Modelling and Forecasting Cruise Tourism Demand to Izmir by Different Artificial Neural Network Architectures

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ABSTRACT

Cruise ports emerged as an important sector for the economy of Turkey bordered on three sides by water. Forecasting cruise tourism demand ensures better planning, efficient preparation at the destination and it is the basis for elaboration of future plans. In the recent years, new techniques such as; artificial neural networks were employed for developing of the predictive models to estimate tourism demand. In this study, it is aimed to determine the forecasting method that provides the best performance when compared the forecast accuracy of Multi-Layer Perceptron (MLP), Radial Basis Function (RBF) and Generalized Regression neural network (GRNN) to estimate the monthly inbound cruise tourism demand to Izmir via the method giving best results. We used the total number of foreign cruise tourist arrivals as a measure of inbound cruise tourism demand and monthly cruise tourist arrivals to Izmir Cruise Port in the period of January 2005- December 2013. We reutilized to appropriate model. Experimental results showed that radial basis function (RBF) neural network outperforms multi-layer perceptron (MLP) and the generalised regression neural networks (GRNN) in terms of forecasting accuracy. By the means of the obtained RBF neural network model, it has been forecasted the monthly inbound cruise tourism demand to Izmir for the year 2014.

1. Introduction

Tourism has become an important sector in many countries as a growing source of foreign exchange earnings. Besides generating foreign exchange earnings and alleviating the balance of payments problems encountered in many countries, international tourism also creates employment. Given the importance of tourism to economic development and trade performance, governments, practitioners and researchers are interested in modelling and forecasting tourism demand (Lim, 2006). Tourism demand is the foundation on which all tourism related business decisions ultimately rest. Companies such as airlines, tour operators, hotels, cruise ship lines and many recreation facility providers and shop owners are interested in the demand for their products by tourists. The success of many businesses depends largely or totally on the state of tourism demand and ultimate management failure is quite often due to failure to meet market demand. Because of the key role of demand as a determinant of business profitability, estimates of expected future demand constitute a very important element in all planning activities. It is clear that accurate forecasts of tourism demand are essential for efficient planning by tourism related businesses, particularly given the perishability of the tourism product (Song et al. 2009).

Cruise tourism is a niche form or type of tourism which has rapid growth industry in the World (Oral and Esmer, 2010). The growth of cruise tourism is phenomenal. The revival of cruising has taken place in the last thirty years. The increase in demand for cruise tourism that is being registered on all markets worldwide confirms that the cruise market is on the upward trend. According to the Cruise Lines International Association (CLIA) global cruise passengers is 20.9 million (CLIA, 2013).The demand for this specific form of tourism has almost doubled in comparison with the number of international arrivals. Today the Mediterranean is the leading European cruising region, second destination in the world after the

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Caribbean islands. At the cruise market, the Mediterranean has assumed the position of a region offering a wide cultural and natural diversity on a relatively small area. The increasing role of the Mediterranean as the cruise region is manifested in the development of home ports and ports of call that are today, in terms of passenger traffic, among the leading world ports. Izmir Cruise Port is one of the leading ports for cruisers in the Mediterranean and the leading port in Turkey with 472.382 passengers in 2013 (Izmir Port Authority, 2013). The present state and prospect of the cruising tourism in Izmir should be contemplated in a wider context, i.e. the context of the whole Mediterranean region and global cruise market trends. In the recent years an increased growth in demand for cruise tourism in the Mediterranean has been noted on all markets worldwide, in particular on the European market, which without doubt influences the tourism trends in the region. Today, Izmir is one of Turkey's most populated (3.7 million) and most thoroughly modern cities, with the second biggest port after Istanbul. The container ships, cranes and concrete high-rises that populate the harbour are a drab sight, and, predictably, most cruise travellers bypass the city. Like Kuşadası to the south, Izmir's main virtue is its proximity to Ephesus, an incredibly well-preserved Roman city that lives up to its lofty reputation. Likewise, the ruins of Pergamum and Asclepion, an ancient Greek centre of culture and health, are easily accessible and are included excursion options on all ships docking in Izmir (Cruise Critic, 2014).Due to its positive effect on the city economies, cruising tourism is a major factor in the tourism development strategy in the Mediterranean countries. The increase in demand for Mediterranean cruises and an almost continuous increase in the number and capacity of ships have already created issues in accepting the passengers and ships in many Mediterranean countries. These issues can only develop if the increase is not followed by development of the city infrastructure and all complementary services on one hand and implementation of the new approach to cruise ship passenger management at a destination on the other.

Objectives of this study were set as follows:

- Constructing and determining the ANN model that provides the best performance when compared the in sample forecast accuracy of Multi-layer Perceptron (MLP), Radial Basis Function (RBF) and Generalized Regression neural network (GRNN).
- Forecasting ex-ante monthly inbound cruise tourism demand to Izmir for year 2014 via the developed ANN architecture giving best results.

Having introduced the research background and the objectives of this study, the rest of this paper is organized as follows. The next section provides the theoretical background and an overview of cruise tourism. Following section summarizes the literature. The next section describes the ANN architectures used in this study. The methodology and the data are then described, followed by the results. Conclusions and suggestions for future researches are presented in the last section.

