CHIRAG YADAV

COMPUTATIONAL INTELLIGENCE AND NEURAL NETWORKING APPROACHES FOR TOURISM

THE INFO LIBRARY

Computational Intelligence and Neural Networking Approaches for Tourism

Computational Intelligence and Neural Networking Approaches for Tourism

Chirag Yadav

THE INFO LIBRARY

Published by The InfoLibrary,
4/21B, First Floor, E-Block,
Model Town-II,
New Delhi-110009, India

Computational Intelligence and Neural Networking Approaches for Tourism
Chirag Yadav
ISBN: 978-93-5590-169-9

Table of Contents

1

Using Deep Learning to Predict Sentiments: Case Study in Tourism

C. A. Martín, J. M. Torres, R. M. Aguilar, and S. Diaz

Department of Computer and Systems Engineering, Universidad de La Laguna, 38200 La Laguna, Tenerife, Spain

Correspondence should be addressed to R. M. Aguilar; raguilar@ull.edu.es

Guest Editor: Ireneusz Czarnowski

Technology and the Internet have changed how travel is booked, the relationship between travelers and the tourism industry, and how tourists share their travel experiences. As a result of this multiplicity of options, mass tourism markets have been dispersing. But the global demand has not fallen; quite the contrary, it has increased. Another important factor, the digital transformation, is taking hold to reach new client profiles, especially the so-called third generation of tourism consumers, digital natives who only understand the world through their online presence and who make the most of every one of its advantages. In this context, the digital platforms where users publish their impressions of tourism experiences are starting to carry more weight than the corporate content created by companies and brands. In this paper, we propose using different deep-learning techniques and architectures to solve the problem of classifying the comments that tourists publish online and that new tourists use to decide how best to plan their trip. Specifically, in this paper, we propose a classifier to determine the sentiments reflected on the http://booking.com and http://tripadvisor.com platforms for the service received in hotels. We develop and compare various classifiers based on convolutional neural networks (CNN) and long short-term memory networks (LSTM). These classifiers were trained and validated with data from hotels located on the island of Tenerife. An analysis of our findings shows that the most accurate and robust estimators are those based on LSTM recurrent neural networks.

1. Introduction

That the world of tourism is changing is not news. There are more and more data, both structured and nonstructured, being generated at ever higher rates, which once transformed into information, which provide a tangible value to businesses. Opinion mining and sentiment analysis is a very active field of study in recent years [1, 2]. The problem is determining how to benefit from these data and how to use them to generate value. Although future data is out of reach, it is possible to predict what will happen based on past data through a process known as predictive analytics.

The use of automatic tools in social networks for the tourism sector has generated ample literature due to the importance of influencing the consumer's participation and affecting the way in which tourists perceive their experience [3]. Thus, for a tourism company to grow, it is essential that it crafts forecasts to optimize its marketing campaigns and the performance of its corporate website in order to improve the feedback from its users. The predictive scores obtained from the models for each client indicate the steps that should be taken to achieve the goals of retaining the client, upselling a product, or offering him a new service. Reliable and consistent information is needed in order to forecast client behavior. The work presented in this paper builds on this idea, testing methods to analyze the reviews clients provide on digital platforms concerning the service they received.

In contrast to the traditional conversations that take place in specific physical locations, the digital conversation is shaped using new methods and tools for engaging the public, whose social interaction characteristic is the focus of its dynamic [4, 5]. Basically, it is the so-called electronic word of mouth (eWOM), the features of which lead to completely different consequences [6] from traditional conversations. These features focus on the ease with which the message is distributed via social media, which are online communications platforms where users create their own content using Web 2.0 technologies that enable the writing, publication, and exchange of information (Kaplan and Haenlein, 2010). The incorporation of eWOM into social media or the Web 2.0 has the following properties:

(i) Great ability to disseminate, where users can access opinions from strangers

(ii) Massive engagement by users of different ages and groups, all sharing different points of view

(iii) The message spreading quickly in several ways: blogs, websites, social media, messages posted in online groups, etc.

(iv) Multidirectional discussion among users, who play an active role by answering questions on the information presented

(v) Persistence over time, since the discussions are uploaded for the current and future reference

(vi) Credibility, since the information is offered by users spontaneously and, in theory, with no profit motive

These features make monitoring of eWOM by tourism companies particularly relevant [7].

According to [7], an eWOM is "any positive or negative statement made by potential, current, or former customers about a product or company that will be made available to a large number of people and institutions through the Internet." The main goal of this paper is to classify the positive and negative statements made by tourists by using various deep-learning techniques.

The tourism industry is of great importance in the Canary Islands, as it is the real engine of growth and development in the archipelago, accounting for a high percentage of its GDP. This has a knock-on effect on the remaining industries and services in the islands, especially in the development of trade, transportation, food production, and industry. Tourism also comprises a very important component in creating jobs in the service sector of the archipelago, which encompasses direct employment in the sun and beach sector, as well as workers in activities that support tourism, such as restaurants, hotels, travel agencies, passenger transport, car rental, and recreational, cultural, and sports activities.

In 2016, Tenerife, one of the Canary Islands, received over seven million tourists, most of them from the United Kingdom, which accounted for thirty-one percent of the passengers arriving at Tenerife's airports in 2016. These figures indicate that the opinion that English tourists have of Tenerife is particularly relevant. As a result, we will conduct our experiments based on the comments in English made about the hotels in Tenerife.

2. Materials and Methods

Below, we describe the estimators implemented, the data used, and the procedures employed to train, evaluate, and compare the estimators.

2.1. Data Sets. The techniques used, which will be detailed in the sections that follow, fall under the category of supervised learning methods. This requires having a set of previously classified data before the prediction system can be trained and a test sample in order to validate how accurately the technique behaves. To satisfy this requirement and in order to use real data in the methods, we extracted information from reviews in English on the http://booking.com and http://tripadvisor.com websites for hotels on the island of Tenerife. The structure of the information varies depending on the portal that is used as the source of data:

(i) Booking

(a) The comment will have a general score between 0 and 10

(b) The comment's author is able to separate positive and negative aspects

(ii) TripAdvisor

(a) The comment features a rating system using bubbles or stars to assign a score between 1 and 5

(b) There is a single field for expressing an opinion

In order to extract the information, we developed Python scripts based on the Scrapy framework and adapted them to the domain using the scripts offered by the MonkeyLearn project [8].

As a result of this process, we obtained more than 40,000 records with different fields, depending on the source portal for the data: title, comment, score, date, and location of the visitor.

