Using Discrete Hidden Markov Model for Modelling and Forecasting the Tourism Demand in Isfahan

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Abstract

Tourism has been increasingly gaining acceptance as a driving force to enhance the economic growth because it brings the per capita income, employment and foreign currency earnings. Since tourism affects other industries, in many countries, tourism is considered in the economic outlook. The perishable nature of most sections dependent on the tourism has turned the prediction of tourism demand an important issue for future success. The present study, for the first time, uses the Discrete Hidden Markov Model (DHMM) to predict the tourism demand. DHMM is the discrete form of the well-known HMM approach with the capability of parametric modeling the random processes. MATLAB Software is applied to simulate and implement the proposed method. The statistic reports of Iranian and foreign tourists visiting Isfahan gained by Iran Cultural Heritage, Handicrafts, and Tourism Organization (ICHHTO)-Isfahan Tourism used for simulation of the model. To evaluate the proposed method, the prediction results are compared to the results from Artificial Neural Network, Grey model and Persistence method on the same data. Three errors indexes, MAPE (%), RMSE, and MAE, are also applied to have a better comparison between them. The results reveal that compared to three other methods, DHMM performs better in predicting tourism demand for the next year, both for Iranian and foreign tourists.

Keywords: Modeling; Tourism Demand Function; Demand Prediction; Discrete Hidden Markov Model; Iran; Isfahan.

1. Introduction

For many years and in different parts of the world, tourism has been a driving force for boosting the economic growth through increasing the per capita income, employment rate and foreign currency earnings. Fulfilling these objectives, however, requires appropriate investment in both public and private sectors [1]. Since the tourism affects other industries, in many countries, whether developed or developing, tourism has gained great acceptance in the economic outlook and has increased the development of many other sectors such as agriculture, handicraft, beverages, transportation, etc. [2]. The perishable nature of most related sectors to the tourism has turned the prediction to a very important issue for future success. The long-term and short-term predictions, however, are important for different management objectives; for example, the long-term predictions of tourism demand for next following years help the tourism infrastructure planning in the destination, while short-term demand predictions help the destination flexibility for the next two or three months [3]. Precise estimation of tourism demand helps the tourism managers and industry decision makers in the destination to have a better strategic planning. Hence, in recent years, the prediction of tourism demand has been considered by a number of researchers so that the prediction methods are increasingly being introduced [4]. The superior prediction models are identified based on the features and data used in different studies and help the experts to choose the better prediction methods; finally, it would result in commercial decision makings and effective policies [5].

Regarding the tourist attractions, Iran is among the top ten countries and can gain advantages by the tourism. This is particularly important for the countries that their economies are highly dependent on single-product export (oil) because the sustainable tourism has the unique potential of direct injection of money to the economic cycle. On the other hand, employment on the base of tourism doesn’t need the high level of skill and training and it can encompass all level of the society. All the mentioned points express the importance of sustainable tourism growth particularly through economy perspective, attention to the infrastructures and planning in this domain; however, the success key in the planning is the prediction of tourism demand and attempt for increasing this demand.

2. Literature Review

Tourism demand forecasting has been an interesting subject for many research studies on the tourism and hosting. Song and Li (2008) examined the proposed methods for tourism demand prediction in recent decades and they found out that prediction techniques usually consist of time series, econometric models, artificial

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intelligence approaches, and hybrid methods [6]. The time series models predict the tourist arrivals according to the historical patterns. Most of the research studies have used the time series models to predict and analyze the tourism demand [3],[7]-[9]. The most popular model among them is the Autoregressive Moving Average Model [6]. The econometric models examine the cause-effect relationship between incoming tourists and the effective factors [10] and this model is particularly useful when there is a correlational relationship between the factors. The artificial intelligent methods use the neural networks and vector machines for the nonlinear data modeling [11],[12]. Some research studies have proposed the hybrid methods by combining data mining and econometric models [4],[13]. The researchers have also used the meta-analysis and singular spectrum analysis in modeling and prediction of tourists visiting a place [5],[14]. Regarding the prediction exactness, different models have some advantages and disadvantages. No single model can be steadily superior to other models in all situations [6]. The artificial intelligence techniques can only model limited observations. For example, Wang (2004) used fuzzy time series models to estimate the tourism demand using 12 data points [15]. The econometric models need a large number of observations to have higher precision in prediction; in comparison, the artificial intelligence models have no theoretical bases for modeling the tourism demand and the researchers are not able to show the partial effects of each explanatory variable on another explanatory variable [6]. In contrast, the econometric models have an appropriate theoretical basis and can confirm the relations between the explanatory variables through the economic perspective. Other quantitative methods such as gravity models, artificial neural networks (ANNs) and single-variable time series models have also an important role in the tourism demand prediction.

