the MLP and the NARX. For both networks, the input data, and the series to be modeled are identical.

The first network model is the MLP (figure 5) that uses a sigmoid function in the hidden level, linear at the output, two inputs, one output (target values) without feedback, and the way to set the network parameters is by gradient descent training process. The input parameters in the model are the first and 12th delays of the values in the series. Their selection is made based on previous analysis of autocorrelation and partial autocorrelation analysis of delays (Table 3). The series has a serial autocorrelation, for which the first delay is used, and for the seasonal component of the series, the 12th lag is used. Batch heteroskedasticity can be removed by preprocessing batch values using a logarithmic function [29], but nonlinear models can adapt inner values to the variance change without pre-processing of input data [15],[30][16]. No series stationing has been done, as nonlinear models can model non-stationary series. The only change to the original time series is to normalize the series using the maximum value method. The series was devided on three parts: training part 7 years, testing part 18 months and forecasting part 18 months.

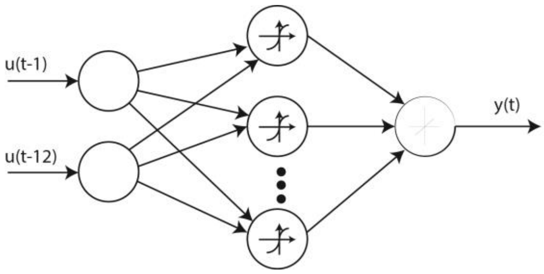

Figure 5. MLP network for time series modelling

The second model is the NARX neural network (figure 6), which is a recurrent neural network that uses exogenous values at the input. Concerning linear ARMA models, this network provides the possibility to use autoregressive parameters in time series modeling. These networks are intended for modeling dynamic nonlinear systems and are widely applied [31][32]. Yet, this network does not have the Moving Average (MA) component of the linear model but can model the non-linear behavior of the series. The basic formula for determining the output values from the network is given by (1).

$$y(t)=f(y(t-1),y(t-2),\dots,y(t-n_y),u(t-1),u(t-2),\dots,u(t-n_u)) \quad (1)$$

where y (t) is the value of the output at moment t, and u(t) is the value of the exogenous input at moment t.

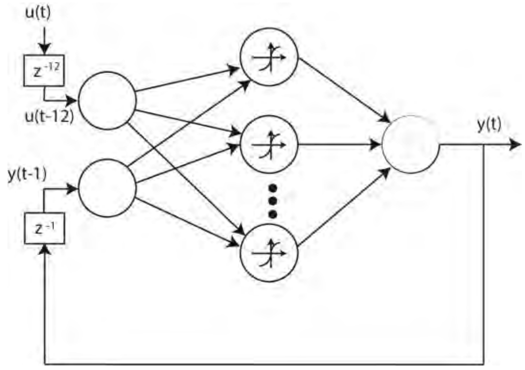

Figure 6. NARX network for time series modelling with one delayed input of 12th lag and one delayed output

For our NARX network, as inputs we use the 12th delay of the input series, and the first delay of the output y(t-1). The recurrent input is intended for elimination of serial correlation, and the input is another valid lag for time series modelling according to the results of autocorrelation table.

Both networks were trained using the Levenberg Marquardt - LM optimization algorithm, which enables faster adjustment of the network weights, using larger memory. As the series is not large, this method is optimal for faster modeling results. Networks with 3, 4, 5, and 10 neurons in the hidden level were used for modeling, testing, and forecasting. The Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE) calculations were used to measure the modeling results, test the model, and predict future values for the model output error, relative to the original series. In the process of model testing, the so-called 'In-sample' forecasting is done. Opposing, in the forecasting process, the network output is closed at the input, and out of sample forecasting is done to calculate the real error of the model in predicting data. Those data were not part of the series used for adjustment of internal parameters.

In the NARX neural network, one network delay is used to eliminate the serial correlation and different initial values are used to determine whether they will lead to better results in modeling and forecasting. Only the best values are presented and elaborated. Due to the detected serial correlation in the series, a dynamic one-step-ahead prediction was used. Both series have one output at the output level of the network, which is sufficient for forecasting values with one-step ahead.