The preparation of the data set so that it can be used in the deep-learning techniques studied in this paper is an important part of the work. In the initial phase and in an effort to standardize the information taken from the two sources used, we developed programs in Python to build a CSV file with two columns:

(i) Comment (free text)

(ii) Label ("Bad" or "Good")

Depending on the portal from which the data were sourced, the scripts had different functionalities.

In the case of the samples taken from TripAdvisor, the original title and comment were used to comprise a single text containing the visitor's full opinion. Those reviews scoring three or higher were labeled "Good," and those scoring two or below were labeled "Bad." Any samples with an intermediate rating were discarded so as not to hamper the training.

In the case of the samples taken from Booking, we evaluated the number score awarded by the visitor. For scores higher than six, which were labeled "Good," the comment was generated by concatenating the title and comment fields. For scores of four and below, the title and negative comment were concatenated and labeled "Bad."

Once the structure of the samples was standardized, the data set was divided into three parts. For the first set, a random balanced selection (half of the samples labeled "Good"

Figure 1: Negative review words.

Figure 2: Positive review words.

and the other half labeled "Bad") of 9640 samples was carried out. The second set was used to evaluate the models after each training epoch, and finally, the test sample was created using 2785 samples in which the scores assigned by the tourists were known and which we used to compare the accuracy of the various models.

The second phase to prepare the data sets for the deep-learning models involved adapting them to the data domain that can be input into the models. Each comment used from the training set was subject to preprocessing before it could be used. Fortunately, Python offers an ecosystem of libraries that can be used in several machine learning applications [9] like the Python NLTK library [10] that allow us to perform this task. The comments were processed as follows: separation into words, deletion of punctuation and any nonalphabetic terms, and lastly deletion of words identified as stop words, which provide no information when determining if a comment is positive or negative.

The figures below offer a visual representation of those words that appeared most frequently in the positive and negative comments:

As we can see by analyzing Figures 1 and 2, there are certain words that clearly identify a polarized sentiment like "Good" or "Bad." However, this does not apply to many other words, which are sometimes even included in comments with the exact opposite meaning (note that the group of words used in negative comments contains words like "better," "nice," or "clean"). As a result, a simple classification of the comment based on the appearance or absence of certain words is not sufficient; rather, machine-learning techniques, such as the ones used in this paper, are needed to analyze the relationships between the words.

The algorithms used require as an input a fixed-length vector in which each component is a number. In the technique for coding text into number vectors known as bag of words (BoW), a dictionary is created with the words found most frequently in all of the training comments. Each comment is then coded into a fixed-length vector corresponding to the number of words in the dictionary created. In BoW, a comment is coded into a vector in which each component counts how many times each word in the dictionary appears in the comment. We ruled out this coding method because even though it represents the frequency of words in the comment, it discards information involving the order in which those words appear in the comment.

The word embedding technique is currently one of the best for representing texts as number vectors. It is a learned representation in which words with similar meanings are given a similar representation. Each vocabulary word is represented with a vector, and its representation is learned based on the use it is given in the training comments. As a result, words that are used in a similar way will have a similar representation. The learning process for embedding is carried out in this paper by adding a layer at the front of the neural network in each of the models. In order to be able to generate our models in Python, we resorted to the Keras library [11].

In order to use this library and add the embedding layer to our models, we have to first transform the tourists' comments into integer vectors in which each word is represented by an index in a list of words. We do so by using the Tokenizer class in Keras, creating an instance based on the training data set and limiting the size of the vocabulary, in our case, to the 5000 most common words. By using the Tokenizer instance, we transform each comment into a vector of variable length in which each word is an integer where the value i corresponds to the i-th most used word in the samples. Since the tourist comments do not all have the same length, the comment vectors are filled in with zeros until the specified fixed length is reached that matches the number of words in the longest comment (582 in this work). Figure 3 shows this process.

The embedding layer is initialized with random weights and trained at the same time as the rest of the models, with the training supplied by the training data set. In every model implemented for this work, the embedding layer was used as the first layer in the model, with the following characteristics:

(i) Input dim (the maximum integer value of the vector component input): its value, based on how we coded the comments, is 5000

(ii) Output dim (the length of the vectors that will represent the words after embedding): in most of the experiments, this length is set to 300

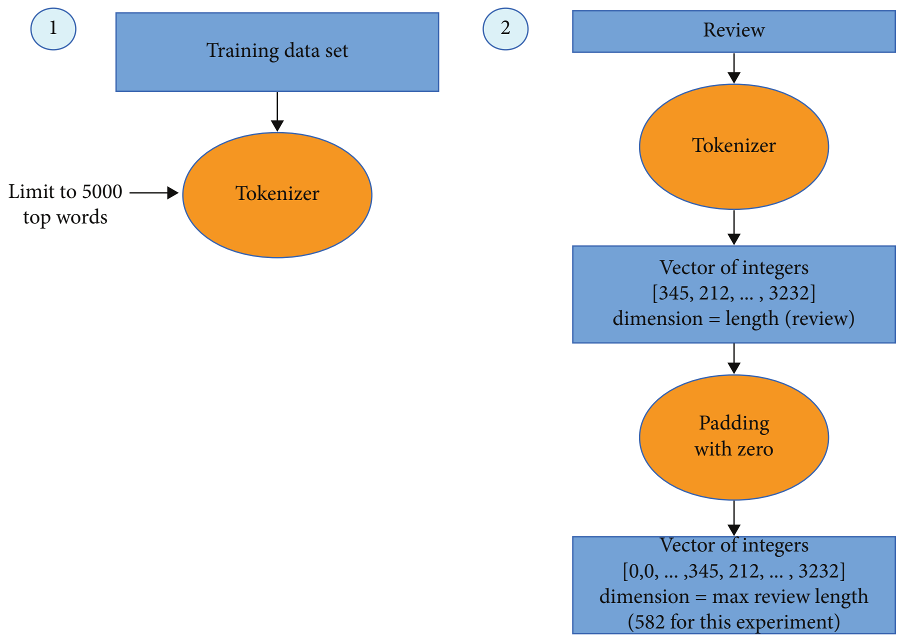


FIGURE 3: Converting review to fixed-length vectors.

(iii) Input length (the length of the vectors in the layer): As defined earlier, it is the maximum length of the comments in words. In the experiments conducted for this work, the maximum comment length was 582 words

As shown in Figure 4, the output of the embedding layer is a 582×300 matrix in which each comment is transformed into a vector with 582 components, in which each component (representing one word) is coded into a vector of length 300.