2. Theoretical Background and Overview

The earliest ocean-going vessels that carried passengers were designed to carry cargo. By the 1830s, English companies, making luxurious steamships the norm, led by the British and North American Royal Mail Steam Pocket (Katsoufis, 2006). In 1867, Mark Twain was a passenger on the first cruise vessel Quaker City through Europe and the Holy land. It was the first American- originated cruise. His record of the trip is preserved in his first travel book "The Innocents Abroad" (Churchwell, 2009). In 1890 Albert Balin, general director of HAPAG, explored his idea to increase vessel utilization via cruise chips (Yasar, 2012). Regular cruising came later in the mid-1880s. The companies began to make ships more luxurious and to start pleasure cruise industry (Tomlinson, 2007). The cruise industry continued to grow and by the early 1900s the White Star Line, P&O and the Hamburg America Line were offering regular cruises (Pavlic, 2013). By 1903, Germany led the industry by developing four fastest ships on Atlantic. The new German ships were small by today's standards, but they are portraying elegance of new super liners with 15-000 to 20.000 gross tons ships and held around 2000 passengers, of whom 700 were travelling first class (Dickinson and Vladmin, 2007). Cruise development began, after World War II. At the end of the war, Europe saw a re-acceleration of economic development, and high-income growth (Guzel, 2006). European lines then reaped the benefits of transporting refugees to America and Canada; and business travellers and tourists to Europe. The 1960s witnessed the beginnings of the modern cruise industry. Sea cruises as a form of package tours were developed. Alternatively the start date for this form of tourism is considered to be December 1966 when the company Norwegian Caribbean Line offered the first annual cruise schedule on board the m/v Sunward the first voyage with 540 passengers (Wilkinson, 2006). Today, cruise ships themselves have swollen dramatically in size, now sometimes carrying over 5.000 people on board and the entertainment available on board cruise ships ranges from gambling to karaoke to art auctions (Klein, 2002). In addition to size, cruise lines also increased their numbers by adding to their respective fleets. Therefore, famous worldwide seaway companies emerged; Cunard Line (United Kingdom), Companie Generale Transatlantique (France), Holland American Line and North German are first cruise lines, today Carnival Cruise Lines and Disney Cruise Lines are very popular (Yaşar, 2012; Boyd 1999).In the 1990s, the cruise phenomenon reached five regions; the Caribbean, Alaska, the Bahamas, Hawaii and the Mediterranean – Greek Islands and Turkey- in which World cruise tourism leans. The global demand for cruising throughout the world was about 600.000 at the beginning of the 1970's; this figure reached 3.7 millions in 1990, 9.7 millions in 2000, 19.1 millions in 2010, 20.4 millions in 2011 and 20.9 millions in 2012 (Yaşar 2012; CLIA 2013). The North American countries are traditionally the leaders in cruise destinations, contributing 55.7% of the total demand worldwide. During the same period, the European share in the industry increased from 21.6% in 2001 to 30% in 2011 at an average annual growth rate of 10.12% (Pavlic, 2013). This indicates that Europe as a cruise destination constitutes a big proportion of the cruise tourism market. Today, the Mediterranean region in Europe is the leading cruise region, being the second most visited region in the world after the Caribbean islands. Turkey, which offers a coast on both the Mediterranean and Aegean Sea in the Mediterranean basin and Black Sea, takes its position as the region offering cultural and natural variety in a relatively small area. In the last ten years, Turkey has begun to provide a multicultural experience in the Eastern Mediterranean basin within cruise tourism (Yaşar, 2012). According to the data from British GP Wilds consulting company in 2011, 20.6 percent of Turkey's share in the number of passengers is 2 million and in the world cruise market share rate is 9.66% (BREA, 2012).

3. Cruise Tourism in Izmir

In accordance with the global growth in the number of cruise voyages and cruise passengers, and the growth in the Mediterranean region, Izmir has recently been recording a significant growth in the number of cruisers calling Izmir ports. This growth is particularly shown in the number of cruise passengers that has more than doubled in the last eight years. Izmir coast is very attractive for navigation due to many islands and coastal places and towns with rich history, sights and other attractions that appeal to tourists. Cruise ships mostly call the ports and towns that offer facilities for their calls, but are also attractive to visitors. At the mention cruise tourism in Turkey, Izmir has been drawing attention with increasing voyage and the number of visitors in recent years. Cruise tourism in the last eleven years, the number of trips has been 1424, and the number of cruise ship tourists has been 3.091.335 in Izmir (Izmir Chamber of Commerce, 2013). In Table 1,Cruises and the number of tourists coming to Izmir by cruise ships are given by years.

Table 1. Izmir Port Demand forCruises andPassengers (2003-2013)

Year	The Total Number of Cruises	The Total Number of Passengers
2003	5	3.271
2004	32	77.000
2005	26	58.042
2006	94	183.198
2007	122	288.017
2008	128	321.279
2009	127	309.603
2010	141	355.899
2011	272	504.921
2012	286	510.042
2013	191	480.063
Total	1424	3.091.335

Source: Izmir Chamber of Commerce, 2013

With the increasing the effect of the crisis in Europe in 2013, the decline in cruise tourism has also affected Turkey's cruise tourism. However, despite predictions, this decline would leave its location and increase again in 2014. After the events of "Gezi Parkı", there are few ships which have not come to Izmir in summer time, but the total decline was not affected by the events. It is observed that some companies did not want to take passengers on the same route and so made changes to those routes. At the same time, although the port of Izmir has less that 1 % of Turkey's total cruise tourism in 2003, it had reached 20 % by the end of 2008. According to statistics of Ministry of Transport, Marine Affairs and Communications 12 months of the year 2012, Izmir has risen to third place behind Kuşadası and Istanbul with the 26.37% share of total cruise traffic in Turkey. In table 2, the statistics of cruise ships and passengers are given as of the first three months of 2013. In the Tourism Strategy Action Plan2023 of Turkey, it has been determined as a target that increasing the capacity and development of Izmircruise port and also port of Istanbul is designated as target of increasing its capacity (Ministry of Culture and Tourism of Turkey, 2007).

Table 2. Cruise Ships and Passengers Statistics under the Port Authorities2013 (First 3 Months)

CRUISE SHIPS				CRUISE PASSENGERS			
Port Authority	Type of Cruise Ship	Passenger Ship	Total	Incoming passengers	Departing passengers	Transit passengers	Total
ALANYA	4	0	4	2	48	9.297	9.347
ANTALYA	0	1	1	0	351	71	422
BODRUM	0	1	1	0	0	314	314
DİKİLİ	1	0	1	0	0	48	48
İSTANBUL	5	1	6	230	434	13.974	14.638
İZMİR	**6**	**4**	**10**	**75**	**70**	**25.088**	**25.233**
KUŞADASI	9	5	14	118	540	7.669	8.327
TOTAL	25	12	37	425	1.443	56.461	58.329

Source: Izmir Chamber of Commerce, 2013.

