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Forecasting Alisadr Cave Tourism Demand using Combination of Short-term and Long-term Forecasts

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ABSTRACT

Nowadays, the tourism industry has become one of the most important sectors in the world economy. Due to the perishability of this industry, accurate forecasting of the demand is very important for tourism planning and resource allocation. Studies show that due to the diversity and complexity of the factors affecting tourism demand, the combination of different approaches may increase the forecasting accuracy. The aim of this paper is to forecast the tourism demand of Alisadr cave. For this purpose, a method based on artificial neural networks is presented, in which the results of linear and non-linear methods and short-term and long-term forecasts are combined. This method is applied to a dataset of Alisadr cave tourists. The evaluation results show that in most cases, the proposed combined method can predict the tourism demand with higher accuracy than the monthly and seasonal methods based on neural networks and random forest models. The predictive models obtained from this study can enhance customer service and improve the interaction between users and tourist ticketing web applications and online reservation programs.

Keywords: ***Demand Forecasting; Tourism; Alisadr Cave; Neural Networks; Combined Forecasting.***

1. Introduction

Tourism industry is an important part of economic activities. However, in recent years due to the Covid-19 pandemic, this industry has experienced stagnation. According to the statistics announced by the World Tourism Organization (UNWTO), the number of tourists in the first 7 months of 2022 was 57% of tourists before the start of the pandemic. These statistics show that tourism demand has grown between 20 and 78 percent in 2022 compared to 2021 and is approaching the tourism statistics before the pandemic [1]. In Iran also the number of international and domestic tourists has grown a lot over the past years, and attention to this industry has increased. Due to the perishability of tourism services, the optimal management of resources in this industry is vital. In addition, knowing the amount of tourism demand is particularly important to provide better services to tourists [2], [3]. To have effective strategies in tourism management, it is necessary to forecast tourist arrivals and study the patterns of their entrance. The demand forecasting is one of the most important modules of tourism planning because it improves the customer services[4]. For this reason, many studies have been conducted in the field of tourism demand forecasting in both academic and industrial areas. The predictive model obtained from this study may play an important role in websites and online systems for providing services to tourists and adjusting the supply of tourism services and products according to market needs.

The forecasting methods are divided into two categories: 1) linear methods and 2) non-linear methods. Naive Bayes method, exponential smoothing, Box-Jenkins, and Autoregressive Integrated Moving Average (ARIMA) are examples of linear methods. The last two methods have been more successful in tourism demand forecasting. On the other hand, neural networks and SVR are two examples of the most common non-linear methods that extract a non-linear pattern from time series[5]. In general, non-linear methods are more efficient for complicated problems. In many studies, artificial neural networks have been widely used due to their ability to extract relationships from experimental data using non-linear functions. Studies show that backpropagation neural network (BPNN) works better than regression models and time series methods in terms of prediction accuracy [2], [6], [7].

Many factors affect tourism demand and thus, make forecasting difficult [7]. So, it is necessary to use efficient methods to make accurate forecasts in the tourism industry.

One approach to increase forecasting accuracy is to combine forecasting methods. In several studies, the effect of combining forecasting methods on increasing forecasting accuracy has been investigated. The results of these studies show that, in most cases, using a appropriate combination of forecasting methods has better outcomes than using only a single method [8]. The study of Song et. al., [9] in 2019 showed that the combined forecasting results are significantly more accurate than single forecasts, and this is true for all forecasting methods. The results of studies have shown that even if combined forecasting does not improve the overall forecasting accuracy, still the combination of different methods prevents the risk of forecasting failure[10]. Another

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motivation for combining forecasting methods is that we can combine complementary methods that compensate for each other's weaknesses [3].

In this paper, a combined forecasting method is presented to predict the monthly demand of Alisadr Cave tourists. In this combined method, the forecasts obtained from linear and non-linear methods, as well as the forecasts of different time frames, are combined. The proposed method is applied to the dataset of Alisadr Cave, and the performance of the proposed method for predicting the monthly tourism demand of Alisadr Cave is investigated.

In the rest of the paper, first in Section 2, previous studies related to tourism demand forecasting are reviewed. Then, in Section 3, the proposed method for forecasting tourism demand is described. In Section 4, the proposed method is applied to Alisadr Cave dataset, and the results are evaluated. Finally, in Section 5, the paper is concluded with a summary.

2. Literature Review

Various models have been used to forecast tourism demand, which can be divided into three main categories: time series models, economic models, and machine learning models [11]. Meanwhile, new researches have usually used a combination of the above methods for forecasting.