V. Modeling Results And Discussion

Table 4 presents the modeling results of the series, with the MLP model, with different numbers of neurons (3, 4, 5, and 10) in the hidden level to determine whether a larger number of neurons affects the model performance. The values of the parameter R^2 are also presented to identify the degree of variance modeling of the original series.

Table 4. Parameters of the MLP network

Neurons	Process	R	R^2	RMSE	MAPE
3	Training	9.72E-01	9.44E-01	1914.467	7479.918
	Valid.	9.94E-01	9.88E-01	1196.718	5489.201
	Forec.	9.69E-01	**9.39E-01**	**1743.005**	7096.724
4	Training	9.81E-01	9.62E-01	1666.191	5564.072
	Valid.	9.81E-01	9.62E-01	1692.736	5197.05
	Forec.	9.82E-01	**9.65E-01**	**1116.864**	4592.031
5	Training	9.80E-01	9.60E-01	1683.177	4502.398
	Valid.	9.93E-01	9.87E-01	1040.613	5166.994
	Forec.	9.68E-01	**9.36E-01**	**1617.207**	3574.327
10	Training	9.83E-01	9.65E-01	1580.946	5717.576
	Valid.	9.72E-01	9.46E-01	1231.411	6004.149
	Forec.	9.89E-01	**9.78E-01**	**1648.797**	3847.769

Figure 7 visually presents the errors (RMSE and MAPE) for the forecasted values by the MLP model. According to the presented values of the errors, the network with four neurons in the hidden level has better results compared to all others, because the value of RMSE error is lowest compared to other networks, MAPE error is close to the lowest value, and the R^2 parameter has higher value than the model with threor five neurons. So, increasing the number of neurons in the hidden layer to some extent improves the performance of the network, in terms of better prediction.

Table 5 presents the corresponding parameters for the NARX network.

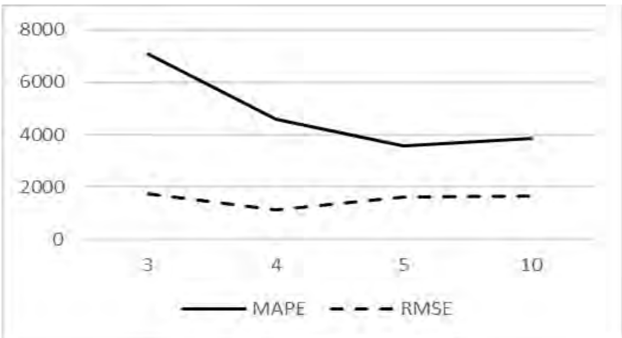

Fig 7. RMSE and MAPE errors of the time series with the MLP network

Yet, Figure 8 gives a glance that a bigger number of neurons than five does not necessarily lead to further performance improvement. The same conclusion derives when screening the degree of follow-up of the variance of the predictions (Table 4, MLP values). Namely, the R^2 does not increase.

Table 5. Parameters of the NARX network

Neurons	Process	R	R^2	RMSE	MAPE
3	Training	8.26E-01	6.83E-01	4758.3522	12502.686
	Valid.	8.03E-01	6.45E-01	4829.5567	6201.3085
	Forec.	9.32E-01	**8.68E-01**	**2845.4526**	7393.1373
4	Training	8.31E-01	6.90E-01	4663.392	1411.7103
	Valid.	8.64E-01	7.47E-01	4556.742	2416.408
	Forec.	9.19E-01	**8.44E-01**	**3235.7296**	2109.4327
5	Training	8.25E-01	6.81E-01	4730.9297	14187.085
	Valid.	8.42E-01	7.10E-01	4201.033	9118.467
	Forec.	8.58E-01	**7.35E-01**	**14151.295**	10143.034
10	Training	8.15E-01	6.64E-01	5031.637	5587.0758
	Valid.	8.98E-01	8.07E-01	4738.0125	2553.4265
	Forec.	8.61E-01	**7.42E-01**	**4338.8036**	3064.3625