2.2. Recurrent Neural Networks. To predict the sentiment of the comments, we use models based on neural networks. Each comment is a sequence of encoded words that can be processed as a time series. However, the most common neural networks (e.g., feed-forward neural networks) lack the memory to store information over time. Recurrent neural networks [12] (RNN) solve this problem by making the network output y_j at step j depend on previous computations through a hidden state s_j that acts as a memory for the network.

Figure 5 shows the RNN we used, unfolded into a full network. By unfolded, we simply mean that we write out the network for a complete sequence of N steps, where x_j is the j-th encoded word in the comment, which we used as the input to the network in the j-th step.

In a RNN, the relationship between output y_j, input x_j, and state s_j in step j is determined by the type of RNN cell. As Figure 5 shows, we used a kind of cell called long short-term memory [13] (LSTM). LSTM recurrent neural networks are capable of learning and remembering over long input sequences and tend to work very well for labeling sequences of word problems [14].

As (1) shows, output y_j depends on the state s_j of the LSTM cell through the activation function $\sigma_y(x)$ (which is generally $\tanh(x)$). The state s_j depends on the state of the previous step s_{j-1} and on the candidate for the new value of the state $\tilde{s}_j$. The output gate o_j controls the extent to which the state s_j is used to compute the output y_j by means of the Hadamard product ($\circ$). The input gate i_j controls the extent to which $\tilde{s}_j$ flows into the memory, and the forget gate f_j controls the extent to which s_{j-1} remains in memory.

The o_j, f_j, and i_j gates and the candidate for the new value of the state of the cell $\tilde{s}_j$ can be interpreted as the outputs of conventional artificial neurons whose inputs are the input to cell x_j at step j and the output of cell y_{j-1} at $j-1$. The activation function for the gates σ_g is usually the sigmoid function, while for σ_s it is usually $\tanh(x)$.

$$\begin{aligned}
f_j &= \sigma_g\left(W_f x_j + U_f y_{j-1} + b_f\right),\\
i_j &= \sigma_g\left(W_i x_j + U_i y_{j-1} + b_i\right),\\
o_j &= \sigma_g\left(W_o x_j + U_o y_{j-1} + b_o\right),\\
\tilde{s}_j &= \sigma_s\left(W_s x_j + U_s y_{j-1} + b_s\right),\\
s_j &= f_j \circ s_{j-1} + i_j \circ \tilde{s}_j,\\
y_j &= o_j \circ \sigma_y\left(s_j\right).
\end{aligned} \tag{1}$$

As Figure 5 shows, each input x_j in (1) is the coded value of the successively coded sequence of words $(x_j)_{j=0}^{N-1}$ in the comment. The RNN cell provides an output at each step j,

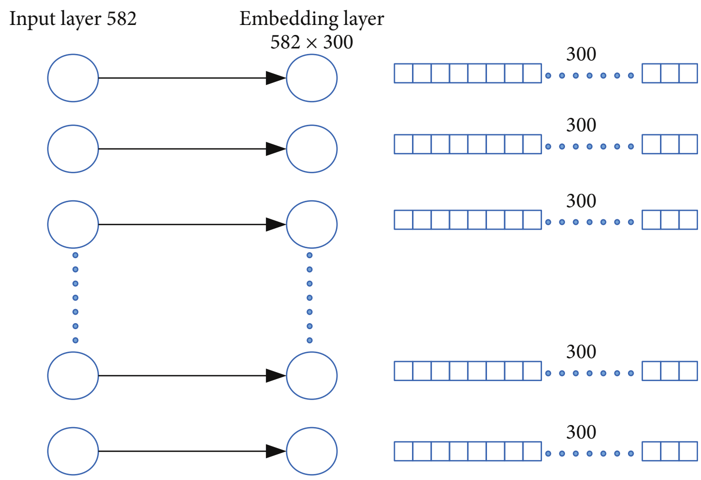


Figure 4: Embedding layer.

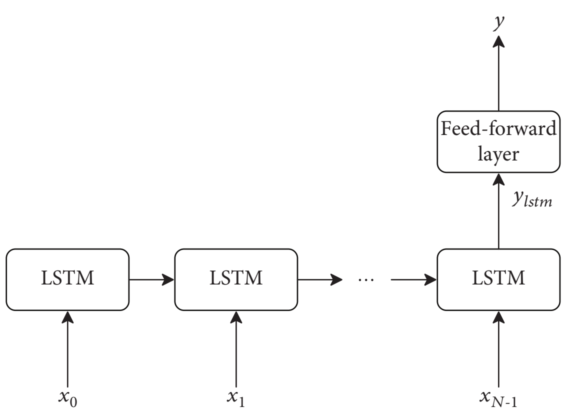


Figure 5: LSTM unfolded into a full network.

but for the prediction, only output y_{N-1} of the network is considered when the last word x_{N-1} is input into the network. This output is what we refer to as y_{lstm} in Figure 5.

Output y_{lstm} is used as an input to a one-neuron feed-forward layer with a sigmoid activation function, the output of which, between 0 and 1, is the network's prediction for whether the sentiment is positive or negative. The output y of that single neuron can be expressed as indicated in

$$y = \sigma_{\text{sigmoid}}\left(\sum_k w_k y_{\text{lstm}} + b\right)\sigma_{\text{sigmoid}}(x) = \frac{e^x}{e^x + 1}, \quad (2)$$

where w_k is used to denote the weight of the k-th input, b is the bias, and $\sigma_{\text{sigmoid}}(x)$ is the sigmoid activation function of the output neuron in the layer.

2.3. Convolutional Neural Networks. Another type of neural network that can be used to predict time series is a convolutional neural network (CNN). These are biologically inspired variants of feed-forward neural networks used primarily in computer vision problems [15], although their ability to exploit spatially local correlation in images can also be used in time-series problems, like sentiment analysis.

In these models, the output of each neuron a_j^l is generated from the output of a subset of spatially adjacent neurons. Every neuron in the same layer shares the same weight and bias, meaning the layer can be expressed in terms of a filter that is convoluted with the output of the previous layer. Equation (3) shows the output a_j^{lk} of the j-th neuron of the l-th convolutional layer:

$$a_j^{lk} = \sigma^{lk}\left(\left(W^{lk} * a^{l-1}\right)_j + b^{lk}\right), \quad (3)$$

where $\left(W^{lk} * a^{l-1}\right)_j$ is the j-th element resulting from the convolution of the filter defined by W^{lk} with the output of the previous layer a^{l-1}, $\sigma^{lk}(x)$ is the activation function for the convolutional layer, and $k \in [0, \ldots, K]$ indicates that it is the output of the k-th channel of the layer. In each convolutional layer, different filters can be applied to the output of the previous layer to generate different representations or channels k, thus yielding a fuller representation of the data.

