# Artificial Neural Network-Based Applications in Travel and Tourism Research: A Review and Case Study

## - WORKING PAPER -

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### INTRODUCTION

Although frequently referred to as “black boxes”, artificial neural networks (ANN) find increasing application in intelligent- and recommender systems in a wide range of industries. In travel and tourism research ANNs have, however, not been extensively used so far. This is despite the fact that first empirical studies in peer-reviewed tourism journals have already been published in the late nineties, introducing ANNs as a valid alternative to traditional regression-based approaches, mostly with regard to demand forecasting purposes.

The aim of the present working-paper, on the one hand, is to provide an overview of available ANN-based studies published in top international travel and tourism journals, which may serve as a starting point and reference list for tourism researchers unfamiliar with ANNs. Basic concepts, main areas of application, as well as major advantages and disadvantages of ANN-based approaches, compared to traditional approaches, are highlighted.

On the other hand, this study aims to demonstrate the particular advantages and shortcomings of ANN-based applications using an empirical case example. For this purpose, this study uses data from a survey on attitudes and expenditures of tourists in Sarajevo, Bosnia and Herzegovina, conducted by the Institute for Tourism, Zagreb during summer 2010. In particular, a multilayer perceptron-based key-driver analysis is performed on the data to obtain insight into those destination attributes that have a predominant influence on the overall tourist experience in Sarajevo. Finally, results from the ANN-based analysis are opposed to results from a (traditional) regression-based key-driver analysis in order to identify possible significant differences between the approaches.

## LITERATURE REVIEW

### TIME-SERIES STUDIES

According to Chen *et al.* (2012), there is a growing interest in using ANN approach for forecasting tourism demand. This is mostly due to its ability to capture functional relationships within the empirical data, even though the underlying relationships are unknown or hard to describe. Unlike the classical forecasting tool, i.e. regression analysis, ANN approach does not require assumptions about underlying relationships within the empirical data. For example, regression analysis implies assumptions of linearity and the Gauss-Markov assumptions. The by-product of these assumptions is rigidness and tapered space for adaptation and adjustment.

The most interesting examples of using ANN for forecasting tourism demand, published in peer-reviewed tourism journals, are as follows.

One of the first studies applying ANN for tourism demand forecasting was published by Pattie and Snyder (1996). These authors compare forecasting performance of ANN and different univariate time series techniques, and conclude that ANN is rather accurate model when forecasting 12 months ahead, thus it could be regarded as a valid alternative to classical forecasting techniques in tourism research.

Law (2001) compares the forecasting accuracy of ANN and six different mostly simple forecasting techniques in the context of an unusual environmental change—i.e. Asian financial crises. He concludes that naïve method delivers most accurate short-term forecasts, but on the other hand, ANN is most useful technique in the mix of short and long term forecasting. The similar conclusion is also drawn in the study by Burger *et al.* (2001), where the forecasting performance of ANN and different forecasting techniques are compared in the context of usual environment. These authors conclude that ANN performs the best, especially in the short time period into the future.

Cho (2003) compares ANN method, exponential smoothing, and autoregressive integrated moving average (ARIMA) to predict travel demand, i.e. number of arrivals. He concludes that ANN seems to be the best method for forecasting visitor's arrivals without obvious pattern.

Kon and Turner (2005) compare the forecasting accuracy of ANN method and basic structural model of time series (BSM). They conclude that correctly structured ANN model can outperform BSM in the short-term forecasting. They also conclude that the significant advantage of ANN is its ability to deal with short data series. They also conclude that there is a lack of systematic procedure in ANN approach and the model building is usually achieved through trial and error experiment.

Law (2000) examines the forecasting performance of ANN method based on the back-propagation learning process and thus obtains back-propagation (neural) network (BPN). He concludes that utilizing a BPN outperforms regression models and time-series models in terms of forecasting accuracy.

Besides the studies that deal with comparison of forecasting performance of ANN and other forecasting techniques, there are few studies that are focused on extensions and modifications of basic artificial neural network approach.

Chen *et al.* (2012) combine BPN method and empirical mode decomposition method (EMD), i.e. a method of time series decomposition, to obtain more accurate forecasting scores. They conclude that the BPN model based on properly decomposed original nonlinear and non-stationary data could outperform the BNP model without time series pre-decomposition and ARIMA models.