Time series are traditional models which predict tourism demand by linear methods. In this category, Autoregressive Moving Average (ARMA), ARIMA, and improved versions of them[12], [13] are the most widely used models.

In economic methods, the causal relationship between affecting factors of tourism demand and the amount of demand is investigated and modeled. Popular models of this category include error correction models [14], vector autoregressive models [15], and autoregressive distributed lag models [16].

The machine learning models that have been widely used in the field of tourism demand forecasting include artificial neural network models [17] and support vector machines [18]. One of the main advantages of machine learning methods is that these methods do not require prior knowledge about the probability distribution and there is no need to consider specific assumptions on the data. In addition, the non-linear nature of these methods is suitable for tourism data [19].

Palmer et al. [20] used a multi-layer perceptron neural network to forecast tourism demand in Spain. They worked on different forecast horizons and several neural network architectures. The prediction results showed that their neural network is suitable for predicting tourism demand. Chen et al. compared ARIMA, the BPNN method, and a combination of genetic algorithm and SVR for predicting the number of tourists arriving in China. They concluded that the BPNN method is more accurate than ARIMA[21].

Teixeira and Fernandes compared three types of neural networks for forecasting the monthly tourism demand for the northern region of Portugal. He showed that these three models had almost accurate results. The error was between 4% and 6% which was a better result compared to using the linear and ARIMA methods[22].

Claveria compared the neural network with various time series models, including ARIMA and self-exciting threshold autoregressions (SETAR) and showed that the neural network was successful in predicting the non-linear behavior[23]. Another study was conducted by the same author with the aim of investigating the effect of combining regional forecasts using machine learning methods. In that study, three methods of SVR, neural networks, and GPR were evaluated on both the aggregate series and individual series, and the ARMA model was used as a benchmark. The results showed that machine learning methods for combined long-term and medium-term forecasts are more accurate than the ARMA method obtained from a disaggregated approach[24].

Recently, Nguyen et al. [25] predicted tourism demand in Vietnam using artificial neural networks. The results showed that if the architecture of the neural networks is well designed, having the demands of 12 months ago, it is possible to predict the demand of the following month with an error between 7.9% and 9.2%.

Some of the new studies have also used machine learning methods to predict tourism demand on social variables affecting tourism demand. For example, Hu et al. [26] predicted the demand for foreign tourism for Hong Kong in 2020 using the recorded opinions of tourists about the tourism attractions in that country. They showed that the use of user comments can improve the accuracy of demand forecasting. Also, in another study, Park et al. predicted tourism demand based on online news. They concluded that the published news has a significant impact on the tourism demand [27]. Also, in another study [28], tourism demand was modeled and predicted based on the information from Google searches.

In recent years, the combination of linear and non-linear methods has been used by researchers, and many combined models have been proposed, which have shown better performance than single methods. Chen et al. achieved good results by combining the EMD (Empirical mode decomposition) and neural networks methods to forecast tourism demand on the data of tourists' arrival in Taiwan. Comparing this method with ARIMA and BPNN showed that the proposed combined method could increase the forecasting accuracy[7].

Regarding the combination of forecasting methods in tourism demand, Wong et al. concluded that the combined forecasting methods are superior to the worst single forecasts and avoid the risk of complete forecast failure [29]. Andrews et al. achieved good results in forecasting Egypt's tourism demand by combining long-term and short-term forecasting and concluded that further research in this field could be significant and promising [3]. In another study [30], it has been emphasized that the combination of forecasts improves forecasting accuracy.

In another study, a hybrid model based on neural networks and ARMA methods was presented to forecast the monthly demand of tourist arrivals to China and it is showed that forecasting by one method is not optimal, and the accuracy of the combined method is superior to using the single methods alone[31].

Hu et al. [32] proposed a non-additive combined method using fuzzy integral to integrate the forecasts obtained from single forecasting models. They evaluated the proposed method using the tourism demand of China and Taiwan. The result showed that the proposed method works better than the other methods considered in that study.

3. The Proposed Method

In this section, the proposed method for forecasting tourism demand is introduced. As mentioned before, the proposed method, which is presented to increase the accuracy of tourism demand forecasting, is a hybrid method that includes the following steps:

- Short-term and long-term forecasting by extracting the non-linear patterns of data
- Converting long-term forecast to short-term forecast using a linear method
- Combining the obtained short-term forecasts by assigning weight to them

An overview of the proposed method is shown in Figure 1.

In the rest of this section, the BPNN is introduced. Then, how to make long-term and short-term forecasts are described, and finally, how to combine forecasts is explained.