In recent years, researchers have paid attention to artificial intelligence (AI) and hybrid methods in addition to studying on improving accuracy. Li, Song, and Shen (2011) evaluated six hybrid methods for prediction of British outbound tourism demand in seven destination countries [16]. Their numerical results show that generally speaking, the hybrid methods yield better results than single techniques. Chen (2011) combined the linear and non-linear statistical models to predict the foreign tourists in Taiwan [17]. The empirical results showed that the hybrid Support Vector Regression (SVR) models can detect the directional change. Peng et al. (2014) reviewed 65 published studies from 1980 to 2011; they examined the accuracy of different prediction models, data features, and the conditions of each study by meta-regression analysis [5]. They showed that the origin and destination of the tourists, time period, modeling method, data alternation, number of variables, variables measurement, and the data volume considerably affect the prediction accuracy. Cheng and Liu (2014) compared gray forecasting model and cubic polynomial for Guilin tourism demand data [18]. They proposed a hybrid prediction model to improve prediction accuracy. Wang, Zhang, and Guo (2015) used the synthetic index method to calculate the tourism market growth index in order to achieve the annual tourism forecast [19]. The sample data were trained using the machine learning algorithm. Ultimately, they obtained a model based on Extreme Learning Machine (ELM) for forecasting tourism demand in Liaoning province and compared the results with the SVR algorithm. Liang (2016) combined the autocorrelation function (ACF), neural networks, and genetic algorithms to forecast tourism demand [20]. They compared the hybrid model with neural networks and the Seasonal Autoregressive Integrated Moving Average (SARIMA) models in forecasting Taiwan’s tourism demand from 2001 to 2009. Sadati, Bateni, and Bateni (2016) examined the effectiveness of ANNs as an alternative approach to the use of SVR in the tourism research [21]. They evaluated the method by prediction the tourism demand in Iran. Sun et al. (2016) used a new prediction model called Cuckoo-Markov Chain-Segment Grey model (1,1) to evaluate the prediction accuracy undergoing tourism market fluctuations [13]. They showed that this method is considerably more efficient and precise than the usual Markov Chain-Grey models (1,1). Rossello and Sanso (2017) found out that the entropy and relative abundance are quite appropriate as the seasonal indexes and can be applied as a new information tool for the seasonal analysis of tourism [22]. Kazak (2018) used the statistical and econometric modeling of tourist expenses to evaluate and forecast tourism development [23]. He showed that the dynamics of demand for tourism can be affected by a wide range of factors, such as political factors and economic relations.

Although many studies in forecasting tourism demand are based on the combination of the previous methods, some researchers use the new methods in this area. Li and Cao (2018) used Short-Term Memory Neural Networks (LSTM) to predict the flow of tourism [24]. They showed that this method performs better than the ARIMA model and the Back Propagation Neural Network (BPNN) on the data obtained from the Xi'an Museum. Yao et al. (2018) presented a new model of the neural networks [25]. In their proposed model, tourist arrival data were decomposed by two low-pass filters into a long-term trend and short-term seasonal components and then modeled by a pair of autoregressive neural networks as a parallel structure. This method was evaluated by the data of tourist arrival to United States from twelve markets. Sun et al. (2019) proposed a prediction framework that used machine learning and internet search indexes to predict the arrival of tourists to popular destinations in China [26]. They compared the proposed model performance with Google and Baidu's search results. The study confirmed the Granger causality and co-integration relationship between the Internet search index and the arrival of tourists to Beijing.

In the present study, in order to forecasting the tourism demand, the Discrete Hidden Markov Model (DHMM) is used for the first time.