For the $\sigma^{lk}(x)$ activation function, we used the ReLU function because it does not suffer from the vanishing gradient problem [7] when training the neural network. Equation (4) shows the expression for the activation function.

$$\sigma^{lk}(x) = \sigma_{\text{relu}}(x) = \max(0, x). \quad (4)$$

Figure 6 shows a general diagram of the CNN developed in this paper to analyze sentiment. In order to apply a CNN to a time series, we arranged the encoded words in the same order as they appear in the comment, such that adjacent words in the comment are spatially adjacent at the input to the neural network. Moreover, each word embedding dimension is a different input channel to the network. In this way, the convolutional layers can exploit the local correlation between words in each comment.

After each convolutional layer with a ReLU, activation function is a max-pooling layer, which partitions the input into a set of nonoverlapping ranges and, for each range,

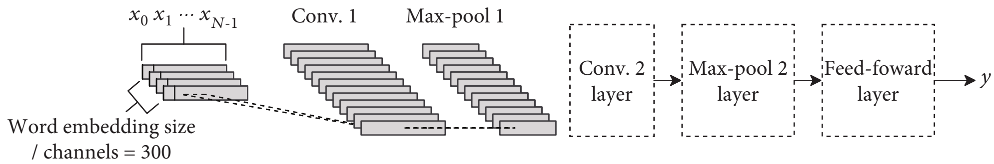


FIGURE 6: General diagram of the CNNs used.

TABLE 1: Model structure.

Model	Model description
1	(582) embedding→(582 × 300) LSTM→(30) dense [sigmoid]→(1)
2	(582) embedding→(582 × 300) LSTM→(50) dense [sigmoid]→(1)
3	(582) embedding→(582 × 300) LSTM→(70) dense [sigmoid]→(1)
4	(582) embedding→(582 × 300) LSTM→(100) dense [sigmoid]→(1)
5	(582) embedding→(582 × 300) LSTM→(200) dense [sigmoid]→(1)
6	(582) embedding→(582 × 300) LSTM→(300) dense [sigmoid]→(1)
7	(582) embedding→(582 × 300) LSTM→(500) dense [sigmoid]→(1)
8	(582) embedding→(582 × 300) Conv1D→(575 × 64) MaxPooling1D→(287 × 64) flatten→(18,368) dense [relu]→(10) dense [sigmoid]→(1)
9	(582) embedding→(582 × 300) Conv1D→(575 × 128) MaxPooling1D→(287 × 128) flatten→(36,736) dense [relu]→(10) dense [sigmoid]→(1)
10	(582) embedding→(582 × 300) Conv1D→(575 × 32) MaxPooling1D→(287 × 32) Conv1D→(280 × 64) flatten→(17,920) dense [relu]→(10) dense [sigmoid]→(1)
11	(582) embedding→(582 × 300) Conv1D→(582 × 32) MaxPooling1D→(291 × 32) LSTM→(100) dense [sigmoid]→(1)

TABLE 2: Training data set.

Training data set	
Positive reviews	4820
Negative reviews	4820
Total reviews	9640
Mean review length (chars)	53
Max review length (chars)	582

outputs the maximum value. Following the convolutional and max-pooling layers is a feedforward layer (as described in (2)) to yield the output of the entire network.

3. Results and Discussion

In order to compare some of the deep-learning techniques mentioned in this paper, we conducted a series of experiments on different models based on LSTM neural networks and CNN. Table 1 shows the structure of each of the models used with the lengths of the inputs at each layer. The first column will be used to refer to the models in subsequent references.

TABLE 3: Test data set.

Test data set	
Positive reviews	1408
Negative reviews	1377
Total reviews	2785

TABLE 4: Test results.

Model N	Training time	Good hits	Bad hits	False good	False bad	Accuracy end
1	2208	1227	1228	149	181	88.15
2	2734	1211	1239	138	197	87.97
3	4658	1215	1237	140	193	88.04
4	4406	1198	1261	116	210	88.29
5	4388	1213	1256	121	195	88.65
6	10,630	1221	1263	114	187	89.19
7	13,574	1190	1261	218	116	88.01
8	6994	1210	1247	130	198	88.22
9	9139	1206	1235	142	202	87.65
10	1765	1166	1268	109	242	87.40
11	1602	1187	1272	105	221	88.29

First, we prepared the data as explained in Section 2.1 + 0.1667 emA. The same comment coding technique was used for each test, which included training an embedding layer.

To make the models comparable, we used the same training data set (Table 2) with a total of 9640 reviews. The classification was conducted independently using another data set containing 2785 reviews that were not used during the training. As Table 3 shows, a test data set was employed that was fully balanced between positive and negative reviews.

So as not to use a different number of training epochs based on the model, we decided to use a fixed number, 10, since, for every model, the loss value did not improve significantly with longer training.

Table 4, containing the general results, shows the number of correctly predicted positive and negative reviews, as well as the false positives and negatives.

Models 1 to 6 have the same structure, the number of memory units varying as shown in Table 1. As we can see in Figure 7, the results improve as the number of memory cells is increased, reaching a maximum accuracy of 89.19% in model 6.

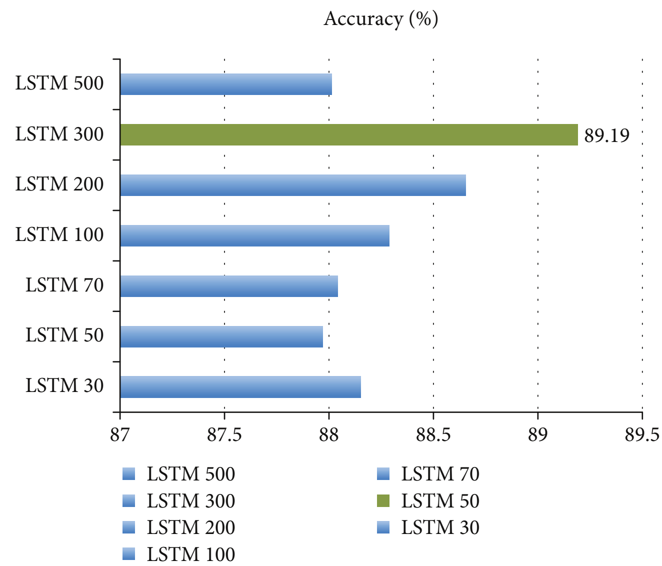


Figure 7: LSTM comparison.