3.1. Using BPNN for tourism demand prediction

BPNN is one of the widely used neural network architectures [24], [33]. This network is a type of multi-layer neural networks that works based on gradient descent [7], [31]. In the proposed method, neural network is used to predict the time series of tourism demand. For this purpose, the following steps are performed:

1. Selection of input variables and definition of output variables: Input variables are the amount of tourism demand at several consecutive time points, and the output variable shows the amount of predicted demand for their following time point. The number of output variables is called the forecast horizon. Here, we have considered the forecast horizon equal to 1. A sliding window of size 6 is considered, and the data of the last 6 months is considered as input and the data of the 7th month as output. By moving this sliding window on the time series, the input data required for forecasting is prepared (see Figure 2). In this study, the optimal window size, i.e., the number of previous tourism demand considered as input, is 6. In the case of the long-term forecast dataset, we have a similar procedure, except that the input data is related to seasonal tourism demand.

2. Determining the number of layers and the number of neurons of the hidden layers: The value of these parameters are obtained by trial and error. The common number of layers is 3. However, the value of this parameter depends on the number of hidden layer neurons and the number of input neurons. In this study, the best architecture obtained by trial and error was 6-10-1 (i.e., 6 neurons in the input layer, 10 neurons in the hidden layer, and one in the output layer).

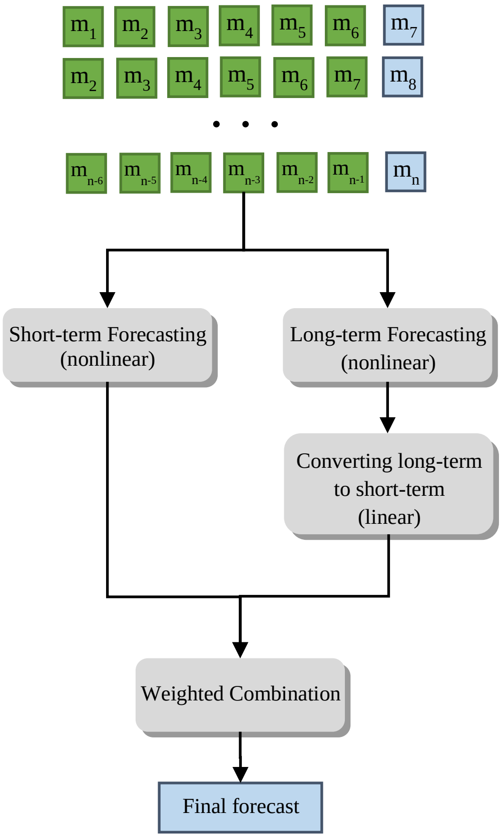

Figure. 1. Overview of the proposed method

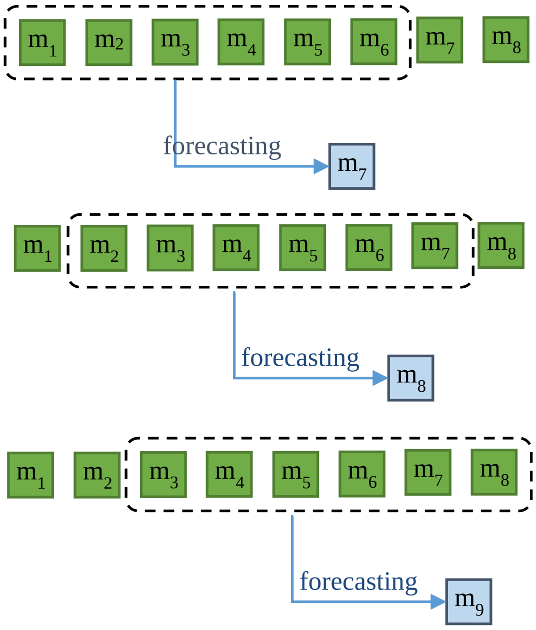

Figure. 2. Preparation of time series data using a sliding window

3. Training: This step starts with initial random weights. After applying training data samples to the network, the weights are updated based on the delta rule[24]. Finally, the training process stops after exceeding a maximum number of iterations or reaching an acceptable error.

4. Testing: After the training the neural network, the network is evaluated on a subsection of historical data that has not been used during training step. To assess the effectiveness of the neural network model, the proposed method was also implemented and evaluated using the random forest algorithm, instead of using BPNN.

3.2. Obtaining short-term forecast and long-term forecast

The seasonal and monthly time series were prepared using the historical data. Here, short-term forecast corresponds to monthly forecast, and long-term forecast corresponds to seasonal forecast. To obtain the seasonal forecast, we give the seasonal time series data as input to the neural network, and the output of the neural network is the predicted demand for each season. For monthly forecasting, monthly time series data is given as input to the neural network, and the output of the neural network is the predicted demand for each month.

