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The Forecasting of The Number of Tourists Arriving in Turkey with an Intuitionistic Fuzzy Regression Functions Approach

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Abstract

The impacts of the tourism sector on countries are felt in various areas such as the economy, cultural heritage and social development. Tourism contributes significantly to a country's foreign exchange earnings and positively affects the trade network. Tourists' spending boosts local economies and increases employment. These effects are particularly important for Turkey. Tourist visits can be used as a tool for regional promotion. Therefore, tourism demand forecasting is necessary to make the best use of these positive effects on Turkey's economic development and to plan tourism activities. Artificial neural network methods and fuzzy systems for time series forecasting problems are frequently used as analysis methods in recent years. In this study, the time series of the total number of tourists visiting Turkey monthly is analyzed with the intuitionistic fuzzy regression functions approach, which is a generalization of the fuzzy regression functions approach. The analysis performance of the intuitionistic fuzzy regression functions approach is evaluated using fuzzy regression functions approach, multilayer perceptron artificial neural network and multiplicative neuron model artificial neural networks. As a result of the analysis, it is concluded that the intuitionistic fuzzy regression approach produces better forecasting results than both some artificial neural network models and the fuzzy regression functions approach. Since this is the first time that the intuitionistic fuzzy regression functions approach has been used in forecasting the number of tourists, the study aims to contribute to the literature and to help tourism industry employees to be more efficient and successful by providing them with the opportunity to make better future planning.

Keywords: Tourism, Intuitionistic Fuzzy Regression Functions, Forecasting.

1. Introduction

To secure a competitive edge in the global market milieu, enterprises must possess the foresight into future trends and developments. The formation of these prognostications necessitates the employment of scientific research, while eschewing forecasting based on mere sentiment, thereby facilitating the making of informed decisions by businesses. The tourism sector, a rapidly evolving component of the global economy, plays a pivotal role in the economic advancement of nations, aspiring to optimize the utilization of tourism resources to maximize the economic benefits for countries. It is amongst the swiftly expanding sectors within the global economic framework. As per the global tourism statistics, the year 2022 witnessed travel by 963 million tourists, generating total tourism revenues of 1 trillion and 12 billion dollars. Data from the World Tourism Organization (UNWTO, 2023) positions Turkey at the fourth rank globally with 50 million 450 thousand tourists.

For enterprises active in the tourism industry, accurate forecasting of tourist demand numbers is crucial for effective planning. Annually, countries adjust their labour numbers, services, and product procurement based on anticipated tourist arrivals. In this context, precise and reliable forecasting is beneficial for all industry stakeholders in managing their various activities. As a nation equipped to meet the shifting demands and new expectations of the global market, Turkey should prioritize tourism demand forecasts in its decision-making processes to harness the maximum benefit from its tourism sector. Çuhadar (2006) delineates

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tourism demand as “a collective of individuals who, within a specific timeframe and with a definite purpose, utilize or wish to utilize tourist products and services.” Accurate forecasting of tourism demand is crucial for the strategic planning of the tourism sector’s future.

Demand forecasts are a procedure that utilizes historical data for making future-oriented assumptions. In scenarios of heightened uncertainty, analyses by artificial intelligence prove to be more efficacious than conventional methods. Various qualitative and quantitative techniques are deployed in demand forecasting, facilitating accurate forecasting by measuring data with different demand structures using suitable analytical methods. Tourism demand forecasting constitutes a significant aspect of sectoral research, and an examination of the literature reveals the exploration of numerous methods and modelling efforts (Şahin and Taşkesen, 2022).

In demand forecasting, methodologies such as neural networks and time series analysis assist in accurately forecasting anticipated demand in tourism and other sectors. These methodologies have been effectively employed across several studies; for instance, Baldemir and Bahar (2003) used recurrent neural networks, multiple regressions, purity, and moving average methods to forecast the number of tourists coming to Turkey in many countries. Aslanargun et al. (2007) used linear artificial neural networks (ANN), multilayer perceptron, and radial basis function network models, along with their various combinations for forcasting number of tourists visiting Turkey employing. Kutlar and Sarıkaya (2012) used autoregressive moving average (ARMA) to forecast the number of tourists who will visit Turkey. Şamkar (2018) proposed the robust ridge regression method to forecast the number of tourists coming to hotels in Antalya.