3. Theoretical Framework

The present study used the discrete type of Hidden Markov model (HMM) to predict the tourism demand. HMM is a statistical modeling tool for time series that has been applied successfully in the speech recognition, error detection, and computational processing. HMM performs statistical analysis and parametric modeling on unstable signals. That is why it can simply be used for probability-based reasoning. This property of HMM has been used to predict tourism demand in the present study.

3.1 Introduction on the Discrete Hidden Markov Model (DHMM)

Based on the observed values, two types of HMMs have been introduced: Continuous Hidden Markov Model (CHMM) in which the observed values are continuous; and Discrete Hidden Markov Model (DHMM) in which the sequence of the observed values are in a defined range of codes or symbols. HMM has two parts: Markov chain and random process. The Markov chain with a sequence of states as the output is described by a vector π and matrix A, and the random process with observed values as the output is described by matrix B [27]. Fig. 1 shows the HMM structure in which T is the length of time sequence.

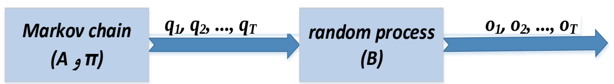

Fig. 1. The HMM Structure [21]

A DHMM is described with the following parameters [28]:

- N: Number of Markov chain states; if $\theta_1, \theta_2, \ldots, \theta_N$ are possible states of the Markov chain and q_t is the state at time t, then $q_t \epsilon (\theta_1, \theta_2, \ldots, \theta_N)$.
- M: Number of observed values in each state; if $v_1, v_2, \ldots, v_M$ are the observed values and o_t is the value at time t, then $o_t \epsilon (v_1, v_2, \ldots, v_M)$.
- Π: Initial probability distribution vector, in which:

$$\pi_i = P(q_i = \theta_i), \qquad 1 \le i \le N \qquad (1)$$

- A: State transition probability matrix, $A = (a_{ij})_{N\times N}$, in which:

$$a_{ij} = P\left(q_{t+1} = \theta_j / \, q_t = \theta_i\right), \quad 1 \le i \le N \qquad (2)$$

- B: Observation probability matrix, $B = (b_{jk})_{N\times M}$, in which:

$$b_{jk} = P(o_t = v_k / q_t = \theta_j), \qquad (3)$$
$$1 \le j \le N, \qquad 1 \le k \le M$$

In short, a DHMM can be expressed in form $\lambda = (N, M, \pi, A, B)$.

3.2 The HMM-based Prediction Procedure

The overall HMM-based prediction procedure consists of two steps:

I. Training Process:

In the training phase, the parameters of $\lambda = (\pi, A, B)$ are trained according to the model. The parameters keep updating until the best adaptation with the model is obtained. This process needs the Baum-Welch algorithm that uses the well-known Expectation-Maximization (EM) algorithm to improve the likelihood $P(O/\lambda)$ or log-likelihood $ln\, P(O/\lambda)$ [23]. To apply this algorithm, an initial guess of matrices A and B is required.

II. Decoding Process:

In this stage, the probability (or probability logarithm) of the observation of a sequence is calculated by trained HMM. To do so, the forward-backward algorithm is used [24]. The sequence with the highest probability of observation is the base of the prediction.

Next section introduces more explanations on the way DHMM is used to predict the tourism demand.

4. Using DHMM for Predicting the Tourism Demand in the Next Year in Isfahan

Fig. 2 and Fig. 3 graphically illustrate the monthly and yearly statistics of Iranian and foreign tourists checked-in to the hotels in Isfahan since 2002 to 2016. These figures were gained by Iran Cultural Heritage, Handicrafts, and Tourism Organization (ICHHTO)-Isfahan Tourism. As Fig. 2 and Fig. 3 show, the number of Iranian tourists in April, September, and August is more and the number of foreign tourists is more in May, October, and August. Generally speaking, it can be inferred that some times of the year (month) are considered as the popular time of visiting. More or less, all the tourist destinations and business centers are facing the seasonal nature of the tourism and this can be a reason explaining why the population of tourists and visitors in a destination is so variable in different seasons. That is why the tourist destinations sometimes are too crowded and populated to meet the needs of the tourists and in some other times, some businesses are facing considerable recession.