The prediction of the neural network is based on the pattern that exists in the historical data. Due to the change of various events such as climatic conditions, infrastructure conditions (e.g., traffic and roads conditions), events and holidays, economic conditions, and social changes, the pattern in the data and their trends may change during different months. Therefore, this reason and considering the advantages of combining long-term and short-term forecasts, in this study, we have combined monthly and seasonal forecasts.

Since the purpose here is the monthly forecast, to combine the seasonal forecast with the monthly forecast, it is first necessary to convert each seasonal forecast into monthly values. For this purpose, we use a linear method. First, based on the training data, the distribution of visitors of each season in the months of that season is estimated. Then, the demand forecasted for each season is divided into three parts according to the relevant distribution. Each part is related to one month of that season. In this way, the seasonal forecast obtained from the neural network is converted into a series of monthly forecasts.

Therefore, we have forecasted two monthly demands, the first one is obtained directly from the monthly forecasting with the neural network, and the second one from the conversion of the seasonal forecast to monthly forecast. In other words, the first is calculated using the non-linear neural network method, and the second is obtained from combining the neural network method with a linear method. In the next step, these two values are combined. So, in addition to combining forecasts of different time frames, we have also used the advantages of combining linear and non-linear methods.

3.3. Combining short-term and long-term forecasts

Often, forecasts are combined by applying weights. There are several ways to define weights. A simple way is to give equal weights to both forecasts. In this study, the rank-based weighting method[3] is used, in which the weights are obtained according to Equ (1):

$$w_1 = \frac{R_1}{R_1 + R_2}, w_2 = \frac{R_2}{R_1 + R_2} \qquad (1)$$

where the values R1 and R2 indicate the efficiency of each forecasting method.

Assume that f_i is the output of the neural network for month i and f_i' is the value obtained for that month from the long-term forecast. By comparing these values with the actual demand of month i, each of these two forecasts is given a rating, the optimal value of which is obtained by trial and error. Then, these values are used in Equ.(1) to obtains the weight of each forecast. Finally, by applying these weights in Equ.(2), the forecasts are combined and F_i, the combined monthly demand for month i, can be obtained.

$$F_i = w_1 f_i + w_2 f_i' \qquad (2)$$

4. Evaluation of the Proposed Method

In this section, the proposed method is applied to the dataset of Alisadr Cave. As mentioned, Alisadr Cave as one of the important tourist destinations of Iran and the world, has about 650 thousand visitors annually. Accurate forecasting of the number of visitors can be very effective in better management of this complex. In this section, the dataset and the error measure are introduced first, and then the evaluation results are presented.

4.1. Dataset

In this paper, the dataset of the tourist arrivals to Alisadr Cave tourism complex have been used in the form of monthly and seasonal time series. As mentioned, this tourism destination has a significant number of visitors every year, and on certain days of the year, it faces an unpredictable number of visitors. In addition, since this cave is an important and famous tourist destination, almost all the tourists who enter Hamadan province, also visit this region. Therefore, The visitors of Ali Sadr Cave can be considered as the total number of visitors of Hamadan province with a slight difference.

The dataset is in the form of monthly statistics from April 2007 to March 2014. In the monthly forecast, the data of the monthly time series of six years from April 2007 to March 2013 is given as input to the neural network, and the output value of the neural network is the predicted demand for the months between April 2013 to March 2014. In the seasonal forecast, the seasonal time series data of these six years are given as input to the neural network, and the output of the neural network is the predicted demands for the four seasons between April 2013 to March 2014. In both predictions, 25% of the data are randomly selected as test data. Descriptive statistics of monthly data are given in Table 1.

4.2. Evaluation Metrics

Given that the monthly demands have a broad range (from 500 to 247,000), for calculating the average error, the relative error metrics are better than the ones that calculate the absolute difference between the predicted value and actual value.

Therefore, in this paper, the mean absolute value of percentage error (MAPE), given in Equ.(3), is used.

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{E_t}{D_t}\right|\times 100}{n}, \qquad (3)$$
$$E_t = F_t - D_t$$

Where, D_t is the actual value of demand at time t, and E_t is difference between the predicted value denoted by F_t and the actual values of the demand at time t.