Zorlutuna and Bircan (2019) compared autoregressive integrated moving average, ARMA and ANN methods for tourist demand forecasting. Erdogan et al. (2021) used multiple linear regression methods, ANN and support vector regression techniques to forecast the number of tourists. Numerous studies within the tourism domain have demonstrated that ANN yield the most favourable outcomes in forecasting (Çuhadar, 2009; Kaynar and Taştan, 2009; Dolgun, et al., 2014; Chen, et al., 2012; Karahan, 2015; Özden and Öztürk, 2018).

The tourism industry plays a vital role in the economies of developing nations. Its beneficial impacts are observed across various facets; most notably, its contributions to the balance of payments. Tourism, by fostering foreign exchange income through tourist expenditures, aids in balancing a country’s external trade equilibrium. Cinel and Yolcu (2021) used an ANN model to explain the effects of tourism revenues on Turkey's current account balance.However, when studies on the sustainability of tourism are examined; Rafique (2021), ANN methods were used to analyze the spatial movements of domestic and foreign tourists in 123 districts in 8 regions of the Aegean.

In this study, the intuitionistic fuzzy regression functions (IFRF) approach proposed by Bas et al. (2021) is used for the first time in the literature for a tourism demand forecast. The IFRF approach is based on intuitionistic fuzzy sets, which are characterized by having both membership and non-membership values, distinguishing them from both classical and fuzzy sets. Due to these sets containing more information than both classical and fuzzy sets, the IFRF approach can be considered an extension of the fuzzy regression functions (FRF) approach. Because of these features, the IFRF approach emerges as a suitable method for demand forecasting in the tourism sector. In this study, the time series of the total number of tourists visiting our country on a monthly basis from 2012 to 2022 has been analyzed with the IFRF approach.

The second section of this document details the intuitionistic fuzzy c-means method. The third section presents the IFRF approach through a step-by-step algorithm. The fourth section provides analysis results for the monthly time series of total tourist visits to our country, obtained via the IFRF method and compared with results derived from some renowned methods in the literature. The fifth and final section is allocated to discussions and conclusions.

2. Intuitionistic Fuzzy C-Means Method

Atanassov (1986) proposed intuitionistic fuzzy sets as an extension of the fuzzy set theory introduced by Zadeh (1965). He suggested that not only membership values but also non-membership values are as significant as membership values in fuzzy set theory. From this perspective, intuitionistic fuzzy sets can be considered a generalization of fuzzy sets. An intuitionistic fuzzy set encompasses both membership and non-membership values, and it also introduces a degree of hesitation, which represents the uncertainty about whether an element belongs to a set. This approach makes intuitionistic fuzzy sets more suitable for decision-making processes. An effective method for deriving intuitionistic fuzzy sets from a dataset is the "Intuitionistic Fuzzy C-Means" (IFCM) method proposed by Chaira (2011).

Algorithm 1: Step by Step IFCM Method

Step 1. Setting the method's parameters and creating traditional fuzzy membership values

The parameters include the number of observations (n), the number of intuitionistic fuzzy clusters (c), the number of iterations (k) and the error value (ε) determined by the researcher. Based on these parameters, traditional fuzzy membership values $(u_{ik}\ i = 1,2,\cdots,c; k = 1,2,\cdots,n)$ are randomly generated and stored in a U matrix.

Step 2. Determining hesitation degrees

The hesitation degrees for each intuitionistic fuzzy cluster are obtained using Equation (1) and stored in a π matrix.

$$\pi_{ik} = 1 - u_{ik} - (1 - u_{ik}{}^{\alpha})^{1/\alpha}, \ \alpha > 0 \tag{1}$$

Step 3. Determining intuitionistic fuzzy membership values

The intuitionistic fuzzy membership values ($u_{ik}{}^{*}$) are determined by Equation (2) and stored in an Uy matrix.

$$u_{ik}{}^{*} = u_{ik} + \pi_{ik} \tag{2}$$

Step 4. Updating cluster centers and obtaining updated intuitionistic fuzzy membership values

In each iteration, cluster centres (v_i) are updated using Equation (3) and subsequently, the updated fuzzy membership values ($u_{ik}{}^{\#}$) are obtained by Equation (4) and stored in an Uy^{*} matrix, updated hesitation degrees ($\pi_{ik}{}^{*}$) by Equation (5) in a π^{*} matrix, and updated intuitionistic fuzzy membership values ($u_{ik}{}^{**}$) by Equation (6) in an Uy^{**} matrix.

