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FORECASTING INTERNATIONAL TOURISM DEMAND IN CROATIA USING GOOGLE TRENDS

Abstract: *Assuming that the rise of the Internet dramatically changed the modern ways of communication and trends in the tourism sector, as well as the tourist behaviour, the aim of the paper is to quantitatively analyse the influence of the information communication technology development on international tourism demand in Croatia. The purpose of this paper is therefore to demonstrate that Google Trends data can be used as a significant proxy in modelling and forecasting international tourism demand in Croatia. In modelling the number of foreign tourist arrivals a neural network approach was used. The input variable set consisted of nine variables. Beside the traditionally used independent variables, several variables that reflect the ICT and Google Trends influences were included in the model. The research results showed that those variables are strongly correlated in forecasting international tourism demand in Croatia. The empirical results and findings in this paper could certainly contribute to increase the understanding and the knowledge of foreign tourist interest and behaviour and therefore, assure more reliable information to all stake-holders involved in the Croatian tourism sector.*

Key words: *international tourism demand, Croatia, ICT, Google Trends, forecasting.*

Introduction

It is a well-known fact that information and communication technology development and the exponential growth of Internet usage have significantly affected the global industry as well as tourism all over the world, including in Croatia. The Internet is undoubtedly the most significant nowadays global social phenomenon which - as a global and certainly controversial media, its usage and its impact on everyday life - is an issue of great interests and researches. Assuming that the rise of the Internet dramatically changed the modern ways of communication and trends in the tourism sector, as well as the tourist behaviour, the aim of the paper is to quantitatively analyse the influence of the information communication technology development on international tourism demand in Croatia. The aim of the proposed research is to find an adequate quantitative model of tourist demand in Croatia as a mathematical function that expresses the relation between the number of tourist arrivals and the most commonly used explanatory variables, and the inclusion of an additional independent variable that reflects the great influence of ICT and Google Trends data on modern tourist trends. The purpose of this study is to investigate whether, including Google Trends indices in modelling international tourism demand in Croatia, accurate forecast and prediction models can be obtained. According to Dinis, Costa and Pacheco (Dinis, Costa and Pacheco, 2016) the search engine that was the market leader (Google Stats, 2016), since 2008 till 2016, was Google, dominating almost 90% of the search worldwide. Furthermore, the way the consumers query formulation in the search engine, namely the search terms used, provide important information about the interests of the future tourist consumer. The authors stated also that Google Trends data can provide useful information about the intentions, the interests and the desires of potential tourists, that can be used as a proxy of future international tourism demand. Starting from those premises, this paper seeks to investigate the extent and the potentials of using Google Trends data as a predictor variable in modelling international tourism demand in Croatia. In order to demonstrate the research hypothesis, the neural network approach is chosen.

Theoretical and methodological issues

The research methodology presented in this study follows the basic standard econometrics methodology phases and consists mainly of several main steps, i.e. previous research and literature reviewing and defining the research design, the modelling phase and the forecasting accuracy and model performance analysing. The neural network model building process was based on the assumption of the significant influence that the ICT has on the tourism sector determinants. In fact, considering the importance ofinternationaltourism and its considerable share in the Croatian GDP, the research attempt to investigate a quantitative model of tourist demand in Croatia as a mathematical function that expresses the relationship between the number of foreign tourist arrivals and the most commonly used exploratory variables, and the inclusion of additional independent variables that reflect the great influence of ICT and Google Trends indices in modelling international tourism demand in Croatia.