CROSS-SECTIONAL DATA STUDIES

In addition to tourism demand forecasting, ANN based approaches have more recently been utilized to obtain *derived measures of attribute importance* needed for subsequent importance-performance analyses (IPA). Application of ANN provides more reliable estimates of attribute importance compared to regression-based approaches and therefore significantly increases detail and reliability of managerial implications (Mikulic *et al.*, 2012). A review of the literature shows that, since this approach is relatively new, the number of research papers applying ANN-based IPA in the tourism area is still relatively scarce.

One of the first papers from this area of research was paper published by Deng *et al.* (2008). The authors raised questions regarding reliability of traditional IPA approaches and proposed a revised IPA approach that combines back-propagation neural networks (BPNN), three-factor theory and natural logarithmic transformation with the aim of determining critical service attributes. In order to demonstrate viability of the proposed BPNN-based IPA approach for service quality and customer satisfaction improvement, authors used a case study of hot spring hotel in Taiwan.

In the paper published by Hu *et al.* (2009) authors argue that application of traditional IPA models implies hidden assumption which, if they are not met, can cause inaccuracies in importance analysis and priority rankings leading to wrongful decision making. Therefore, authors are proposing a revised IPA approach based on the BPNN in conjunction with DEMATEL. It is suggested that proposed BPNN-DEMATEL based IPA approach can successfully solve potential problems typical for traditional IPA approaches. To demonstrate viability of revised IPA approach authors used industrial computer manufacturing industry in Taiwan as a case study.

Following this line of thought, in the paper published by Deng and Pei (2009) the authors combined a fuzzy set theory, back-propagation neural network and three-factor theory and introduced a Fuzzy Neural based IPA (FN-IPA) where the attribute importance is implicitly derived by applying back-propagation neural network (BPNN). According to the authors, FN-IPA approach is useful in assisting practitioners in decision making process regarding the improvements that should be prioritized in order to enhance the overall customer satisfaction.

In a similar vein, Mikulic and Prebezac (2012) propose an extended BPNN-based importance-performance analysis that accounts for dynamics in attribute importance (and for competitor performance). The analysis of the case study in the airline industry shows that conventional BPNN based IPA could produce misleading results and that extended BPNN-IPA, proposed in this research, provides more detailed and reliable results. Therefore, the basis for managerial decision making process is much better and the risk of providing suboptimal recommendations is reduced.

Similar line of research was additionally followed by Mikulic *et al.* (2012) who applied ANN based IPA in order to identify critical attributes impacting the visitor and exhibitor experience

at the *Dalmacija Wine Expo*. The authors concluded that, in order to identify key areas for improvement, the practitioners should not rely on uni-dimensional operationalization of attribute importance but should, instead, use a combination of stated and derived attribute importance, whenever possible. As the authors argue, this approach yields significant improvement in the detail and reliability of managerial implications.

**EMPIRICAL STUDY**

The data used in this paper were collected as part of a research study on attitudes and expenditures of tourists and visitors in the Federation of Bosnia and Herzegovina (FBiH). The study was commissioned by the *Federal Ministry of Environment and Tourism*, and conducted by the *Institute for Tourism - Zagreb* from June to September 2010. The study encompassed four individual pilot surveys in the most visited tourist destinations in the FBiH—i.e., in Medjugorje (religious tourism); Neum (sun-and-sea destination); and in Mostar and Sarajevo (city tourism destinations), the latter being the focal destination of the present case study. Overall, 863 fully completed questionnaires entered the subsequent data analysis.