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^{*}{}^{m} x_k}{\sum_{k=1}^{n} u_{ik}^{*}} \tag{3}$$

$$u_{ik}{}^{\#} = \frac{1}{\sum_{j=1}^{c} \left[d_{ik}^2 / d_{jk}^2 \right]^{1/m-1}} = \left[\sum_{j=1}^{c} \left(\frac{d(x_k, v_i)}{d(x_k, v_j)} \right)^{\frac{2}{m-1}} \right]^{-1} \quad ; \quad i = 1,2,\cdots,c; k = 1,2,\cdots,n \tag{4}$$

$$\pi_{ik}{}^{*} = 1 - u_{ik}{}^{\#} - (1 - (u_{ik}{}^{\#})^{\alpha})^{1/\alpha}, \ \alpha > 0 \tag{5}$$

$$u_{ik}{}^{**} = u_{ik}{}^{\#} + \pi_{ik}{}^{*} \tag{6}$$

The m in Equation (3) represents the fuzziness index.

Step 5. Terminating the algorithm

The process is terminated if the condition $||Uy^{**} - Uy|| < \varepsilon$ is met; otherwise, return to Step 4 and continue.

3. Intuitionistic Fuzzy Regression Functions Approach

The IFRF approach is a method proposed by Bas et al. (2021) and is considered an extension of the FRF approach. The IFRF approach is distinguished from traditional fuzzy inference systems and FRF by not depending on expert opinion or a specific rule base, and it incorporates more information by considering both intuitionistic membership and non-membership values and their nonlinear transformations, as well as lagged variables of the time series. This difference also stems from the fact that while the FRF approach is based on the fuzzy c-means method proposed by Bezdek (1981), the IFRF approach is based on the intuitionistic fuzzy c-means method proposed by Chaira (2011). The step-by-step algorithm for the IFRF approach is provided in Algorithm 2.

Algorithm 2. IFRF Approach

Step 1. Determining the system's parameters

c: Number of intuitionistic fuzzy clusters
m: Number of lags
α: Alpha-cut value
$ntest$: Test set length

Step 2. Forming the system's inputs

The delayed variables of the training set form the system's inputs, which, along with the corresponding outputs, are collected in a D matrix.

Step 3. Obtaining intuitionistic membership and non-membership values

The D matrix created in Step 2 is clustered according to the determined number of intuitionistic fuzzy clusters using the IFCM method, resulting in intuitionistic membership values ($u_{ik}, \ i = 1,2,\cdots,c ; k = 1,2,\cdots,n$) and non-membership values ($\mathrm{\nu_{ik}}, \ \mathrm{i} = 1,2,\cdots,\mathrm{c} ; \mathrm{k} = 1,2,\cdots,\mathrm{n}$).

Step 4. Obtaining updated intuitionistic membership and non-membership values

The cluster centers are reduced by removing the component corresponding to the output, and new intuitionistic membership and non-membership values are obtained.

Step 5. Obtaining normalized intuitionistic membership and non-membership values.

The values u_{ik} and ν_{ik} are set to zero if they are sufficiently small according to the α value, resulting in normalized intuitionistic membership (μ) and non-membership (φ) values obtained by Equations (7-10).

$$\gamma_{ik} = \begin{cases} u_{ik} & u_{ik} > \alpha \\ 0 & u_{ik} \leq \alpha \end{cases} \tag{7}$$
$$\mu_{ik} = \gamma_{ik} / \textstyle\sum_{i=1}^{c} \gamma_{ik} \tag{8}$$
$$\eta_{ik} = \begin{cases} v_{ik} & v_{ik} > \alpha \\ 0 & v_{ik} \leq \alpha \end{cases} \tag{9}$$
$$\varphi_{ik} = \eta_{ik} / \textstyle\sum_{i=1}^{c} \eta_{ik} \tag{10}$$