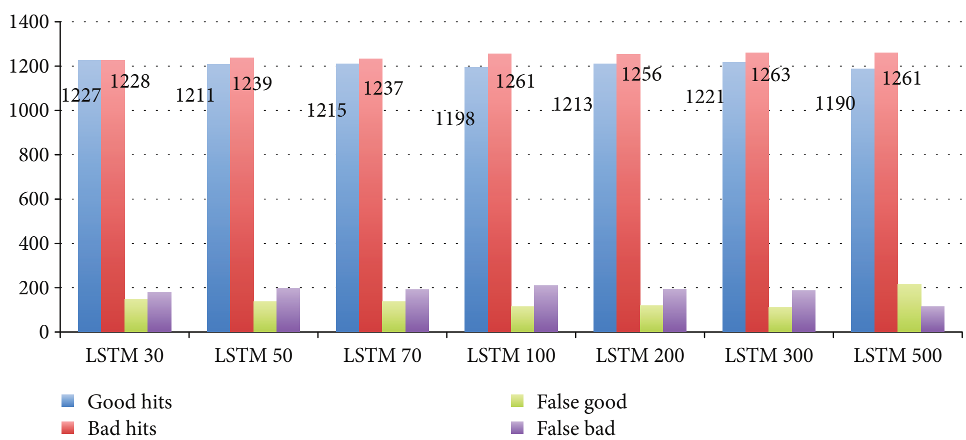


Figure 8: LSTM comparison.

Figure 8 shows the results of the test separated by hits and false positives. The model with the best result improved on the predictions from previous models for negative reviews.

The second part of the experiment consisted of checking for a significant variation when the number of filters was changed in the CNN models. Specifically, we compared models 8 and 9 with one another, yielding the results shown in Figure 9. As we can see, the difference is not significant, and increasing the number of filters does not provide any improvement.

To complete the study, we compared the results for the previous models that yielded the best outcome (model 6 LSTM and model 8 CNN) with models 10 (two-layer CNN) and 11 (CNN and LSTM). As Figure 10 shows, the LSTM models exhibit the highest accuracy, a result that is not improved by adding a convolutional layer.

Figure 11 shows that the best overall result for the LSTM neural networks is based primarily on their better prediction of positive results, in comparison to the other networks trained.

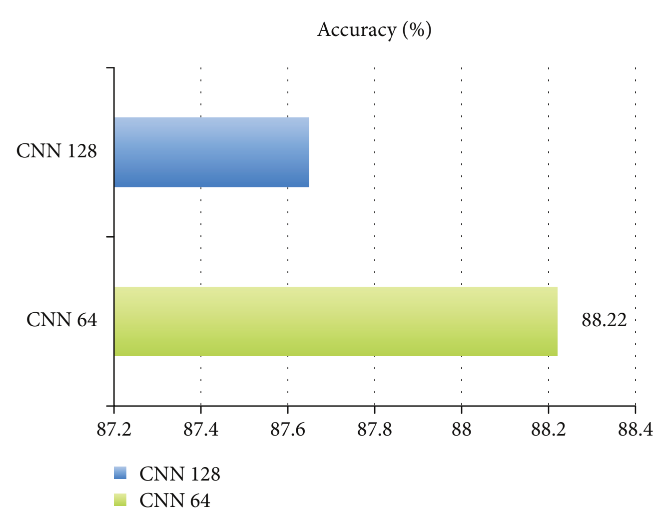


Figure 9: CNN comparison.

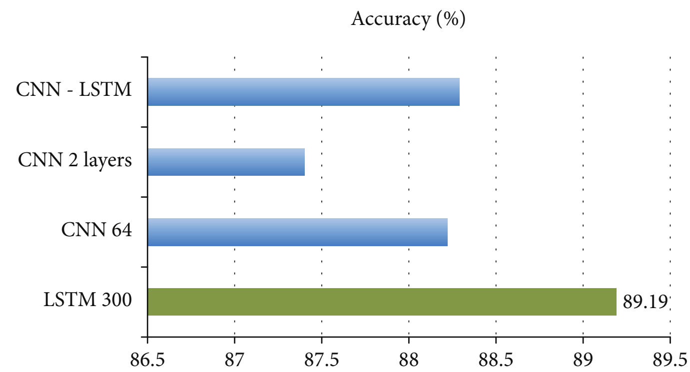


Figure 10: Comparison of LSTM and CNN models.

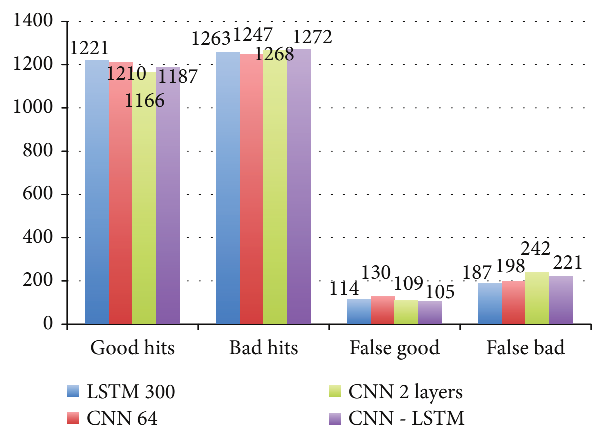


Figure 11: LSTM comparison.

4. Conclusions

In this paper, we considered the problem of predicting sentiment in tourist reviews taken from eWOM platforms for hotels at an important international tourist destination. The use of techniques and automatic tools such as those considered in this paper are very useful for tourism industry practitioners [3]. Specifically, the prediction of positive or negative sentiment expressed by a tourist can be used in different marketing and service management applications:

(i) Comparison of feeling about another local competitor or tourist destination (market positioning)

(ii) Performing a proactive customer service management, generating a job ticket when a negative review is detected (customer management)

(iii) As a measure of indicators to start a campaign to improve the reputation (marketing management)

(iv) As a measure of risk indicators that affect the hotel or destination image (risk management)

Once the models studied in this article have been trained, they can be used in combination with other tools (review extraction or dashboards).