According to the Izmir Chamber of Commerce, as a result of the World Travel Awards European rating, Izmir leaving behind strong competitors as Amsterdam (Netherlands), Athens (Greece), Cannes (France), Copenhagen (Denmark), Dubrovnik (Croatia), Lisbon (Portugal), Oslo (Norway), Reykjavik (Iceland), St. Petersburg (Russia), Stockholm (Sweden) and Venice (Italy) was named "Europe's best cruise destination". Izmir was also named "Europe's Leading Cruise Destination", known as "the Oscars of Tourism" in 2011, 2012, and 2013.

4. Literature Review

There has been a growing interest in tourism demand research over the past decades. Some of the reasons for this increase in the number of studies of tourism demand modelling and forecasting are: the constant growth of world tourism, the utilisation of more advanced forecasting techniques in tourism research and the requirement for more accurate forecasts of tourism demand at the destination level (Claveria and Torra, 2014). As do business forecasting methods, so do tourism demand modelling and forecasting methods can be broadly divided into two categories: quantitative and qualitative methods (Song & Li, 2008; Fretchling, 2001; Petropoulos et al. 2005). Qualitative methods are also called "judgmental methods" such as a desk reviewing method or an expert-opinion technique stresses the qualitative insight, intuition, and non-quantifiable knowledge of a particular tourism event (Law & Pine, 2004). These techniques are appropriate when insufficient data exist and render numerical analysis inappropriate. Quantitative forecasting methods can be classified into two sub-categories: causal econometric approaches and non-casual time series methods. In addition to the methods mentioned above, a number of new quantitative forecasting methods, predominantly artificial neural networks (ANNs) have emerged in the tourism forecasting literature.

ANNs were first introduced to tourism demand forecasting in the late 1990s. Some of them are as follows. Pattie and Snyder (1996) developed an ANN model to forecast monthly over night back country stays in US national parks. Their forecasts are more accurate than those obtained by other classical time-series models especially with large samples. Uysal and El Roubi (1999) developed a neural network model that used

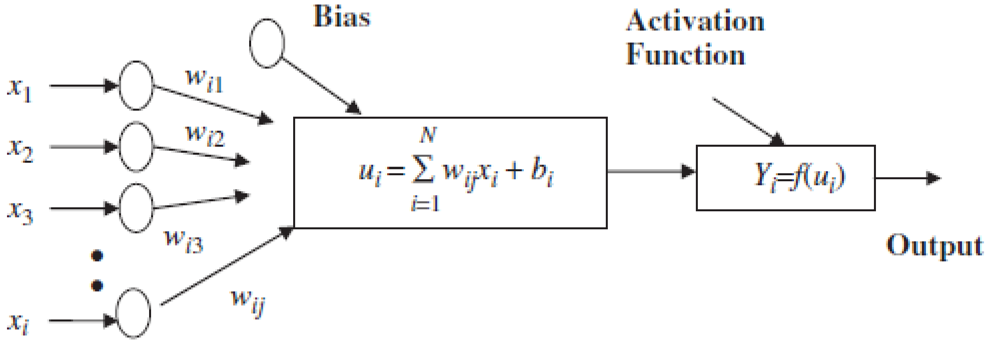
Canadian tourism expenditure in the United States. Their findings showed that the neural network achieved highly accurate results with high adjusted correlations and low error terms. Law (2000) developed a feedforward–back propagation (known as "multilayered perceptron) neural network to model and forecast the Taiwanese demand for Hong Kong tourism. Cho (2003) set an Elman's neural network to forecast the number of visitors from different origins to Hong Kong.His study showed that the ANNs performed the best in five of the six places of origin.Palmer et al. (2006) developed ANN models for forecasting tourist expenditure in the Balearic Islands, Spain. Although the models did not perform well with raw data, they attained very low MAPE values for pre-processed data. Cho (2009) used backward propagation ANN model together with two time series models to forecast arrivals to Asia Pacific region. Lin et al. (2011) tried to build forecasting model of visitors to Taiwan using ARIMA, ANNs and multivariate adaptive regression splines (MARS) methods. Their results demonstrated that ARIMA outperformed ANNs and MARS approaches in terms of RMSE, MAD, and MAPE and provided effective alternatives for forecasting tourism demand. Teixeira and Fernandes (2012) have developed several models based on artificial neural networks, linear regression models, Box-Jenkins methodology and ARIMA models to predict monthly number of guest nights in the hotels of one region. Their study showed that ANN models have always had their performance at the top of the best models. Goh and Law (2011) providedan extensive review of the applications of ANNs on tourism demand modelling and forecasting.Cuhadar (2013)analysed ex-post forecasting accuracies of Feed Forward-Back Propagation (MLP), Radial Basis Function (RBF) and Time Delay (TDNN) artificial neural network architectures for forecasting inbound tourism demand to Turkey. As a consequence of several attempts, it has been observed that 12 lagged MLP model which has [4-5-1-] architecture has presented best forecasting performance. Majority of studies in modelling and forecasting tourism demand have showed that ANNs scored as good as, or significantly better than, the classical methods considering different data periodicity.Although there are a number of studies on modelling and forecasting tourism demand by ANNs, limited research is available in academic journals concerning modelling and forecasting cruise tourism demand. It is seen that only one study has been completed and published by Pavlic (2013). The author forecasted monthly cruise ship passenger flows in Dubrovnik by Box-Jenkins methodology known as seasonal ARIMA model.A review of the existing literature shows that most of tourism demand modelling and forecasting studies are applied to country based and yearly data sets instead of applying to a specific region or destination. It is also observed that there have been limited published studies in academic journals concerning the modelling and forecasting cruise tourism demand. Because of the lack of both studies concerning modelling and forecasting cruise tourism demand to Izmir and studies concerning monthly forecasting tourism demand mounted by ANNs, it is strongly believed that this study prepared on the basis of inter-disciplinary approach is remarkably important since it will enlighten the future studies on these mediums.