Step 6. Assembling the inputs for each cluster

For each i cluster, the inputs consisting of $\mu_{ik}$and φ_{ik} values, their exponential and various logarithmic transformations, and lagged variables are assembled into an X matrix, and the $i.$ intuitionistic fuzzy function $Y^{(i)} = X^{(i)}\beta^{(i)} + \varepsilon^{(i)}\ ;\ i = 1, 2, \dots c$ is forecasting as a multivariate regression model. The $X^{(i)}$ and $Y^{(i)}$ matrices are obtained by Equations (11-12)

$$X^{(i)} = \begin{bmatrix} 1 & \mu_{i1} & \mu_{i1}{}^2 & exp\,(\mu_{i1}) & \varphi_{i1} & \varphi_{i1}{}^2 & exp\,(\varphi_{i1}) & x_1 & x_2 & \cdots & x_p \\ 1 & \mu_{i2} & \mu_{i2}{}^2 & exp\,(\mu_{i2}) & \varphi_{i2} & \varphi_{i2}{}^2 & exp\,(\varphi_{i2}) & x_2 & x_3 & \cdots & x_{p+1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \mu_{in} & \mu_{in}{}^2 & exp\,(\mu_{in}) & \varphi_{in} & \varphi_{in}{}^2 & exp\,(\varphi_{in}) & x_{n-p} & x_{n-p+1} & \cdots & x_{n-1} \end{bmatrix} \tag{11}$$
$$Y^{(i)} = \begin{bmatrix} x_{p+1} \\ x_{p+2} \\ \vdots \\ x_n \end{bmatrix} \tag{12}$$

Step 7. Forecasting IFRF

The IFRF for each intuitionistic fuzzy cluster are forecasted using Equations (13-14).

$$\hat{\beta}^{(i)} = (X^{(i)'}X^{(i)})^{-1}X^{(i)'}Y^{(i)} \tag{13}$$
$$\hat{Y}^{(i)} = X^{(i)}\hat{\beta}^{(i)}\ ;\ i = 1, 2, \dots c \tag{14}$$

Step 8. Obtaining final forecasting values for the training set

Initially, the corresponding intuitionistic membership values and non-membership values proportional to the $\hat{Y}^{(i)}$' obtained in Step 7 are derived using Equations (15-16). The final forecasting values for training set $(Yegt)$ are then obtained by Equation (17). Here, the beta coefficient is a parameter ranging from 0 to 1, used by the researcher in intuitionistic fuzzy clustering.

$$\hat{Y}_k{}^{\mu} = \frac{\sum_{i=1}^{c} \hat{Y}^{(i)}\mu_{ik}}{\sum_{i=1}^{c} \mu_{ik}}\ , i = 1,2, \dots, c,\ \ k = 1,2, \dots, n \tag{15}$$
$$\hat{Y}_k{}^{\varphi} = \frac{\sum_{i=1}^{c} \hat{Y}^{(i)}\varphi_{ik}}{\sum_{i=1}^{c} \varphi_{ik}}\ , i = 1,2, \dots, c,\ \ k = 1,2, \dots, n \tag{16}$$
$$Yegt = \left(\hat{Y}_k{}^{\mu} * (1 - beta)\right) + \left(\hat{Y}_k{}^{\varphi} * beta\right) \tag{17}$$

Step 9. Reconstructing the system inputs for the test set

The system inputs are recreated for the test set, and Steps 2-8 are reapplied for the test to obtain the final values.

4. Implementation

During the implementation phase of this study, the monthly total number of tourists visiting Turkey from January 2012 to December 2022 was analyzed using different approaches than the IFRF approach. The methods used were the FRF approach proposed by Türksen (2008), the multilayer perceptron ANN (MLP-ANN) suggested by Rumelhart et al. (1986), and the product neuron model ANN (PNM-ANN) introduced by Yadav et al. (2007). In the analysis phase, the last twelve observations of the TS time series were taken as the test set (ntest). The number of inputs for each method was tested between one and twelve, and the optimal number of inputs for each method was determined based on the validation set, which was also set to twelve in length. The number of fuzzy clusters for FRF and IFRF approaches and the number of intuitionistic fuzzy clusters were tested between three and ten. For the MLP-ANN, the number of units in the hidden layer was tested between one and ten. After deciding on the optimal number of inputs, each method was run ten times due to the influence of initial parameters on these methods, and average, standard deviation, minimum, and maximum statistics for each method was calculated. These statistics were used for comparison using the Root Mean Square Error (RMSE) given by Equation (18) and the Mean Absolute Percentage Error (MAPE) given by Equation (19). The optimal parameters obtained for each method are presented in Table 1.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{ntest}(y_t - \hat{y}_t)^2} \tag{18}$$

$$\text{MAPE} = \frac{1}{ntest}\sum_{t=1}^{ntest}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{19}$$

Table 1. Optimal Parameter Values Obtained From All Methods

Methods	Input Number	Fuzzy/Intuitionistic Fuzzy Cluster Number	Hidden Layer
PNM-ANN	1	-	-
MLP-ANN	8	-	2
FRF	2	4	-
IFRF	2	4	-

Various statistics for the RMSE values obtained from all methods are presented in Table 1, and various statistics for the MAPE values obtained from all methods are provided in Table 2.