We used deep-learning techniques to devise different predictors based on neural networks, which were trained with the extracted data to compare the accuracies of each.

The predictors evaluated were based on recursive neural networks with cell LSTM and convolutional neural networks. Different designs were considered for each. The methodology was checked by training and validating the model with samples taken from Booking and TripAdvisor.

The results show that LSTM neural networks outperform CNN. The optimum result for CNN is attained with a single convolutional layer and 64 channels. More layers or more channels result in symptoms of overfitting. The LSTM neural networks yield higher accuracies, with one LSTM with a vector length of 300 for the internal state yielding an accuracy just over 89%, the highest for any model.

Finally, the results show that the better results of the neural networks are due primarily to their advantage when classifying the positive comments. They also show that combining convolutional layers with recurrent LSTM layers does not yield any advantages.

Acknowledgments

This work is sponsored by the “VITUIN: Vigilancia Turística Inteligente de Tenerife en Redes Sociales” project, through research funds of the Fundación CajaCanarias.

References

[1] R. Piryani, D. Madhavi, and V. K. Singh, “Analytical mapping of opinion mining and sentiment analysis research during 2000–2015,” *Information Processing and Management*, vol. 53, no. 1, pp. 122–150, 2017.

[2] J. A. Balazs and J. D. Velásquez, "Opinion mining and information fusion: a survey," *Information Fusion*, vol. 27, pp. 95–110, 2016.

[3] M. D. Sotiriadis, "Sharing tourism experiences in social media: a literature review and a set of suggested business strategies," *International Journal of Contemporary Hospitality Management*, vol. 29, no. 1, pp. 179–225, 2017.

[4] M. D. Sotiriadis and C. van Zyl, "Electronic word-of-mouth and online reviews in tourism services: the use of twitter by tourists," *Electronic Commerce Research*, vol. 13, no. 1, pp. 103–124, 2013.

[5] R. A. King, P. Racherla, and V. D. Bush, "What we know and don't know about online word-of-mouth: a review and synthesis of the literature," *Journal of Interactive Marketing*, vol. 28, no. 3, pp. 167–183, 2014.

[6] L. de Vries, S. Gensler, and P. S. H. Leeflang, "Popularity of brand posts on brand fan pages: an investigation of the effects of social media marketing," *Journal of Interactive Marketing*, vol. 26, no. 2, pp. 83–91, 2012.

[7] T. Hennig-Thurau, K. P. Gwinner, G. Walsh, and D. D. Gremler, "Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the Internet?," *Journal of Interactive Marketing*, vol. 18, no. 1, pp. 38–52, 2004.

[8] "Hotel review analysis. monkey learn," 2018, https://github.com/monkeylearn/hotel-review-analysis.

[9] R. M. Aguilar Chinea, J. M. Torres Jorge, and C. A. M. Galán, "Aprendizaje automático en la identificación de sistemas. un caso de estudio en la generación de un parque eólico," *Revista Iberoamericana de Automática e Informática industrial*, vol. 16, 2018.

[10] "NLTK python library," 2018, https://www.nltk.org.

[11] "Keras python library," 2018, https://keras.io.

[12] J. Schmidhuber, "Learning complex, extended sequences using the principle of history compression," *Neural Computation*, vol. 4, no. 2, pp. 234–242, 1992.

[13] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[14] A. Graves, *Supervised sequence labelling with recurrent neural networks*, Springer, 2012.

[15] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.

[16] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *Proceedings of the 13th International Conference on Artificial Intelligence and Statistics (AISTATS) 2010*, Chia Laguna Resort, Sardinia, Italy, 2010.

2

Statistical Modeling and Prediction for Tourism Economy Using Dendritic Neural Network

Ying Yu, Yirui Wang, Shangce Gao, and Zheng Tang

Faculty of Engineering, University of Toyama, Toyama-shi 930-8555, Japan

Correspondence should be addressed to Shangce Gao; gaosc@eng.u-toyama.ac.jp

Academic Editor: Francisco Martínez-Álvarez

With the impact of global internationalization, tourism economy has also been a rapid development. The increasing interest aroused by more advanced forecasting methods leads us to innovate forecasting methods. In this paper, the seasonal trend autoregressive integrated moving averages with dendritic neural network model (SA-D model) is proposed to perform the tourism demand forecasting. First, we use the seasonal trend autoregressive integrated moving averages model (SARIMA model) to exclude the long-term linear trend and then train the residual data by the dendritic neural network model and make a short-term prediction. As the result showed in this paper, the SA-D model can achieve considerably better predictive performances. In order to demonstrate the effectiveness of the SA-D model, we also use the data that other authors used in the other models and compare the results. It also proved that the SA-D model achieved good predictive performances in terms of the normalized mean square error, absolute percentage of error, and correlation coefficient.

1. Introduction and Literature Review

With the impact of global internationalization, tourism is also in a state of rapid development. As we all know, tourism's impact on the economic and social development of a country can be enormous. It can not only up business, trade, and capital investment but also create jobs and entrepreneurialism for workforce and protect heritage and cultural values (as shown in Table 1). Each country wants to know the data of its inbound visitors and tourism in order to choose an appropriate strategy for its economic well-being. Hence, a reliable forecast is needed and plays a major role in tourism planning.

Accurate forecasts build the foundation for better tourism planning and administration. Then more efficient forecasting techniques in tourism demand studies are being called for.

Over the past two decades, tourism demand modeling and forecasting which are two of the most important areas in tourism research have attracted more and more attention of both academics and practitioners. As Song and Li concluded, twenty years ago, there were only a handful of academic journals that published tourism-related research [1]. Now there are more than 70 journals that serve a thriving research community covering more than 3000 tertiary institutions across five continents. However, there has not been a panacea for tourism demand forecasting.

In recent years, statistics has been widely applied to the tourism economy under study. Among the statistical methods, time series forecasting is an important area of forecasting. And it can be classified into two categories: the linear methods and the nonlinear methods. The most popular of the linear methods are the Naïve model [2–5], the exponential smoothing (ES) model [2, 6], and the autoregressive integrated moving averages (ARIMA) model [3, 4, 6]. Among them, the most advanced forecasting model of linear methods is autoregressive integrated moving average model (ARIMA) which has been successfully tested in many practical applications. If the linear models can approximate the underlying data generating process well, they could be considered as the preferred models. However, if the linear models fail to perform well in both in-sample fitting and out-of-sample forecasting, more complex nonlinear models should be considered. Based on this view, many scholars have also turned to nonlinear methods such as the neural

Table 1: Inbound tourism consumption.