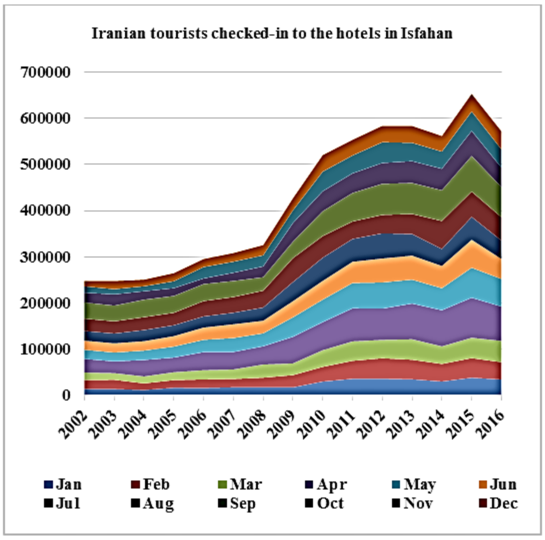

Fig. 2. The number of Iranian tourists checked-in to the hotels in Isfahan since 2002 to 2016

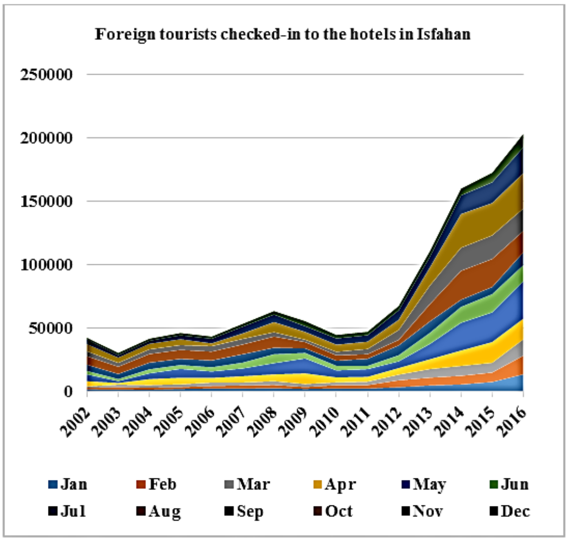

Fig. 3. The number of foreign tourists checked-in to the hotels in Isfahan since 2002 to 2016

Since prediction in tourism is one of the measuring methods for tourism demand, preparing the infrastructures and amenities both in long term and short term, and taking into the seasonal nature of tourism, the monthly periods must be compared during consecutive years rather than a general comparison of the yearly demand. To do so, in the proposed method, the tourism statistic in a month (for example April) in the previous years was used to predict the tourism demand of the same month.

To predict the monthly tourism demand in 2016, the monthly statistics of 2002 to 2015 was used to train the DHMM. The year 2016 was chosen because it has a relatively unpredictable statistic particularly regarding Iranian tourists and its real statistic is also available and comparable. To simulate the proposed method, the MATLAB software was used.

Considering the objective- the monthly prediction of 2016-, first the monthly statistic growth of each year (2003 to 2015) relative to the previous year is measured; then the gained values are normalized, coded and used for training the DHMM (for each value a code is taken). Since the tourism demand for each month is predicted according to the same month in the previous year, 12 DHMM models are required to predict 12 months in each mode of Iranian and foreign tourists (24 models in total).

The required parameters for DHMM training are determined as the following:

- The number of Markov chain states (hidden states) is N = 3.
- The number of possible observed values in each state (M) depends on the number of codes. This value is M=702 and M=1865 for Iranian and foreign tourists, respectively.
- The initial guess of the matrix A for use in the Baum-Welch algorithm is chosen randomly for 24 models.
- For the initial guess of matrix B in the Baum-Welch algorithm, a matrix with identical elements is considered, which, given the size of the matrix (N*M), would be different for Iranian and foreign tourists.

For DHMM training the sequences of length 10, indicating the value changes in 10 consecutive years, are considered.

After training the DHMM by the mentioned data, the final matrices A and B are obtained for each model.

In the decoding step, the probability of occurrence for each observable value is measurable. In this stage, the occurrence probability of different 10-element sequences are examined and the corresponding values are predicted according to the codes with the highest probability. For example, to predict the demand for Iranian tourists in April 2016, firstly the corresponding code must be predicted. To do so, the codes of April in the last 9 years are used. Considering the training of each 24 models of the DHMM by 10-element sequences (related to 10 consecutive years), the highest probability among the existing codes would be obtained for the 10th year. This code helps to calculate the tourism demand for the year 2016.