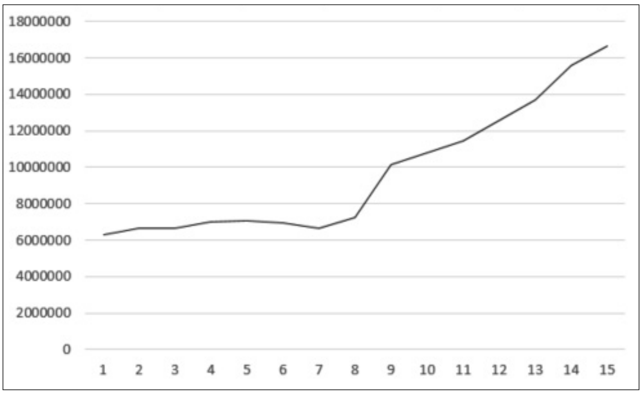
Literature review

A comprehensive desk research and literature review showed that several researches and studies deal with the issues of analysing the benefits of applying quantitative methods in modelling and forecasting tourism demand.Along with the growing significance of the international tourism in Croatia, it should be a growing interest in modelling and forecasting tourism demand and its components. “Modelling tourism demand in order to analyse the effects of various determinants, and accurate forecasting of future tourism demand, are two of the major focuses of tourism demand studies” (Song & Witt, 2005). Accurate forecasts of tourism demand and its features can certainly improve planning and decision-making. Numerous studies on tourism demand modelling and forecasting have been published over the past decades. Law and Au used the neural network approach to forecast Japanese demand for travel to Hong Kong (Law and Au, 1999) Fernandes, Teixeria, Ferreira and Azevedo investigated the usefulness of the Artificial Neural Networks methodology as an alternative to the Box-Jenkins methodology in analysing tourism demand (Fernandes, Teixeria, Ferreira and Azevedo), 2008. Lin, Chen and Lee forecasted tourism demand using time series, artificial neural networks and multivariate adaptive regression splines in analysing tourism in Taiwan (Lin, Chen and Lee, 2011). Gunter and Onder analysed modelling accuracy of uni- and multivariate models in forecasting international tourism demand for Paris (Gunter and Onder, 2015) Folgieri, Baldigara and Mamula (Folgieri, Baldigara and Mamula, 2017) modelled a backpropagation Artificial Neural Network to forecast tourists’ arrivals in Croatia.Baldigara used several extrapolative methods to model domestic tourism in Croatia (Baldigara, 2018).In recent years, there is an increasing interest in researching and investigating the influence of modern ICT, and especially Google Trends tools, on modelling tourism demand. Onder (Onder, 2016) used Google Trends indices in forecasting tourism demand for major European cities. Dinis, Costa and Pacheco (Dinis, Costa and Pacheco, 2016) investigated the use of Google Trends data as a proxy of foreign tourist inflows to Portugal and the research results showed that Google Trend indices can provide useful information about the intentions of individuals about accommodations needs country wise or specifically in its tourism regions. Onder (Onder, 2017) extended previous researches in term of comparing the forecasting accuracy of cities and countries using Google Trends web and image indices.

The dataset

According to Song, Witt and Li (2012) tourist arrivals are the most commonly used measure of international tourism demand, followed by tourist expenditure and tourist nights in registered accommodation. This study considers the number of foreign tourist arrivals as a measure of international tourism demand in Croatia from 2011 to 2018. Data are annual and were taken from the Croatian Central Bureau of Statistics. Figure 1 shows the actual data used in the forecasting model building process.

Figure 1. *Number of foreign tourist arrivals; actual annual data; time span: 2004 to 2018.*



Source: Elaborated by authors

Figure 1 reveals that the time-series presents an upward trend component in the analysed period. The observed time series consists of 15 observations. In the considered period there were on average 9 690 255 foreign tourist arrivals per year with a standard deviation of 3 573 675. The maximum number of foreign tourist arrivals (16 644 871) was registered in 2018, while the minimum (6 278 991) was realised in 2004.

In building the neural network model several inputs variables were experimented as inputs. The considered inputs variables are listed and describe bellow. The input set data consisted of nine variables and it can be split into two subsets: the first containing the traditionally used independent variables and the second consisting of variables that reflects the ICT influences and Google Trends data.