5. Artificial Neural Networks (ANNs)

In recent years, the feasibility of applying ANNs to enhance the accuracy of tourism demand forecasting models has received considerable interest. The reason behind this interest is that ANNs are universal function approximators capable of mapping any linear or non-linear function. ANNs are very versatile and do not require formal specification of the model nor acceptance of a determined probability distribution for data. They can deal with complex patterns and establish models reflecting nonlinear relationships without pre-assumption about the system because of their data-driven nature. ANNs perform well even with a missing or incomplete data with their capability of generalization. Furthermore, being universal approximators, it is proven mathematically that they can approximate any continuous function to any desired accuracy. All these features of ANNs make them a very useful tool for forecasting tasks.ANNs can be used to predict future events based on the patterns that have been observed in the historical training data. (Palmer et al. 2006; Zhang, 200; Kuvulmaz et al. 2005).

ANNs are computing models for information processing and pattern identification. They grow out of research interest in modelling biological neural systems, especially human brains. An ANN is a network of many simple computing units called neurons, nodes or cells, which are highly interconnected and organized in layers. Each neuron performs the simple task of information processing by converting received inputs into processed outputs. Through the linking arcs among these neurons, knowledge can be generated and stored regarding the strength of the relationship between different nodes (Zhang, 2004). The basic element of an ANN is the artificial neuron as shown in Fig.1 which consists of three main components namely as weights, bias, and an activation function.

Fig. 1 Basic Elements of an Artificial Neuron



Source: Cevik and Guzelbey; 2008

Each neuron receives inputs $x_1, x_2, x_3 \ldots. x_i$ attached with a weight (w_i)which shows the connection strength for that input for each connection. Each input is then multiplied by the corresponding weight of the neuron connection. A bias (b_i)can be defined as a type of connection weight with a constant nonzero value added to the summation of inputs and corresponding weights (u_i) given by

$$u_i = \sum_{j=1}^{n} w_{ij} x_j + b_i \qquad (1)$$

The summation u_i is transformed using a function called an "activation or transfer function", $f(u_i)$ yielding a value called the unit's "activation", given by

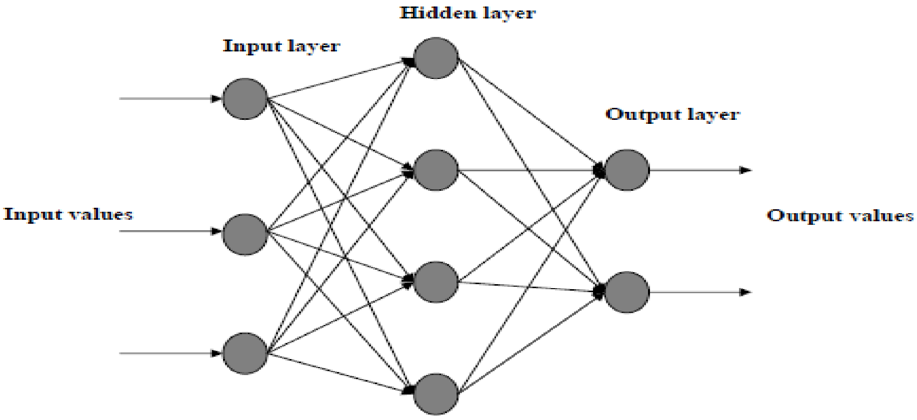
$$Y_i = f(u_i). \qquad (2)$$

The activation function is the mechanism of translating input signals to output signals for each processing element. There are three types of transfer functions, as listed below (Khare and Nagendra, 2007):

- Hard limit transfer function (Step function)
- Linear transfer function (Ramp function)
- Log –Sigmoid transfer function (Sigmoid function)

Neurons in an ANN are connected in different topological configurations. Two most common types of configurations are "feed-forward" and "recurrent or feed-back" topology. Usually, a feed-forward network contains a number of layers, each layer consisting of a number of neurons. Signal propagation in such networks usually takes places in the forward direction only. In a recurrent neural network, there exists feedback from or more neurons to others. Feed-forward networks are commonly used in pattern recognition tasks while recurrent networks are used to construct a dynamic model of the process (Patan, 2008). ANN architecture includes defining the number of layers, the number of neurons in each layer, and the interconnection scheme between the neurons. In the typical neural network, there are three layers: the input layer, the hidden layer and the output layer. All these layers are connected and the architecture of the neural network design is itself a worthy field. Fig.2 shows ANN architecture for three-layer network with fully connected neurons of different layers.

Fig. 2 A Typical Three-layer ANN Architecture



Before an ANN can be used to perform any task, it must be trained. A neural network learns from its environment and improves its performance through an interactive process of adjustments in which a system of connected weights and biases adaptively changes. In general, any neural network model can be categorized into two fundamental learning paradigms: (1) supervised learning and (2) unsupervised learning. A supervised neural network can be explained by the "learning with a teacher" concept in which the "conceptual" teacher has the built-in knowledge represented by a set of input-output examples (data source in the environment). In contrast to a supervised learning, unsupervised learning does not require a teacher in presence and, therefore, no desired response is supplied(Hu, 2002). ANNs consist of a large class of different architectures. Multi Layer Perceptron (MLP) and Radial Basis Function (RBF) are two of the most widely used neural network architecture in literature (Yilmaz and Kaynar, 2011). In the following subsections, a brief overview about MLP, RBF and GRNN architectures used in this study is given.