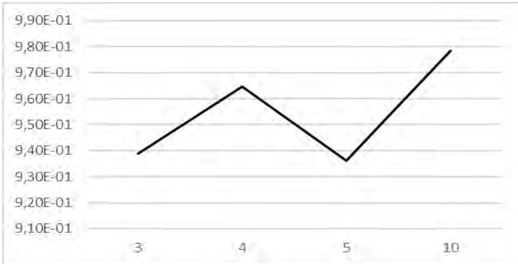

Fig 8. R^2 Parameter for the forecasting with the MLP network

Figure 9 visually presents the errors for forecasted values with the NARX network, where the network with four neurons in the hidden level has better-comparing results. In the NARX networks, there is no defined tendency for the error to decrease or increase with different number of neurons in the hidden layer. So, the network with four neurons in the hidden level shows the best results. These values are not followed by the parameter R^2 presented in figure 10. This parameter decreases its values as the number of neurons in hidden layer increase. The values of R^2 parameter is much lower for the model of NARX network, compared with the same parameter of MLP network.

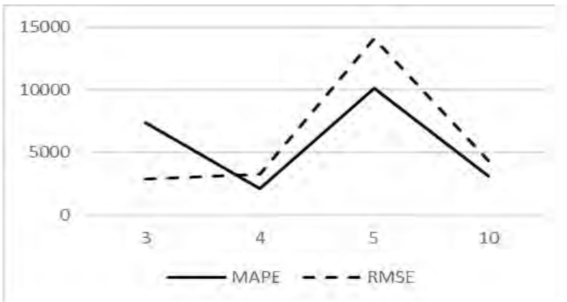

Fig 9. RMSE and MAPE errors of the time series with the NARX network

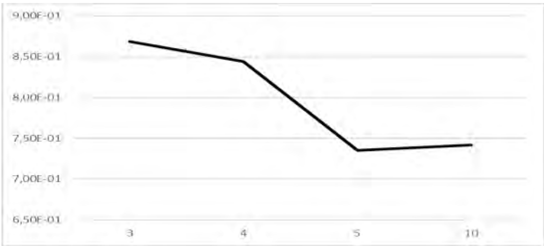

Fig 10. R^2 Parameter for the forecasting with the NARX network

Finally, when comparing the results of the modeling and prediction of the series made with two different types of neural networks, it may be concluded that the MLP network offers significantly better forecasting results than the NARX network. Values of RMSE error are lower for the MLP network in comparison with NARX error. According to the values of MAPE error, NARX networks give better results, but the MLP network gives us information about the optimal number of neurons in the hidden layer.

Despite many scholars who recommend that the NARX networks are suitable for modeling dynamic systems or time series with sufficiently rich input [22],[31], this research revealed the opposite, but only for time series with previously discussed features. The time series that we analyze in this paper has 120 input data. On the other hand, the most complex network that we use has 2*10+10=30 internal variables (weights). We have four time more input data than the number of weights that ensures sufficiently rich input. In cases of dynamic tourism time series with structural breaks and uncertain trends, the MLP network provides better results in forecasting tourism demand.

VI. CONCLUSION

Planning tourism development, particularly in times of uncertainties like the COVID-19 pandemics, must be relied on consistent forecasting values. Due to fact that tourism trend is often interrupted by structural changes, linear models are disabled to successfully model the original time series, particularly if missing sufficient data after the occurrence of the structural change. However, lasting changes in structure of the series prevent any known model on identification and forecasting of different behavior of the same series. Periods of crisis, such as the current COVID-19 pandemics, require models that after completing the change in a relatively short time will be able to make valid modeling of the series and predict future values. Neural networks, due to the nonlinear functions used in creating the model, are suitable for modeling complex time series that have short time built-in structural changes, an evident trend in the series, and the occurrence of heteroskedasticity.