4.3. Experimental Results

Table 2 reveals the results of three prediction methods. The "difference" column represents the difference between the output and the actual value, and the "error" column stands for the error percentage calculated from Equ.(4).

$$ErrorPercentage = \left|\frac{E_t}{D_t}\right|\times 100 \qquad (4)$$

The results represented in Table 2 confirm the benefits of combining the short-term and long-term methods and the impact of varying the time frame of the data. For example, the error of February, which was very high in the short-term forecast and equal to 78%, was reduced by 62% with the combination of long-term forecast, which is a very good improvement. Another example is related to the demand of January, whose long-term forecast error is 79% and has decreased by 43% after being combined with short-term forecast.

Table 3 compares the efficiency of these three methods. Also, in this table, the neural network method is compared with the random forest method in monthly, seasonal, and combined forecasts. As can be seen, in the first method, i.e., forecasting with short-term time series, the minimum error is 0.01% (obtained for March) and the maximum error is 78% (obtained for February). Also, the average error is 27.58%. The average error of the second method is 33.83%. The minimum error in this method is 4% (obtain for November), and the maximum error is 79% (obtained for January).

Therefore, it can be concluded that the percentage of error has been reduced by the proposed method in most of cases compared to the other two methods. The maximum error is 63% (obtained for December), but the minimum error (obtained for March), has slightly increased compared to the short-term forecast. In addition, the average error has been reduced to 24.37%.

From Table 3, it can also be concluded that, as mentioned in the literature review, the neural network method is more effective than other methods, such as the random forest, in forecasting tourism demand. The average prediction error in the monthly, seasonal, and combined forecasting using the neural network is lower than the random forest error. On the other hand, the results mentioned in Table 3 confirm the superiority of the combined method over both seasonal and monthly forecasting methods using the random forest model.

Table 1. Descriptive Statistics of The Dataset

Parameter	*Value*
Number of samples	84
Average	56916
Standard deviation	68330
Minimum	517
Maximum	368723

Table 2. The Results of Three Forecasting Methods

	Monthly forecast		*Seasonal forecast*		*Combined prediction*	
	difference	*error*	*difference*	*error*	*difference*	*error*
April	54398	41%	51502	39%	51906	39%
May	6723	32%	4542	39%	4416	21%
June	14432	21%	15365	22%	15493	22%
July	16612	19%	12818	15%	12324	14%
August	25622	23%	20172	18%	19441	17%
September	87287	43%	77939	38%	78599	38%
October	7283	23%	6843	22%	6964	22%
November	205	2%	343	4%	383	4%
December	440	15%	1255	64%	1239	63%
January	791	34%	662	79%	845	36%
February	1520	78%	780	47%	482	16%
March	1	0.01%	1132	19%	41	0.5%

Table 3. Comparing the Results of Three Forecasting Methods

Model	*Error Measure*	*Monthly Forecast*	*Seasonal Forecast*	*Combined Prediction*
Neural Networks Model	*Minimum error*	0.01%	4%	0.5%
	Maximum error	78%	79%	63%
	Average error	27.58%	33.83%	24.37%
Random Forest Model	*Minimum error*	3.5%	7.4%	2.4%
	Maximum error	248%	3.408%	148.4%
	Average error	33.95%	28.48	31.47%

5. Conclusion

In this paper, a combined tourism forecasting method based on neural networks was presented. In the proposed method, the focus is on combining forecasts with different time frames. For this purpose, the seasonal and monthly time series were used as input data. In the long-term forecasting stage, the input time series were converted to monthly values using a linear method. Both long-term and short-term forecasts are made using neural networks and combined with rank-based weighting method. This method was evaluated on the dataset of the visitors of Alisadr Cave. We used the MAPE measure to calculate the error. The results showed that the accuracy of the proposed method compared to both of the long-term forecasting method and short-term forecasting method has improved in most cases. In addition, the average accuracy has increased. Also, by comparing the neural network and the random forest algorithm, it was found that the neural network had a better performance in predicting tourism demand than the random forest method. However, the combination of the random forest forecast is more accurate than monthly and seasonal forecasts.

As mentioned, in our proposed method, monthly and seasonal forecasts were combined. As a future guideline, other time frames such as daily, annual, biennial, etc. can also be combined and their effect on forecasting accuracy can be studied. Also, instead of the rank-based weighting method, other weighting methods can be used to combine the forecasts and improve the forecasting accuracy. In addition, in the future, the proposed method can be evaluated on the datasets of other tourism destinations.

Declarations

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Authors' contributions

EMH: Study design, acquisition of data, interpretation of the results, statistical analysis, drafting the manuscript;
MK: Supervision, study design, interpretation of the results, revision of the manuscript;
ZZ: revision of the manuscript, data analysis, visualization, interpretation of the results.

Conflict of interest

The authors declare that there is no conflict of interest.

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