Products	(Billion Yen) Same-day visitors	Tourists	Total visitors
Characteristic products	0	1167	1167
Accommodation services	0	496	496
Food and beverage servicing services	0	303	303
Passenger transport services	0	328	328
Travel agency, tour operator, and tourist guide services	0	8	8
Cultural services	0	10	10
Recreation and other entertainment services	0	8	8
Miscellaneous tourism service	0	14	14
Connected products	0	483	483
Total	0	1650	1650

network (NN) [3, 4, 7, 8]. Although there are still a few doubts about neural network based tourism demand forecasting, it is generally believed that the nonlinear methods outperform the linear methods in modeling the economic behavior and efficiently helping wise decision-making.

Neuron networks have been regarded by many experts as a promising technology for time series forecasting. Consequently, in the last few decades, more than 2000 articles on neural network forecasting have been published covering a wide range of applications [9]. Compared to statistical forecasting techniques, neural network approaches have several unique characteristics, such as (1) being both nonlinear and data driven, (2) having no requirement for an explicit underlying model, and (3) being more flexible and universal and thus applicable to more complicated models [10]. Furthermore, Nelson et al. and Zhang and Kline [11, 12] suggested that time series preprocessing (e.g., detrending and deseasonalizing) contributes significantly to neuron network model performance.

Up to now, there are many researchers using a lot of methods to forecast the tourism demand. And they can be divided into three types: time series, neural network, and combined models. In 2014, Teixeira and Fernandes published [13], in which the three methods are all mentioned. Except those, there are also a lot of authors using the three methods separately. For example, Box et al., Cho, Chu, Song, and Li, Law, Qu, and Zhang, Shahrabi et al., Li et al., and Kawakubo and Kubokawa have used the traditional time series methods to forecast the tourism demand [1, 3–7, 14–17]. As neural network is widely known, there are many authors turning to use the neural network to forecast the time series data such as Chen et al., Claveria and Torra, Davies et al., Constantino et al., Law, Lin et al., and Pai and Hong [3, 4, 8, 18–22]. With the progress of science, more and more methods are being used. The combined models are the most popular methods in them. And, up to now, Bates and Granger, Chen, Shen et al., and Yan have used this method and got the expected results [23–26]. Besides these, some other methods such as support vector regression [27, 28] and novel hybrid system [29, 30] are proposed. They have made great achievements in the optimization problem and the prediction problem; however, the data preprocessing and the late parameter selection problem are relatively complex.

When analyzing time series data, we should pay particular attention to the seasonality of the time series involved. Seasonality is a notable characteristic of tourism demand and cannot be ignored in the modeling process when monthly data are used. How to handle the seasonal fluctuations of tourism data has always been an important issue in tourism demand forecasting. We always use normal quantile transform or seasonal difference method to eliminate the impact of seasonality [31, 32].

In this paper, we mix the most advanced linear model (SARIMA model) with the innovative neural network model (DNN model) together and call the mixed model SA-D model. We obtained that the SA-D model performs much better than the DNN model in the tourism demand forecasting as the comparing results showed.

This paper is organized as follows. In Section 2, the SARIMA model, the DNN model, and the combined model (SA-D model) are described. Section 3 describes the data set and discusses the evaluation methods to compare the forecasting methods and takes statistical tests to check the SA-D model and then compares the models that other authors had given by using the same data. After that, the experimental results are given. Section 4 provides concluding remarks.

2. Modeling (Statistical Modeling and Neural Network)

A time series model explains a variable with regard to its own past and a random disturbance term. Time series models have been widely used for tourism demand prediction in the past four decades. In this section, two models are described as follows.

2.1. ARIMA Model and SARIMA Model. ARIMA is the most popular linear model for forecasting time series. It has made great success in both academic research and industrial applications. A general ARIMA model is ordered by (p, d, q), and it can be written as

$$\phi(B)\nabla^d x_t = \theta(B)\varepsilon_t, \quad (1)$$

where x_t and ε_t represent the number of visitors and random error terms at time t, respectively. B is a backward shift operator defined by $Bx_t = x_{t-1}$ and related to ∇ by $\nabla = 1 - B$; $\nabla^d = (1-B)^d$; d is the order of differencing. $\phi(B)$ and $\theta(B)$ are autoregressive (AR) and moving averages (MA) operators of orders p and q, respectively, and they are defined as

$$\begin{aligned}\phi(B) &= 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p,\\ \theta(B) &= 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q.\end{aligned} \quad (2)$$

$\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive coefficients and $\theta_1, \theta_2, \ldots, \theta_q$ are the moving average coefficients.

When fitting ARIMA model to the raw data, the ARIMA model involves the following four steps:

(I) Identification of the ARIMA (p, q, d) structure

(II) Estimation of the unknown parameters

(III) Goodness-of-fit tests on the estimated residuals

(IV) Forecast future outcomes based on the known data

ε_t should be independently and identically distributed as normal random variables with mean = 0 and constant variance = σ^2. The roots of $\phi_p(x_t) = 0$ and $\theta_q(x_t) = 0$ should all lie outside the unit circle. It was suggested by Box et al. that at least 50 or preferably 100 observations should be used for the ARIMA model [14].

If the data has significant seasonal changes periodically. We can use the SARIMA model which uses the seasonal difference method to eliminate the effects of seasonal cycles. However, if the seasonality is regarded as deterministic, introducing seasonal dummies into the time series models would be sufficient in accounting for the seasonal variation. To test for the presence of seasonal unit roots, the HEGY test [33] is widely used. Unlike the HEGY test, an alternative method known as the test for fractional integration to test the seasonal components in the time series was introduced in 2004 [34]. Another approach to model seasonal fluctuations is to use the periodic autoregressive model. This model allows parameters to vary according to the seasons of a year and therefore may reflect seasonal economic decision-making more adequately than constant parameter specifications.

2.2. DNN Model (Neuron Model with Dendritic Nonlinearity). Recently, more and more nonlinear forecasting models are proposed to address the time series' issues. As Song and Li concluded, among them, ANNs (artificial neural networks) are receiving increasing interests due to their ability to imperfect data, functions of self-organizing, self-study, data-driven, associated memory, and arbiter function mapping [1].