Table 2. RMSE Values Obtained From All Methods

Methods	Average	Standard Deviation	Minimum	Maximum
PNM-ANN	515414,0911	109617,6502	244917,4104	591245,5043
MLP-ANN	155163,1528	11373,0885	**132674,0686**	170316,2584
FRF	147089,1373	14,1030	147049,0786	147094,0969
IFRF	**145526,8578**	**0,0018**	145526,8551	**145526,8612**

From the analysis results given in Table 2, it is clear that according to the RMSE criterion, the IFRF method is the best method in terms of average, standard deviation, and maximum statistics. Especially, the standard deviation statistic of the IFRF method indicates that the method is minimally affected by random initializations.

Table 3. MAPE Values Obtained From All Methods

Methods	Average	Standard Deviation	Minimum	Maximum
PNM-ANN	0,9033	0,2147	0,4192	1,1427
MLP-ANN	0,2151	0,0140	**0,1911**	0,2373
FRF	0,2027	0,0000	0,2026	0,2027
IFRF	**0,1930**	**0,0000**	0,1930	**0,1930**

From the analysis results presented in Table 3, it is clear that according to the MAPE criterion, the IFRF method is again the best. Furthermore, considering the high standard deviation values, it can be stated clearly that ANN methods are significantly affected by random initial values compared to FRF methods, as evidenced by both Tables 2 and 3.

The graph showing the forecasting obtained by the IFRF method alongside the observation values of the TS time series test set is presented in Figure 1.

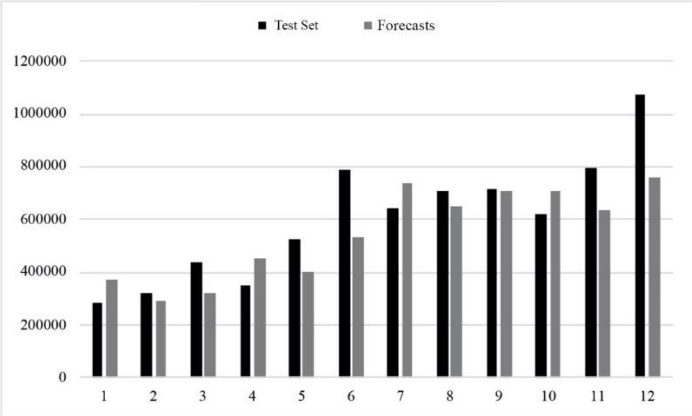

Figure 1. Graph of forecasting from the IFRF Method Alongside Observation Values of the TS Time Series Test Set

Upon examining Figure 1, it can be said that the forecasting made for many months is quite consistent and close to the observations of the test set.

5. Conclusions and Discussions

Tourism stands out as one of the fastest-growing sectors worldwide. This sector represents a significant portion of the global Gross Domestic Product (GDP) today. Tourist visits promote a country's cultural heritage and touristic appeal, creating a positive image in the international arena. Despite the presence of global economic challenges, the tourism sector continues to grow, empowering other industries. Tourism not only contributes significantly to the national income but also helps balance the payment balance by generating foreign exchange earnings. With its intensive employment support, it offers job opportunities to a wide range of people and serves as an effective marketing and advertising tool for the country. While considering the revenue-generating aspect of tourism, attention must also be paid to the environmental and cultural destruction of this sector. Uncontrolled tourism leads to the overuse of natural resources, destruction of local cultural heritage, and environmental impacts. Therefore, the sustainability of tourism should be ensured. Making tourism forecasts is important for understanding and managing future tourist flows. These forecasts can be used for environmental impact assessments, conservation of natural resources, and prevention of excessive tourism. Additionally, plans to promote sustainable tourism can be used to balance the revenue-generating feature of tourism with environmental and cultural conservation.

In this study, the time series analysis of the total number of tourists visiting Turkey was carried out using the IFRF method. Upon examining the analysis results, it has been concluded that the IFRF method produces better forecast results than both the FRF method and some ANN methods for the relevant time series. In light of this information, it can also be said that the IFRF method could be used as an alternative to ANN methods in analyzing time series related to tourist numbers. In further studies, the IFRF method can be used as a tool to help businesses in the tourism industry forecast future demands.

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