5.1 Multi-layer Perceptron (MLP)

The first neural ANN model employed in this study is the multi-layer perceptron (MLP). MLP has been the most widely used neural network topology in tourism demand forecasting studies (Smith, 2002; Zhang and Qi, 200; Moreno et al. 2011; Teixeira and Fernandes, 2012). According Wong et al. (2000), over fifty percent of reported neural network business application studies utilize multilayered feed forward neural networks with the back propagation learning rule. This type of ANN is popular because of its broad applicability to many problem domains of relevance to business: principally prediction, classification, and modelling. MLPs are appropriate for solving problems that involve learning the relationships between a set of inputs and known outputs. (Smith, 2002). The MLP is a feed-forward neural network model that estimates a relationship between sets of input data and a set of corresponding output. Its basis is the standard linear perceptron and it uses three or more layers of neurons, also called nodes, with non-linear activation functions (Marwala, 2013).The topology consists of layers of parallel perceptrons, with connections between layers that include optimal connections that either skip a layer or introduce a certain kind of feedback. The number of neurons in the hidden layer determines the MLP network's capacity to approximate a given function. In this type of framework, the connections between neurons always feed forwards, that is, the connections feed from the neurons in a certain layer towards the neurons in the next layer (Moreno et al. 2011).The main task of the input units is preliminary input data processing$\boldsymbol{u} = [u_1, u_2, \dots u_n]^T$and passing them onto the elements of the hidden layer. Data processing can comprise scaling, filtering or signal normalization, among others. The fundamental neural data processing is carried out in hidden and output layers. It is necessary to notice that links between neurons are designed in such a way that each element of the previous layer is connected with each element of the next layer. These connections are assigned with suitable weight coefficients which are determined, for each separate case, depending on the task the network should solve. The output layer generates the network response vector y. Non-linear neural computing performed by the network can be expressed by (Patan, 2008);

$y = \boldsymbol{\sigma}_3\{\boldsymbol{W}_{\boldsymbol{3Q_2}}[\boldsymbol{W}_{\boldsymbol{2Q_1}}(\boldsymbol{W}_{\boldsymbol{1u}})]\}$, (3)

where σ_1, σ_2 and σ_3 are vector-valued activation functions which define neural signal transformation through the first, second and output layers; W_1, W_2 and W_3 are the matrices of weight coefficients which determine the intensity of connections between neurons in the neighbouring layers; u, y are the input and output vectors, respectively. The fundamental training algorithm for MLP networks is the Back-Propagation

(BP) algorithm. It gives a prescription how to change the arbitrary weight valueassigned to the connection between processing units in the neighbouring layersof the network. This algorithm is of an iterative type and it is based on theminimisation of a sum-squared error utilizing the optimisation gradient descentmethod. The modification of the weights is performed according to the formula;
$w(k+1) = w(k) - \eta\nabla J\big(w(k)\big)$,(4)

where *w(k)* denotes the weight vector at the discrete time *k*, η is the learning rate, and $\nabla E\ w(k))$ is the gradient of the performance index *J* with respect to the weight vector *w*.

5.2 Radial Basis Function Neural Network (RBF)
The other ANN technique that is applied in this study is the radial basis function(RBF) network.It is based on supervised learning. RBF networks were independently proposed by many researchers and are a popular alternative to the MLP. RBF networks are also good at modelling nonlinear data and can be trained in one stage rather than using an iterative process as in MLP and also learn the given application quickly. The structure of RBF neural network is similar to that of MLP. It consists of layer of neurons. The main distinction is that RBF has a hidden layer which contains nodes called RBF units. Each RBF has two key parameters that describe the location of the function's centre and its deviation or width. The hidden unit measures the distance between an input data vector and the center of its RBF. The RBF has its peak when the distance between its center and that of the input data vector is zero and declines gradually as this distance increases. There is only a single hidden layer in a RBF network there are only two sets of weights, one connecting the hidden layer to the input layer and the other connecting the hidden layer to the output layer. Those weights connecting to the input layer contain the parameters of the basis functions. The weights connecting the hidden layer to the output layer are used to form linear combinations of the activations of the basis functions (hidden units) to generate the network outputs (Yilmaz and Kaynar, 2011).The output ϕ_i of the *i*-th neuron of the hidden layer is a non-linear function of the Euclidean distance between the input vector $\boldsymbol{u} = [u_1, \ldots, u_n]^T$ and the vector of the centres $c_i = [c_{i1}, \ldots, c_{in}]^T$, and can be described by the following expression:
$\phi = \varphi(\| u - c_i \|, \rho_i), \quad i = 1 \ldots \ldots, v$,(5)
where ρ_i denotes the spread of the *i*-th basis function, $\|.\|$is the Euclidean norm, and *v* is the number of hidden neurons. The network output *y* is a weighted sum of the hidden neurons' outputs:
$\boldsymbol{y} = \boldsymbol{\Theta}_{\boldsymbol{\phi}}$, (6)
where Θ denotes the matrix of connecting weights between the hidden neurons and output elements, and $\phi = [\phi_1, \ldots \phi_v]^T$. Many different functions $\varphi(.)$have been suggested. The most frequently used are Gaussian functions:
$\varphi(z,p) = exp\left(\frac{z^2}{\rho^2}\right)$ (7)
Advantages of RFB are that it can be trained in a short time according to MLP and approximate the best solution without dealing with local minimums. Additionally, RBF are local networks compared to the feed-forward networks that perform global mapping. This means that RBF uses a single set of processing units; each set is most receptive to a local region of the input space. Because of its features mentioned above, RBF neural networks were used as alternative ANN model in applications such as function approximation, time series forecasting as well as classifying task in recent years (Kaynar, 2012).

5.3 Generalized Regression Neural Network (GRNN)
Another ANN technique that is applied in this study is the Generalized Regression neural network (GRNN). The GRNN does not require an iterative training procedure as required in the back propagation method. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. In addition, it is consistent that as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function. It is related to the radial basis function network and is based on a standard statistical technique called kernel regression (Cıgızoglu, 2005). The topology of GRNN primarily consists of four layers of processing units. Each layer of processing units is assigned with a specific computational function when nonlinear regression is performed. The first layers of processing units, termed "input neurons" are responsible for reception of information. There is a unique input neuron for each predictor variable in the input vector *X*. No processing of data is conducted at the input neurons. The input neurons then present the data to the second layer of processing units called pattern neurons. A pattern neuron is used to combine and process the data in a systematic fashion such that the relationship between the input and the proper response is "memorized". Hence, the number of pattern

neurons is equal to the number of cases in the training set. A typical pattern neuron i obtains the data from the input neurons and computes an output θ_i using the transfer function of (Leung et al. 2000);

$$\theta_i = e^{-\frac{(X-U_i)'(X-U_i)}{2\sigma^2}} \quad (8)$$

where X is the input vector of predictor variables to GRNN, $U_i$is the specific training vector represented by pattern neuron i, and σ is the smoothing parameter.