The primary objective of this empirical study is to compare three derived measures of destination-attribute importance—i.e. (i) coefficients from correlation analysis (CA), (ii) coefficients from multiple regression analysis (MRA), and (iii) importance estimates based on an ANN. In all three cases, destination attribute-performance ratings were specified as predictors, and scores of the overall value of the tourist's trip to Sarajevo as the criterion variable (all measured on a 5-point rating scale). The first two measures (i.e. CA- and MRA-coefficients) are very common measures used in many studies to derive the importance of particular product/service/destination attributes in explaining overall customer evaluations. The latter (ANN) estimates were obtained as follows:

1. *Network training and evaluation:* A one hidden-layer multilayer perceptron (MLP) was constructed with attribute-performance ratings set as input-layer nodes and OS as the output-layer neuron. Prior to training, the original dataset was partitioned into training, test, and holdout samples (70%, 15%, and 15% of samples, respectively). Following a trial-and-error procedure, several hundreds of network configurations were tested, with different activation functions and numbers of hidden-layer neurons. Training was stopped when the network error started to increase in the test sample, while still decreasing in the training sample (stopping rule). Each trained network was further tested on the holdout samples to assess its performance on unseen data. Based on an assessment of the correlation between predicted and actual output values (i.e. scores of overall value of the tourists stay in Sarajevo), the best performing network was chosen for further analysis (training performance: $R^2 = 0.475$; holdout performance: $R^2 = 0.484$; number of hidden-layer neurons: 11; activation functions in hidden/output-layer: hyperbolic tangent/identity).

2. *Determining attribute importance*: A sensitivity analysis of the network error was performed by iteratively setting the performance ratings for each attribute to the arithmetic mean. The resulting changes (i.e. increase) in network error, attributed to the omission of a particular attribute can then be interpreted as the attribute's importance in explaining the criterion variable. All estimations were conducted with *Statsoft Statistica 9.1*.

To facilitate a more straightforward comparison of the three derived importance measures, all scores were expressed as percentages of the highest score within each type of measure (Table 1).

**Table 1.**

| Destination attribute | ANN[a] | MRA[b] | CA |
|---|---|---|---|
| DA1. Picturesqueness (urban and architectural harmony) | 5,09% | 22,14%* | 76,39% |
| DA2. Cleanliness of the city | 0,03% | 6,02%[ns] | 53,49% |
| DA3. Cultural heritage | 3,77% | -8,37%[ns] | 48,55% |
| DA4. Cultural events | 6,83% | -2,97%[ns] | 82,28% |
| DA5. Gastronomy | 5,68% | 2,46%[ns] | 48,66% |
| DA6. Entertainments | 5,52% | 27,92%* | 82,36% |
| DA7. Shopping | 8,19% | 39,61%*** | 79,10% |
| DA8. Souvenirs | 2,80% | -13,64%[ns] | 51,87% |
| DA9. Suitability for short break holidays | 100,00% | 100,00%*** | 100,00% |
| DA10. Personal safety | 23,64% | 58,49%*** | 85,83% |
| DA11. Friendliness of locals | 27,79% | 57,11%*** | 80,70% |

**Notes:** [a]$R^2$=0.475; [b]$R^2$=0.392; Significance: ***=0.0001, *=0.05, ns=not significant.

## DISCUSSION

With regard to model quality, the results show that the ANN significantly outperforms MRA with regard to explained variance. However, scores of $R^2$ are rather low for both the models.

With regard to scores of attribute importance, all three methods consistently identified DA9 as the most important predictor. Moreover, both ANN and MRA identified the same top three most important predictors (i.e. DA9, DA10 and DA11). CA also yielded a classification of DA10 as a top three attribute, but DA4 and DA6 emerge as more important attributes than DA11 does. DA4, in turn, appears insignificant in MRA and has a negative weight, whereas DA6 is ranked fifth according to its importance score and it is significant at the 5% level. Interesting to note, the two attributes show the strongest correlation among all predictors.

Another interesting observation can be made with regard to the discrimination of importance scores across the different approaches. Evidently, the MRA is plagued by multicollinearity since several predictors yield negative weights although respective bivariate correlation coefficients are positive. The CA-based scores certainly are 'looking best' with regard to the distribution of their values. Their reliability as indicators of attribute importance is, however, questionable as these are bivariate measures. Finally, the ANN-based scores look fine, but the approach yields a rather weak discrimination of attributes DA1–DA8 with all scores being below the 10%-level. Accordingly, looking for the 'more important' destination attributes within this set of attributes would be rather unreliable.[1] Generally, however, the larger variance explained, and the distorted effect sizes in MRA, are findings that speak in favor of the ANN-based approach.

[1] Here it would be interesting to see how all the scores would behave if the most important predictor was omitted from the analysis (i.e. DA9).

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