This study employed two artificial neural networks (MLP and NARX) to investigate their accuracy when forecasting international tourism demand for the city of Ohrid, the most popular tourist destination in North Macedonia. By employing monthly data for the international tourist arrivals for the period 2010-2019, the study elaborated and found that generally, does not mean that more neurons will result in better model performance. According to the number of neurons in the hidden level, it is necessary to determine the optimal number of neurons to obtain the optimal solution. The bigger the number of neurons may not lead to further performance improvement of the model.

Moreover, the study argued that the MLP network is more accurate compared to the NARX network and suggests applying this model more intensively when forecasting tourism demand. Further, it practically raises the need for using the ANN for predicting tourism values, particularly the MLP network for its better performance in modeling series when unexpected short-term challenges occur. Totally different behavior of the series are more challenging, and in the period of lasting different behavior impossible to identify and predict. However, in these challenging periods, we can compare actual and forecasted data to be able to detect the losses and to make decisions about support of tourism.

Some further refining in forecasting may be additionally added if employing the Convolutional neural networks for batch modeling. The research may be upgraded with a larger number of time series with similar characteristics to obtain more information on the benefits of different series modeling networks with several structural changes.

REFERENCES

[1]. UNWTO. *UNWTO World Tourism Barometer* (Vol. 18, Issue 2, May 2020). Madrid, Spain: UNWTO, 2020

[2]. Gössling, S., Scott, D., and Hall, C.M., „Pandemics, tourism and global change: a rapid assessment of COVID-19”. *Journal of Sustainable Tourism*, https://doi.org/10.1080/09669582.2020.1758708, 2020

[3]. Hall, C.M., Scott, D., and Gössling, S., „Pandemics, transformations and tourism: be careful what you wish for”. *Tourism Geographies*. https://doi.org/10.1080/14616688.2020.1759131, 2020

[4]. Casini, A. and Pierre, P., „Structural Breaks in Time Series. In *Oxford Research Encyclopedia of Economics and Finance”*. Boston: Palgrave Macmillan., 2018

[5]. Hang Xie, Hao Tang and Yu-He Liao, "Time series prediction based on NARX neural networks: An advanced approach," *International Conference on Machine Learning and Cybernetics*, Baoding, China, pp. 1275-1279, 2009

[6]. Zhang, P., Neural Networks for Time-Series Forecasting. Berlin: Springer. 2012

[7]. Petrevska, B., „Forecasting International Tourism Demand: the Evidence of Macedonia”. *UTMS Journal of Economics*, 3(1), pp. 45-55. 2012

[8]. Petrevska, B., „Estimating tourism demand: the case of FYROM. *Tourismos” An International Multidisciplinary Journal of Tourism*, 8(1), pp. 199-212. 2013

[9]. Petrevska, B., „Predicting tourism demand by ARIMA models”. *Economic research-Ekonomska istraživanja*, 30(1), pp. 939-950., 2017

[10]. Song, H., Witt, S.F., Wong, K.K.F. and Wu, D.C., „An empirical study of forecast combination in tourism”. *Journal of Hospitality & Tourism Research*, 33(1), pp. 3-29., 2008

[11]. Song, H. and Li, G., „Tourism demand modelling and forecasting” – A review of Recent research. *Tourism Management*, 29(2), pp. 203-220., 2008

[12].Wong, K., Song, H., Witt, S.F. and Wu, D.C., 2007. Tourism forecasting: to combine or not to combine? *Tourism Management*, 28(4), pp. 1068-1078.