The outputs of the pattern neurons are then forwarded to the third layer of processing units, summation neurons, where the outputs from all pattern neurons are augmented. Technically, there are two types of summations, simple arithmetic summations and weighted summations, performed in the summation neurons. In GRNN topology, there are separate processing units to carry out the simple arithmetic summations and the weighted summations. Equations (9) and (10) express the mathematical operations performed by the "simple" summation neuron and the "weighted" summation neuron, respectively.

$$S_s = \sum_i \theta_i, \quad (9)$$

$$S_w = \sum_i w_i \theta_i \quad (10)$$

The sums calculated by the summation neurons are subsequently sent to the fourth layer of processing unit, the output neuron. The output neuron then performs the following division to obtain the GRNN regression output y:

$$y = \frac{S_w}{S_s} \quad (11)$$

The main advantage of the GRNN model with respect to the MLP model is that it does not require an iterative training process. What is more, it can approximate any arbitrary function just like the previous models described, by adjusting the function directly from the training data (Moreno et al. 2011).

6. Data Collection and Analysis

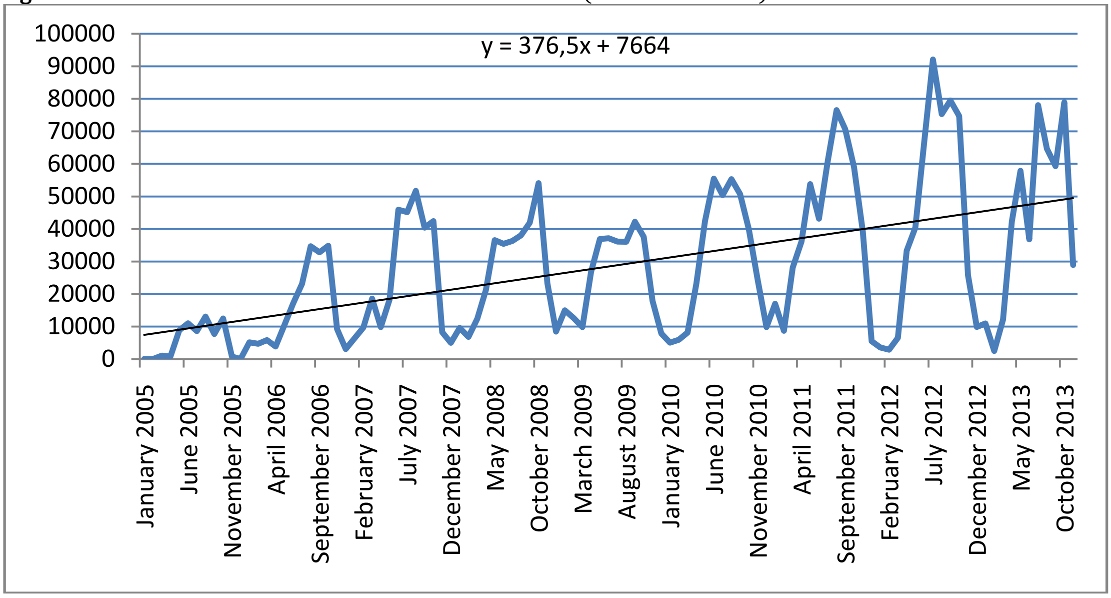
6.1 The Data

Tourism demand is usually regarded as a measure of visitors' use of a good or service. It can be measured in terms of tourist arrivals and/or departures, tourist expenditures and/or receipts, travel exports and/or imports, tourist length of stay, nights spent at tourist accommodation, and other. Tourist arrivals are the most frequently used measure of tourism demand, followed by tourist expenditure and tourist nights in registered accommodation (Fretchling, 2001; Lim, 2006; Song et al. 2009). In his literature survey, Li (2004) pointed out that amongst the 45 selected studies published since 1990, 37 of them used tourist arrivals while only six employed tourist expenditure as the measure of tourism demand. In this study,as measure of cruise tourism demand the number of monthly foreign tourist arrivals by cruise to Izmircover the period between January 2005 – December 2013 data were utilized to build appropriate model. Monthly cruise tourist arrival statistics wereprovided by Port Authority of Izmir. The monthly data was preferred to be able to more detailed analyze by taking into account of seasonal and trend components. Annual data only provide limited information for tourism decision making. Calling for the use of higher data frequencies (monthly and quarterly data) in tourism demand forecasting is necessary. Generally, the more observations in the studied model, the more likely the forecasting method will capture the patterns of the activity (i.e., tourism/travel demand patterns) to be forecasted (Frechtling, 2001).

6.2 Analysis of Time Series Features of the Data

Fig. 3 displays the time series behaviour of the cruise tourist arrivals data between January 2005 and December 2013, corresponding to 108 monthly observations over the 9-years' period.

Fig. 3 Time Series chart of cruise tourist arrivals in Izmir (2005:1-2013:12)



The behaviour of the series indicates that there is seasonality (higher values during the summer months and lower values in winter).It is also clear that there is a progressive trend over the period. As a result of trend analysis applied to the data, increasing and linear trend of the series has been found to have the structure. The validity of the F test for testing trend equations and t tests coefficients of the equation were found statistically significant at the significance level of 0,01.To identify seasonality in the data set, seasonal decomposition process was applied by the method of ratio-to-moving average.As a result of the analysis, obtained seasonal factor values show that the influence of seasonal fluctuations on the data periodically. Seasonal factor values are given in the Table 3.