Table 1. Predicted values of the Iranian tourists in 2016 by DHMM in comparison with the actual values, Persistence, Grey, and ANN methods

	Real	*Persistence*	*Grey(1,1)*	*ANN*	*DHMM*
Jan	34657	38506	44558	53056	38256
Feb	37519	42451	51862	43951	43151
Mar	45911	43839	53210	59389	45689
Apr	74439	86777	99555	80827	82927
May	59603	64887	71465	61737	64687
Jun	43414	60341	66601	68841	57691
Jul	39687	49566	57334	44066	51716
Aug	50490	54836	59376	55386	50886
Sep	65178	77074	82758	78224	71324
Oct	42130	54242	63100	47542	53342
Nov	39558	42052	52978	41802	41652
Dec	39117	38096	44545	31446	38696
Total	571703	652667	747341	666267	640017
MAPE(%)		15.24	30.72	19.22	12.17
RMSE		8766	15851	11402	7413
MAE		7263	14637	9159	5800

Table 2. Predicted values of the foreign tourists in 2016 by DHMM in comparison with the actual values, Persistence, Grey, and ANN methods

	Real	*Persistence*	*Grey(1,1)*	*ANN*	*DHMM*
Jan	13781	7749	7085	9659	8429
Feb	14684	7421	8088	6491	10171
Mar	12957	7668	8169	9458	8768
Apr	16118	16294	13540	15854	16244
May	29696	23384	21154	21854	26094
Jun	12489	14337	12622	15397	13777
Jul	10144	5666	6952	11416	7776
Aug	16731	22025	17402	14255	21635
Sep	17763	18564	7084	19614	17554
Oct	27807	25490	9944	39480	27840
Nov	20419	16376	15553	12326	17626
Dec	10381	7535	6974	8645	8335
Total	202970	172509	134568	184449	184249
MAPE(%)		23.01	34.49	26.57	15.48
RMSE		4462	7472	5645	3200
MAE		3892	5834	4494	2619

Using this method, the demand for Iranian and foreign tourism in Isfahan for 12 months in 2016 was predicted. Table 1 and Table 2 indicate the predicted values in this year whereas 12 DHMM models were used to obtain each of them. For comparison, the prediction results were obtained from the Artificial Neural Network (ANN), Grey Model (1,1) and Persistence method in addition to DHMM. ANN is a well-known artificial intelligence method, which is used in many prediction models, Grey model is a popular model for researchers due to its ability to track the fluctuation of observations [29], and finally Persistence Method is also a benchmark model in which the previous latest observed value is considered as the prediction of the next value [30].

To determine the exactness of the proposed method, the Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) were used, which are obtained by the following relationships:

$$MAPE = \frac{100}{N}\sum_{t=1}^{N}\frac{\left|x_p(t)-x_r(t)\right|}{\overline{x_r}} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(x_p(t)-x_r(t)\right)^2} \tag{5}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|x_p(t)-x_r(t)\right| \tag{6}$$

$$\bar{x} = \frac{1}{N}\sum_{t=1}^{N}x_r(t) \tag{7}$$

where $x_r(t)$ and $x_p(t)$ are the actual and predicted values, respectively.

As it is shown in Table 1 the MAPE index gained by DHMM is 12.17 percent, while this index for ANN, Grey and Persistence methods is 19.22, 30.72 and 15.24 percent, respectively. Also, according to Table 2, this index for DHMM, ANN, Grey, and Persistence methods are 15.48, 26.57, 34.49, and 23.01 percent, respectively indicating less error in the proposed method. On the other hand, comparing the RMSE and MAE indexes in Table 1 and Table 2 suggests that DHMM is superior to the three other methods. Given the fact that in 2016 Iranian tourism had a negative growth rate in comparison to 2015 (Fig. 2), the lower error in DHMM prediction suggests the higher ability of this method. It should be mentioned that the more trained data in DHMM, the higher ability in prediction would be achieved.