The traditional independent variables

The traditionally used independent variables that are supposed to influence the international tourism demand in Croatia, used in the neural network building process are:

– *GDP*: GDP per capita in current USD, annual data from 2011 to 2018; collected form the Eurostat Database and

– *CPI*: consumer price indices, annual data from 2011 to 2018; collected form the Croatian Bureau of Statistic Statistical Database.

The independent variables that reflect the

ICT influences and Google Trends variables

In modelling the international tourism demand two variables that reflect the ICT influences and the Internet usage Worldwide were selected:

– *IU*: number of Worldwide internet users (in million), annual data from 2011 to 2018, collected from https://www.statista.com/statistics/273018/number-of-internet-users-worldwide/and

– *MCS*: number of World mobile cellular subscriptions (in million), annual data from 2011 to 2018, collected from https://stats.areppim.com/stats/stats_mobilexpenetr.htm

Google Trends data

Google Trends was launched in 2012 and is an online tool that allows access to daily and weekly frequency search data for a particular keyword, subject, and phrase over a period of time and different geographic locations. Due to the timeliness of Google's trend, a number of studies have shown that this data can be used to investigate economic trends at the time of their creation, thus avoiding the delay time that is a feature of official statistical releases. Google Trends works by analysing a portion of Google searches to compute how many searches have been done for the terms entered, relative to the total number of searches done on Google over the same time and are updated on daily bases.The purpose of this study is to investigate whether using Google Trends indices for web search improves tourism demand forecast accuracy.Starting with the assumption that foreign tourists seek information in several search engines, before arriving in Croatia, in this study is supposed that Google Trends data can be considered and used as approximators of the potential quantity of international tourism demand. Google Trends indices represent the search interest for a given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for the considered term. For the purpose of this study, the originally monthly retrieved Google Trends indices were aggregated on annual basis. Finally, aggregated annual Google Trends indices were used in the neural network building process. The Google Trends indices used in this study are listed and described below:

– *VC*: research interest for the term "*visitCroatia*", annual data from 2004 to 2018; search interest: worldwide, collected fromhttps://trends.google.it/trends/?geo=IT;

– *TC*: research interest for the term "*tourism Croatia*", annual data from 2004 to 2018,; search interest: worldwide, collected fromhttps://trends.google.it/trends/?geo=IT;

– *C*:research interest for the term "*Croatia*", annual data from 2004 to 2018; search interest: worldwide, collected fromhttps://trends.google.it/trends/?geo=IT;

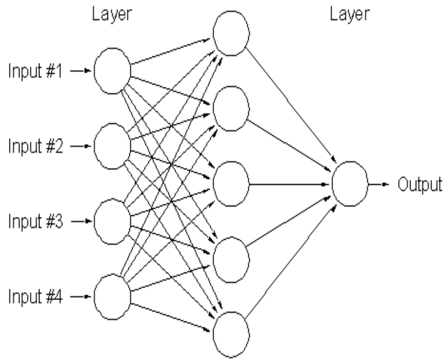
– *CT:* research interest for the term "*Croatiatravel*", annual data from 2004 to 2018; search interest: worldwide, collected fromhttps://trends.google.it/trends/?geo=IT;

– *T*: research interest for the term "*Tesla*", annual data from 2004 to 2018; search interest: worldwide, collected fromhttps://trends.google.it/trends/?geo=IT.

The modelling approach

In this study a neural network model is built in order to examine the relationship between the target variable (the number of foreign tourist arrivals) and the set of inputs variables. Artificial Neural Networks are Machine Learning methods from Artificial Intelligence and are statistical learning models, inspired by biological neural networks that are used in machine learning. These networks are represented as systems of interconnected "neurons", which send messages to each other. The connections within the network can be systematically adjusted based on inputs and outputs, making them ideal for supervised learning.