Table 3. Seasonal Factor Values of the Data

Months	**Seasonal Factor Values (%)**	**Months**	**Seasonal Factor Values (%)**
January	35,3	July	154,9
February	27,5	August	183,8
March	44,4	September	166,6
April	77,9	October	170,8
May	119,2	November	60,6
June	137,4	December	21,3

6.3 Accuracy Measurement of Models

The accuracy of a forecasting model depends on how close the forecast values of y ($\hat{y}$) are to the actual values of y. The accuracy measurement reflects how well a quantitative forecasting model can predict the future. The differences between the actual and forecast values are known as the forecasting errors, which are defined by (Song et al.2009)

$$e_t = y_t - \hat{y}_t \quad (12)$$

Although there are a number of error measures such as Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Deviation (MAD), Mean Absolute Error (MAE), in this study we used the Mean Absolute Percentage Error (MAPE) to evaluate the forecasting performance of the MLP, RBF and GRNN models defined as;

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|e_t|}{y_t}}{n} 100(\%) \quad (13)$$

Where,
y_t =Value of the observation at time t in the time series,
$\hat{y}_t$ = Fitted value for the observation at time t, and
n is the length of forecasting horizon.
MAPE is a common measure for evaluating the accuracy of forecasting models. Suggested by Lewis (1982), this error measure can be interpreted as follows (Hu, 2002);

(1) MAPE smaller than 10% indicates a highly accurate model,
(2) MAPE between 10% and 20% indicates a good and accurate model,
(3) MAPE between 21% and 50% indicates a reasonably accurate model, and
(4) MAPE greater than 50% indicates an inaccurate model.

This measure used to evaluate the forecasting performance of tourism demand models because it is not prone to changes in the magnitude of the data to be forecasted. The use of error magnitude-dependent measures allows us to compare forecasting accuracy between different models

6.4 Applications of MLP, RBF and GRNN to Cruise Tourism Modelling

In this section, the number of monthly cruise tourist arrivals to Izmir examined. Appropriate ANN models were chosen by experiments in order to make forecasts, and these models are also compared. In accordance with the description made, a set of MLP, RBF and GRNN network models were designed. Before modelling the monthly cruise tourist arrivals data with ANNs, data was divided into two parts: training and testing stages. The training set consisted of the first 84 of 108 total observations. These data are used in training to construct the models.And the testing set covered the succeeding 24 monthly observations.In the second part, with the help of the models constructed in the first part, the performances of those models are calculated using the 24 months' data for the January 2012–December 2013 period. The MATLAB neural network toolbox is used to conduct all ANN models training. The data is normalized in the range [0:1] before being entered into the computerusing the equation below;

$$x_n = \frac{x_0 - x_{\min}}{x_{\max} - x_{\min}} \quad (14)$$

where,
x_0 = original data values,
x_n = normalized values,
x_{min} = the lowest number included in the data, and
x_{max} = the biggest number included in the data.

ANN's forecasting capability predominantly depends on its architecture. Since it is not a deterministic method, constructing a most appropriate model for a particular problem is usually quite cumbersome. It must be noted that there is no exact theoretical way of selection procedure for any of the parameters. Therefore, the most common way to implement an ANN model is still using heuristic assumptions based on experimental studies and trial-errors (Kuvulmaz et al. 2005: 506). When constructing appropriate ANN models, different time delays $(y_{t-1}, y_{t-3}, y_{t-12} \ldots\ldots y_{t-k})$ in the input layer and the instantaneous data values (y_t) are used in the output layer. As the data included seasonality, after trying many neural networks with different numbers of input units, as expected, the number of input units (neurons) was determined as 12.In MLP models the learning algorithm used was the Levenberg-Marquardt back-propagation and as activation function of the hidden and output neurons, the sigmoid and linear ones, respectively. Linear transfer function is used in the output layer node, whereas tangent-sigmoid transfer function is preferred in the hidden layer nodes. Network training parameters, epoch number and goal error rate, which stop training, are chosen 5000 and 0,01 respectively. For RBF models the weights are optimized using least mean square LMS algorithm once the centers of RBF units are determined. As far as the different RBF models are concerned, they were constructed by varying the number of centroids, between 5 and 25, and the value of the normalization parameter, between 0,2 and 1,5.In the case of the GRNN models, the only parameter that was manipulated was the normalization parameter with values comprising between 0,05 and 1. Finally, the GRNN models, with recurrent connections in the hidden layer, were constructed by manipulating the same parameters as in the case of the MLP models.

6.5 Experimental Results and Generating Future Forecasts

In this section, the results for the test data (years 2012 and 2013) will be analysed, comparing the values observed with the values forecasted by different NN models. For each of the three types of network model designed, the one that showed the lowest percentage error (MAPE) was chosen from created models. The neural network that showed the best performance among the MLP was found to be the (12:1:1) architecture with the 5 neurons in hidden layer.Among the RBF networks, the (12:1:1) RBF showed the best performance with3 neurons in hidden layer. And the model that showed the best performance among the GRNN was found to be the (12:1:2:1) with 3 neurons in pattern layer and 2 neurons in summation layer.Table 4 presents the accuracy comparisons for the chosen MLP, RBF and GRNN neural network models in terms of MAPE values in the test set.

Table 4. Accuracy Comparisons for the MLP, RBF and GRNN Models

Model	Design of Input Layer	Neurons in Input Layer Layer	Hidden Layer	Neurons in Hidden Layer	Output Layer	Pattern Layer	Summation Layer	MAPE (%)
MLP	$(y_{t-1}, y_{t-2}, \ldots y_{t-12})$	12	1	7	y_t			11,44
RBF	$(y_{t-1}, y_{t-2}, \ldots y_{t-12})$	12	1	5	y_t			**7,10**
GRNN	$(y_{t-1}, y_{t-2}, \ldots y_{t-12})$	12	-	-	y_t	**1**	**1**	15,06