Fig. 4 and Fig. 5 show the curves of predicted Iranian and foreign tourism demand in Isfahan for 12 months in 2016 by using DHMM as well as the actual values and predicted

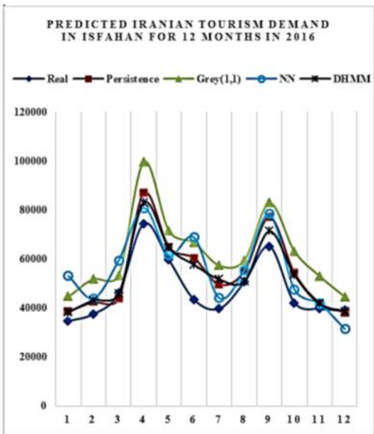

Fig. 4. Comparison between prediction by DHMM and three other methods in Iranian tourism demand

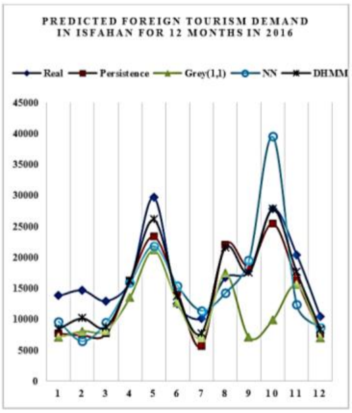

Fig. 5. Comparison between prediction by DHMM and three other methods in foreign tourism demand

values by three other methods. Furthermore, Fig. 6 and Fig. 7 illustrate the absolute errors of four prediction methods. The total absolute errors for Iranian tourism prediction by Persistence, Grey, ANN, and DHMM are 87150, 175638, 109906, and 69600, respectively; moreover, these errors for foreign tourism prediction are 46699, 70011, 53929, and 31423, respectively. These values show that for both Iranian and foreign tourists the total forecast absolute errors of the suggested method are less than three other methods.

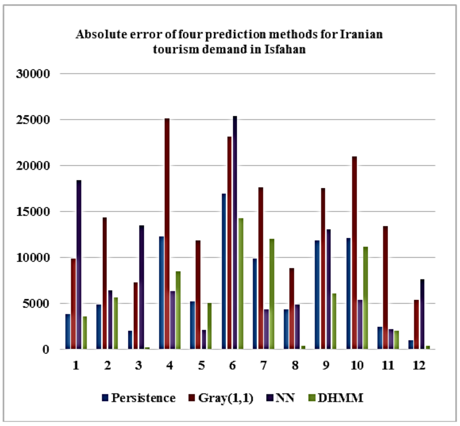

Fig. 6. Comparison between absolute errors of four prediction methods in Iranian tourism demand

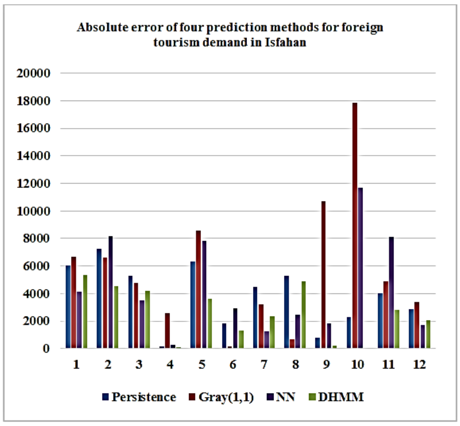

Fig. 7. Comparison between absolute errors of four prediction methods in foreign tourism demand

5. Conclusion

In this research, the Discrete Hidden Markov Model (DHMM) was used to predict the tourism demand in Isfahan. This is the first time that one of the hidden Markov models is being used to predict the demand for tourism. The DHMM was simulated in MATLAB software and it was implemented on the statistic of Iranian and foreign tourists visiting Isfahan. To determine the efficiency of the proposed method, its results were compared with the results of the NN model, grey model, and persistence method. The error rate of these methods was obtained by using three error indexes. The results also showed that DHMM performs more satisfactory than the other mentioned methods; besides, less error in the proposed method suggests a more realistic prediction in tourism demand. Since the state and non-profit organizations are involved in the tourism industry, the tourism demand is simply influenced by social, political, economy, cultural events. Thus, a method with less error in sudden changes is more reliable regarding the prediction. The managers and decision-makers in the tourism industry can enjoy this method to plan the short-term facilities and improve infrastructures in the long-term. The researchers also can use the DHMM as a basic method in producing the hybrid methods for predicting the tourism demand.

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