Figure 2. The structure of a neural network



Source: http://www.cs.trincoll.edu/~ram/cpsc352/notes/neural_approach.html

In general, Machine Learning approach represents a great support in data mining, for the impressive potentiality in hidden pattern recognition and classification in very large dataset. Artificial Neural Networks (ANNs) are one of the most suitable tool, attracting the interest of scholars also in tourism forecast. ANNs, inspired by biology, process information through a number of inter-connected elements (neurons) working to solve the specific problem. A part from the ability to process large datasets, the characteristic making ANNs particularly interesting consists in their tolerance to noise and in the generalization ability, that is the ability to classify or recognise patterns on which they have not being trained.Among the several models of ANNs, the Back Propagation Networks (BPN) are considered particularly effective in prediction based on the gradient approach to minimise the error. In this study a supervised BPN is applied. In an ANN neurons are organized in layers. In the input layer each neuron accepts a single value/variable (distributed input) and generates an output value that will be used as an input for the neurons of the following layer. The *net* input for the neuron *j* of the receiving layer is given by the equation:

$$net_j = \sum_i w_{ij} I_i \qquad (1)$$

where I_i is the signal sent by the neuron *i*, $w_{i,j}$ is the weight associated to the neuron and, consequently, net_j is given by the sum of the weights of each neuron multiplied to the related signal received by the input neuron.The receiving neuron creates the activation on the basis of the signal net_j. The activation becomes the input of the following layer and the process reiterates till the final signals reach the output layer. During the training process, the weights, initially set to very small random values, are determined through the training Back Propagation (BP) algorithm (Buscema, 1998), that stops when the value of the error function achieves the aimed threshold. The weights are updated following the comparison between the obtained output and the expected result, evaluated through the mean squared error function. Once presented to the ANN all the examples selected for the training phase, the weights are updated following the generalized delta rule, so that the total error is distributed among all the ANN's neurons.

Model performance and forecast accuracy analysing

Model performance and forecast accuracy are evaluated using some chosen prognostic errors as forecast accuracy measures and the coefficient of correlation as well as the coefficient of determination as model performance measures. Among the different methods developed to measure the error magnitude accuracy (Frechtling, 2001), this paper will consider the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE). The following describes the basic concepts of the different forecast accuracy measures used in this paper.

The Absolute Error (MAE) is the most popular and simplest to use measure of forecasting accuracy. It is the average of the difference between the actual and the forecasted value and it is measured in the same units as the original data. The expression to calculate MAE is:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|(A_t - F_t)| \qquad (2)$$

The smaller the value of MAE is, the more accurate is the forecast.

The Root Mean Square Error (RMSE) is computed by the following expression:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \tag{3}$$

For purpose of communicating results, it is usually best to report the Root Mean Square Error (RMSE) rather than MSE, because the RMSE is measured in the same units as the data, rather than in squared units, and is representative of a "typical" error (Nau, 2013). The RMSE is usually more sensitive than other forecast accuracy measures. RMSE and MAE can only be compared between models whose errors are measured in the same units.

The Mean Absolute Percentage Error (MAPE) is expressed in generic percentage terms and it is computed by the following formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|(A_t - F_t)|}{A_t}\cdot 100 \tag{4}$$

MAPE is a simple measure that permits to compare the accuracy of different models, with different time periods and numbers of observations.

The coefficient of correlation is a measure of the degree of association between two variables and it is computed as:

$$r = \frac{\sum x_i y_i}{\sqrt{(\sum x_i^2)(\sum y_i^2)}} \tag{5}$$

The coefficient of correlation is a summary measure that quantifies how well the predicted data fit the actual data and it can be computed as:

$$R^2 = \frac{(\sum y_i \hat{y}_i)^2}{\sqrt{(\sum y_i^2)(\sum \hat{y}_i^2)}} \tag{6}$$

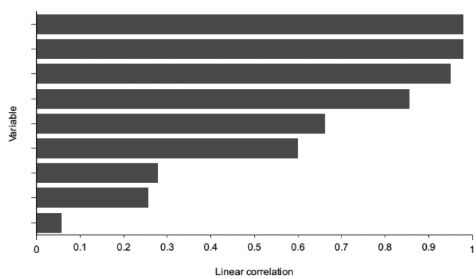
Research results

The following reports the results of the neural network modelling approach as well as the model performance and the forecast accuracy testing.