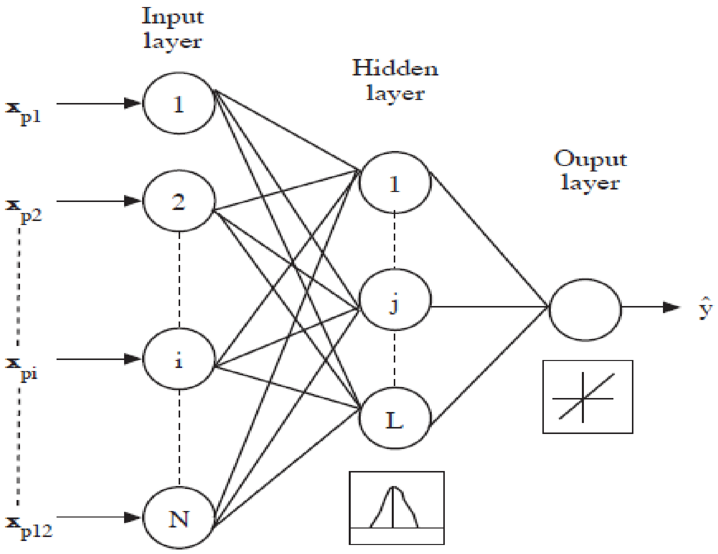
Based on the criteria established by Lewis (1982), it may be said that the chosen models successfully produced highly accurate forecasts for years 2012 and 2013 since the MAPE values of each model is lower than 20 %. As seen in Table4, RBF (12:1:1) architecture model outperforms the MLP (12:1:1) and GRNN (12:1:2:1) models in forecasting accuracy. Experimental results reveal that the number of cruise tourist arrivals estimated by RBF neural network is very close to actual values. In other words, the forecasting output from RBF (12:1:1) model is accurate with a relatively small amount of error (MAPE = 7,1 %). The low MAPE indicates that the deviations between the discrepancies between the predicted values derived by the model and the actual values are very small. Table 5, presents the number of cruise tourist arrivals to Izmirpredicted by different ANN models for the January 2012–December 2013 period.

Table 5. Number of Cruise Tourist Arrivals to IzmirPredicted by RBF, MLP and GRNN Neural Networks

Months (2012)	Actual	RBF	MLP	GRNN	Months (2013)	Actual	RBF	MLP	GRNN
January	3559	4618	5106	4922	January	10945	9637	9423	8956
February	2853	3382	3988	4040	February	2465	3255	3944	3047
March	6524	6703	5863	5794	March	12137	11223	11007	11457
April	33285	34433	31346	4278	April	42262	43871	42784	43249
May	40398	41665	42190	5131	May	57868	56021	55784	55290
June	66438	65844	59772	65907	June	36803	37435	39987	38078
July	92083	87303	88554	90844	July	78072	76570	75051	79521
August	75298	73707	71500	78853	August	64640	65811	67213	67058
September	79500	76963	74673	80058	September	59308	58163	60036	57742
October	74694	72528	72266	76005	October	78957	79818	75378	80045
November	25813	23855	23913	27890	November	28925	27828	29937	26823
December	9835	8113	8211	9497	December	7681	7470	8081	7590

Fig. 4 illustrates the RBF (12:1:1) architecture neural network model constructed after training with the training data set.

Fig. 4 Developed RBF Neural Network Model



By the means of the constructed RBF neural network model which presented best performance, it has been forecasted the monthly inbound cruise tourism demand to Izmir for year 2014 and forecasts presented in Table 6.

Table 6. Monthly Cruise Tourism Demand Forecasts to Izmirfor Year 2014

Months (2014)	**Number of Cruise Tourists**
January	8136
February	3227
March	11940
April	44135
May	59200
June	59433
July	88567
August	72349
September	73092
October	80343
November	31579
December	9034

7. Conclusions and Future Research

Due to perishable nature of tourism products and services, forecasting plays a significant role in tourism planning. Tourism demand forecasts help both the public and private sectors enhance the allocation of resources which plays staminal role in avoiding shortcomings or oversupplies in the tourism sector. Investments in tourism infrastructures require huge financial pledge from both the public and private sectors. Accurate forecasts provide better estimates of expected return on investments that help guide investment decisions. Forecasting is highly important for the tourism industry, which needs accurate predictions of demand so that it can plan effectively from season to season, year to year. For this reason, tourism researchers have been, and shall be, making attempts to develop various kinds of forecasting methods relating to specific aspects of tourism demand.

The non-linear and non-stationery nature of tourism demand makes tourism forecasting studies difficult and drives researchers to investigate new methods to obtain more accurate forecasts. Artificial neural networks have emerged as an important tool for tourism demand forecasting and provide an attractive alternative tool for both forecasting researchers and practitioners. Several distinguishing features of ANNs make them valuable and attractive for a forecasting task. First, as opposed to the traditional methods, ANNs are data-driven self adaptive methods in that there are few a priori assumptions about the models for problems under study. They learn from examples and capture subtle functional relationships among the data even if the underlying relationships are unknown or hard to describe.In this study, it is aimed to determine the forecasting method that provides the best performance when compared the forecast accuracy of Multi-layer Perceptron (MLP), Radial Basis Function (RBF) and Generalized Regression neural network (GRNN) to estimate the monthly inbound cruise tourism demand to Izmir for the year 2014 via the method giving best results. Experimental results revealed that the number of cruise tourist arrivals estimated by RBF neural network outperforms the MLP and GRNN models in forecasting accuracy. Because of its features mentioned earlier, RBF neural networks were used as alternative ANN model in applications such as function approximation, time series forecasting as well as classifying task in recent years. Considering the results obtained not only by this study but also by most recent studies (Law, 2000; Kon & Turner, 2005; Palmer et al. 2006; Goh et al. 2008; Teixeira &Fernandes, 2012; Cho, 2009; Cuhadar, 2013) it has observed that the ANN models without problems such as over-training and structural failures etc. provide accurate forecasts. Therefore, it ought to be attentive to constitute appropriate model that fit the structure of data.Although there has notbeen confirmation that shows any model can everlastingly outperformall others on allconditions, recent studies suggest that the newer and moreadvanced forecasting techniques tend to result in improved forecast accuracyunder specificsituations. Thus, advanced forecasting modelssuch as; support vector machines (SVMs); rough sets; fuzzy logic; genetic algorithms (GA) and adaptive neuro-fuzzy inference system (ANFIS) are recommended for future tourism demandforecasting studies. Considering the limited number of studies forecasting cruise tourism demand in literature by using artificial intelligence methods, suggested methods will contribute to decision making managers and practitioners in tourism sector and the tourism demand literature.

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