[13].Asghar, Y. and Amena , U., „Structural Breaks, Automatic Model Selection and Forecasting Wheat and Rice Prices for Pakistan". *Pakistan Journal of Statistics and Operation Research*, pp. 1-20., 2012

[14].Falat, L., Stanikova, Z., Durisova, M., Holkova, B. and Potkanova, T., „Application of Neural Network Models in Modelling Economic Time Series with Non-constant Volatility". *Procedia Economics and Finance* 34, pp. 600-607., 2015

[15].Claveria O., Monte, E., and Torra, S. "*A multivariate neural network approach to tourism demand forecasting".* Barcelona: University of Barcelona, Regional Quantitative Analysis Group., 2014

[16].Shi, X. „Tourism culture and demand forecasting based on BP neural network mining algorithms". *Personal and Ubiqutous Computing*, pp. 1-10., 2019

[17].Timmermann, A., Pettenuzzo, D. and Pesaran, M.H., „Forecasting time series *subject to multiple structural breaks"* (No. 1237). CESifo Working Paper. 2004

[18].Kulendran, N. and Wong K.K.F. „Modeling Seasonality in Tourism Forecasting". *Journal of Travel Research*, 44, pp. 163-170., 2005

[19].Turner, L.W. and Witt, S.F., „Factors influencing demand for international tourism: Tourism demand analysis using structural equation modelling", Revisited. *Tourism Economics*, 7, pp. 21-38. 2001a

[20].Petrevska, B. and Nikolovski, B.. „Level of seasonality in Macedonian tourism and strategies and policies for coping with it". 3rd International Thematic Monograph: "Modern Management Tools and Economy of Tourism Sector in Present Era", Association of Economists and Managers of the Balkans (Belgrade, Serbia) & Faculty of Tourism and Hospitality – Ohrid, Macedonia, pp. 17-29., 2018

[21].Petrevska, B. „Effects of tourism seasonality at local level." Scientific Annals of the "Alexandru Ioan Cuza" University of Iasy, Economic Sciences Series, 62(2), pp. 241-250., 2015

[22].UNESCO. [online]. World Heritage List. Available at: <https://whc.unesco.org/en/list/>.

[23].Statistical Yearbook for [online]. Available at: <http://www.stat.gov.mk/ Publikacii/SG2020/SG2020-Pdf/14-TransTurVnatr-TransTourTrade.pdf>., 2019

[24].Statistical data for 2020. [online]. Available at: <http://makstat.stat.gov.mk/PXWeb/ pxweb/mk/MakStat/MakStat__TirizamUgostitel__Turizam__TuristiNokevanja/125_Turizam_Op_BrTurNok_ml.px/table/tableViewLayout2/?rxid=46ee0f64-2992-4b45-a2d9-cb4e5f7ec5ef>.

[25].Kaushik, R., Jain, S., Jain, S. and Dash, T., „Performance evaluation of deep neural networks for forecasting time-series with multiple structural breaks and high volatility". *Computer Science, Mathematics* (arXiv preprint arXiv:1911.06704). 2019

[26].Box, G.E.P. and Jenkins, G.M., „*Time Series Analysis: Forecasting and Control"*. San Francisco: Holden-Day Inc., 1976

[27].Juntila, J., „Structural breaks, ARIMA model and Finnish inflation forecasts". *International Journal of Forecasting,* 17(2), pp. 203-230., 2001

[28].Turner, L.W. and Witt, S.F. „Forecasting tourism using univariate and multivariate structural time series models". *Tourism Economics*, 7, pp. 135-147. 2001b

[29].Andreeski, C. and Mechkaroska, D., „Modelling, Forecasting and Testing Decisions for Seasonal Time Series in Tourism". *Acta Polytechnica Hungarica,* 17(10), pp. 149-171, 2020

[30].Mamuda, M. and Sathasivam, S., „On the fusion of neural network models in the case of heteroscedasticity". In *AIP Conference Proceedings* (Vol. 1974, No. 1, p. 020010). AIP Publishing LLC., June 2018

[31].Boussaada, Z., Curea, O., Remaci, A., Camblong, H. and Mrabet Bellaaj, N., „A nonlinear autoregressive exogenous (NARX) neural network model for the prediction of the daily direct solar radiation". *Energies*, 11(3), p. 620., 2018

[32].Xie, H., Tang, H., & Liao, Y.-H. ""Time series prediction based on NARX neural networks: An advanced approach", *International Conference on Machine Learning and Cybernetics. doi: 10.1109/ICMLC.2009.5212326*, (pp. 1275-1279). Baoding. 2009