As stated, in the study the neural network approach was used in the attempt to model and forecast foreign tourism arrivals in Croatia using a set of independent variables in order to investigate if the input variables that reflect the ICT can be used as predictors of the international tourism demand. The data set used for creating a predictive model contained 10 variables and 15 observations. The number of input variables was 9 and the annual number of foreign tourist arrivals variable was used as the target. There were no missing values in the considered data set. In order to analyse the importance of the inputs and their potential influences on the target variable modelling, the linear correlations were performed.

Figure 3. Absolute values of the linear correlations between all input and target variables

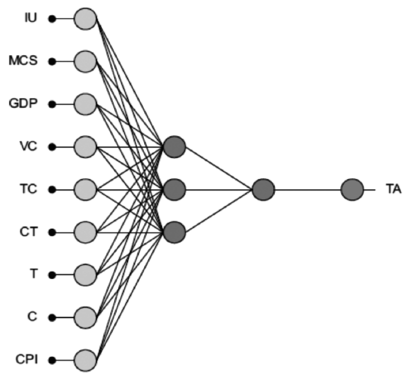
	TA
T	0.979
VC	0.978
IU	0.948
MCS	0.854
GDP	0.659
CT	-0.598
C	0.276
TC	0.255
CPI	0.0555



Source: Elaborated by authors

As shown the maximum correlations are yield between the input variables that represent the Google Trends indices and the ICT influences which is a preliminary confirmation of the research hypothesis. Following the ANN building principles, the data set was split into two parts, i.e. the training data and the testing data.The total number of instances is 15. The number of training instances is 60%, the number of instances selected for the validation phase is 20% and the number of testing instances is 20%.Data pre-processing has been performed. All data have been normalized and data has been inspected and selected so that were no missing values in the considered data set. In the study the supervised BPN was applied. The neural networks represent the predictive model. It has been developed using the Neural Designer, a professional machine learning software. The neural networks represent predictive models and in Neural Designer neural networks allow deep architectures, which are a class of universal approximators. In the modelling process a deep architecture has been applied and a neural network shows in Figure 4 was created.

Figure 4. *The Neural Network architecture*



Source: Neural Designer output

A deep architecture has been applied and created the neural network presented in Figure 4, consisting of 9 input variables, one input layer, 2 hidden layers consisting respectively of 3 and 1 neurons each, and one output variable. The architecture of the neural network can be therefore written as 9:3:1. The complexity, represented by the numbers of hidden neurons, is 3:1. For the first hidden layer signal activationthe hyperbolic tangent function was used. The hyperbolic tangent function is given by:

$$y = x \ \frac{1\text{-}e^{-2x}}{1+e^{2x}} \tag{7}$$

For the second hidden layer a linear function was selected. The linear function is given by the following equation:

$$y = x \tag{8}$$

The ANN error has been calculated as the sum of square error obtained comparing the expected (target) and the obtained output. As the regularization method applied, to control the complexity of the neural network by reducing the value of the parameters, the neural parameters norm weight with a value of 0.001 was used. As the training algorithm the quasi-Newton method was used in order to obtain the best possible loss. The quasi-Newton method is based on Newton's method, but does not require calculation of second derivatives. Instead, the quasi-Newton method computes an approximation of the inverse Hessian at each iteration of the algorithm, by only using gradient information. The initial value of the training loss was 0,741575, and the final value after 80 iterations was 0.00121286. The initial value of the selection loss was 0,47432, and the final value after 80 iterations was 0.00526935. The next table shows the training results by the quasi-Newton method.

Table 1. *The quasi-Newton method training results*

	Value
Final parameters norm	1.19
Final loss	0.00121
Final selection loss	0.00527
Final gradient norm	0.000548
Iterations number	80
Elapsed time	00:00
Stopping criterion	Gradient norm goal

Source: Neural Designer output

A standard method to test the loss of a model is to perform a linear regression analysis between the scaled neural network outputs and the corresponding targets for an independent testing subset. This analysis leads to 3 parameters for each output variable. The first two parameters, *a* and *b*, correspond to the y-intercept and the slope of the best linear regression relating scaled outputs and targets. The third parameter,, is the correlation coefficient between the scaled outputs and the targets. If there is a perfect fit (outputs exactly matching the targets), the slope is supposed to be 1, and the y-intercept 0. If the correlation coefficient is equal to 1, then there is a perfect correlation between the outputs from the neural network and the targets in the testing subset. The next table lists the linear regression parameters for the scaled output.

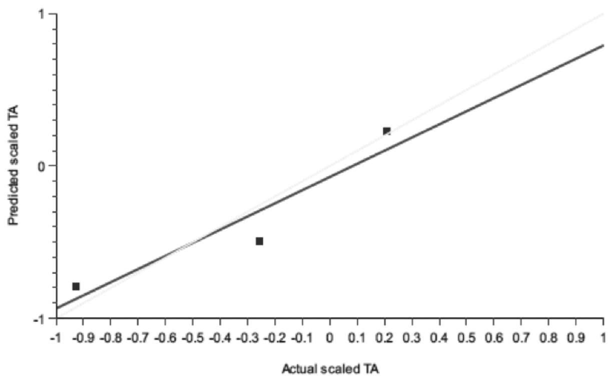
Table 2. *The linear regression parameters*

	Value
Intercept	-0.0316
Slope	0.938
Correlation	0.974

Source: Neural Designer output

The intercept, slope and correlation are very similar to 0, 1 and 1, respectively, so the neural network is predicting well the testing data. The next chart illustrates the linear regression for the scaled output the number of foreign tourist arrivals *(TA)*.

Figure 5. *Actual Vs Predicted target variables value*



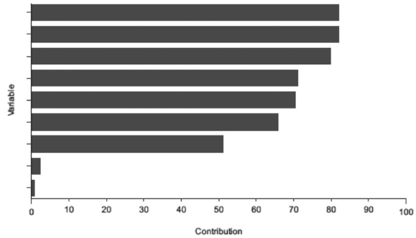
Source: Neural Designer output

The predicted values are plotted versus the actual ones as squares.The coloured line indicates the best linear fit. The grey line would indicate a perfect fit.Finally, the importance input analysis was performed in order to establish the inputs that have more influence on the outputs.

If the importance takes a value greater than 1 for an input, it means that the selection error without that input is greater than with it. In the case that the importance is lower than 1, the selection error is lower without using that input. Finally, if the importance is 1, there is no difference between using the current input and not using it. The most important variable is *CT*, that gets a contribution of 82% to the outputs, followed by the variables *T*, *TC*, *IU* and *VC*.Following the results of the importance of each input.

Figure 6. *Input importance results*

	Contribution
IU	71.1
MCS	51.1
GDP	65.9
VC	70.4
TC	79.8
CT	82
T	81.9
C	2.29



Source: Neural Designer output

As displayed the most important input variables are those concerning the influence of ICT and the Google trends indices. The input variables, traditionally used in predicting tourism demand denote a less significant influence on the number of foreign tourist arrivals in Croatia. The quality model testing was performed using the errors listed in the table 3.

Table 3. *The data errors*

	Training	Selection	Testing
Sum squared error	5.46479e+009	4.24627e+011	2.05129e+012
Mean squared error	6.07199e+008	1.41542e+011	6.83762e+011
Root mean squared error	24641.4	376221	826899
Normalized squared error	4.92641e-005	0.00845811	0.116917
Minkowski error	3.06713e+007	5.93343e+008	2.00969e+009

	Minimum	Maximum	Mean	Deviation
Absolute error	97513.4	1.23979e+006	682575	571647
Relative error	0.00940713	0.119603	0.065848	0.0551468
Percentage error	0.940713	11.9603	6.5848	5.51468

Source: Neural Designer output

The table below shows the minimums, maximums, means and standard deviations of the absolute, relative and percentage errors of the neural network for the testing data.The mean percentage error is very low, which indicates the neural network high forecasting accuracy in modelling and forecasting the annual number of foreign tourist arrivals. The forecasting accuracy is evaluated using the previously mentioned forecast errors and model performance indicators depicts in table 4.

Table 4. *Forecasting evaluation results*

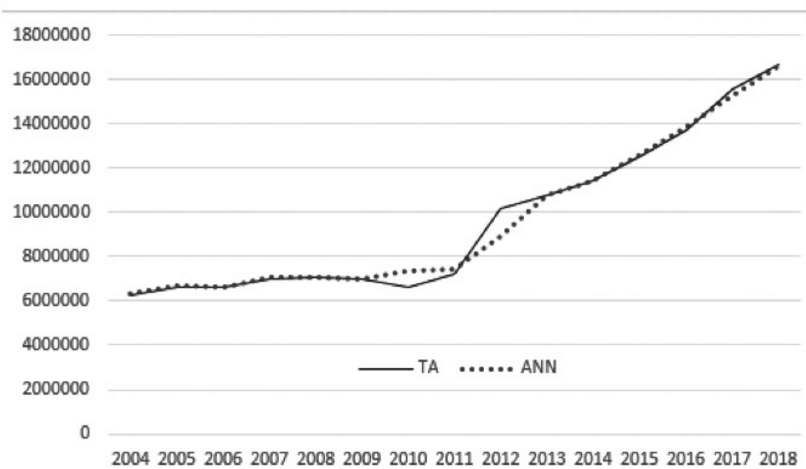
MAE	201136,3
MAPE	2,22
RMSE	388042,97
r	0.99
R^2	0.99

Source: Elaborated by authors

The forecast error and model performance analysis confirm that the predicted number of annual tourist arrivals fit well the actual data. Figure7 displays the actual and the fitted number of annual tourist arrivals.

Figure7. Actual VS Fitted annual number of foreign tourist arrivals

YEAR	TA	ANN
2004	6278991	6293180,47
2005	6625370	6667054,99
2006	6645640	6599514,66
2007	7028323	7050814,26
2008	7081920	7078358,18
2009	6962451	6988773,20
2010	6652832	7363252,32
2011	7237077	7467564,51
2012	10138696	8898905,99
2013	10775000	10740623,10
2014	11438806	11465443,30
2015	12543509	12641006,40
2016	13707444	13886025,80
2017	15592899	15253543,00
2018	16644871	16639348,20



Source: *Elaborated by authors*

It is clearly shown that the models fit well the actual data throughout the whole sample period and the predicted values are close to the actual values. Research findings confirmed that Google Trends data are statistically significant predictors of international tourist arrivals in the analysed span period.

Conclusions

The aim of this paper was to approach international tourism demand modelling and forecasting using Google Trends data and variables that reflect the ICT influences. The research design was based on the assumption that Google Trends indices could be used as predictors in modelling foreign tourist arrivals. In the research modelling approach, a neural network model was used. The set of input variables consisted of some traditionally used variables, like the GDP per capita and the consumer price indices. Beside those variables, some additional predictors, that reflect the impact of ICT on tourism demand and Google Trends indices were included in the model. The research finding showed that Google Trends indices were highly correlated to the number of foreign tourist arrivals and that they can be used in analysing and modelling international tourism demand in Croatia. Thus, the results of the analysis are in favour of the research hypothesis of this study in highlighting the value of information obtained through the Google trend tool, and it can be concluded that data on internal search can be used as valuable predictor of foreign tourist arrivals in Croatia, generating accurate forecasting models.

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