As we all know, the structure of every neuron is unique; it contains three parts: the cell body, dendrite, and axon. The dendrite receives the signal from other neurons; then the signal is computed at the synapse and transmitted to the cell body. If the signal into the cell body exceeds the holding threshold, the cell will fire and send the signal down to other neurons through axon.

In 1943, a simple neuron model is proposed by McCulloch and Pitts in which the dendrites and synapses are independents and there are no effects on them from one to another (Figure 1) [35]. However, in 1987, Minsky and Papert indicated that the McCulloch-Pitts model is limited to solving complex problems [36].

Different from the McCulloch-Pitts model which does not consider the dendritic structure in the neuron, neuron model with dendritic nonlinearity model (DNN model) is proposed in our researches. The DNN model can be generalized as follows:

(1) The dendrites can be initialized by any arbitrary decision.

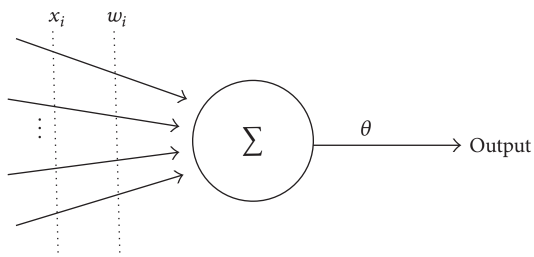


Figure 1: McCulloch-Pitts model.

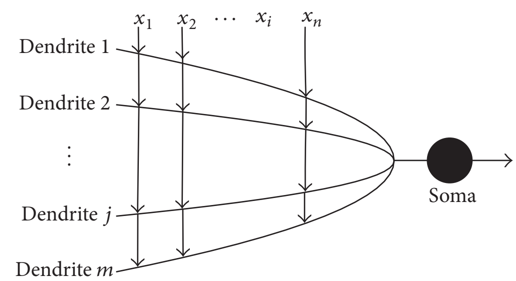


Figure 2: Neuron model with dendritic nonlinearity.

(2) The synapses on the same branch interact with each other.

(3) The nonlinear interaction produced in a dendrite can be expressed by a logical network.

(4) After learning, the branches' ripened number and the locations and types of synapses on the branches will be synthesized.

As shown in Figure 2, the dendritic branches receive signals from x_1 to x_n and then perform a simple multiplication on their own signal. At the junction of the branches, the outputs are summed up and then conducted to soma (the cell body). If the input of the soma exceeds a threshold, the cell will fire it and send it to other neurons through the axon.

Synaptic Function. In the connection layer, a sigmoid function reflects the interaction among the synapses in a dendrite. The output of the synapse whose address is from the ith ($i = 1, 2, \ldots, m$) input to the jth ($j = 1, 2, \ldots, n$) branch is given by the following equation:

$$Y_{ij} = \frac{1}{1 + e^{-k(w_{ij} - \theta_{ij})}}. \quad (3)$$

w_{ij} and θ_{ij}, respectively, mean the connection parameters, and k is a positive constant. When k becomes large enough, the sigmoid function will turn out to be similar to a step function. Through the change of the value of w_{ij} and θ_{ij}, four types of synaptic connections can be defined: a direct connection, an inverted connection, a constant-0 connection, and constant-1 connection.

Dendritic Function. It performs a simple multiplication on various synaptic connections of the branch. The output of the jth branch is given by

$$Z_j = \prod_{i=1}^{n} Y_{ij}. \quad (4)$$

Membrane Function. It is approximated as follows:

$$V = \sum_{j=1}^{m} Z_j. \quad (5)$$

Soma Function. The function of the soma is described by a sigmoid operation; when k is taken as a positive constant, γ is taken as a threshold from 0 to 1.

$$O = \frac{1}{1 + e^{-k(V-\gamma)}}. \quad (6)$$

Learning Function. Because DNN is a feed-forward network with continuous functions, the error back-propagation-like algorithm is valid for DNN. By using the learning rule, the error between the target vector and the actual output vector can be expressed as follows:

$$E = \frac{1}{2}(T - O)^2. \quad (7)$$

And, according to the gradient descent learning algorithm, the synaptic parameters w_{ij} and θ_{ij} can be modified in the direction to decrease the value of E. The equations are shown as follows:

$$\Delta w_{ij}(t) = -\mu \frac{\partial E}{\partial w_{ij}}, \qquad \Delta \theta_{ij}(t) = -\mu \frac{\partial E}{\partial \theta_{ij}}, \quad (8)$$

where μ is a positive constant that represents the learning rate. A low learning rate makes the convergence very slow, while a high learning rate is difficult for making the error converge. And the partial differentials of E with respect to w_{ij} and θ_{ij} are computed as follows:

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial O} \cdot \frac{\partial O}{\partial V} \cdot \frac{\partial V}{\partial Z_j} \cdot \frac{\partial Z_j}{\partial Y_{ij}} \cdot \frac{\partial Y_{ij}}{\partial w_{ij}}, \qquad \frac{\partial E}{\partial \theta_{ij}} = \frac{\partial E}{\partial O} \cdot \frac{\partial O}{\partial V} \cdot \frac{\partial V}{\partial Z_j} \cdot \frac{\partial Z_j}{\partial Y_{ij}} \cdot \frac{\partial Y_{ij}}{\partial \theta_{ij}}. \quad (9)$$

2.3. The Combined Model (SA-D Model). Both linear and nonlinear models have achieved successes in their own linear or nonlinear problems. However, none of them is a universal model that is suitable for all situations. Bates and Granger said that a combined model having both linear and nonlinear modeling abilities will be a good alternative for forecasting the time series data [23]. Both the linear and nonlinear models have different unique strength to capture data characteristics in linear or nonlinear domains, so the combined model proposed in this study is composed of the linear component and the nonlinear component. Therefore, the combined model can model linear and nonlinear patterns with improved overall forecasting performance.

It may be reasonable to consider a time series to be composed of a linear autocorrelation structure and a nonlinear component which can be performed as

$$Y_t = L_t + N_t \,(10), \quad (10)$$

where L_t is the linear component and N_t is the nonlinear component of the combined model. Both L_t and N_t have to be estimated for the data set. First, the author let linear model (here we use the SARIMA model to perform the obvious seasonal trends) to model the linear part; then the residuals from the linear model will contain only the nonlinear relationship. Let R_t represent the residual at time t; then we can know

$$R_t = Z_t - \widehat{L_t} \,(11), \quad (11)$$

where $\widehat{L_t}$ denotes the forecast value of the linear model at time t. By modeling residuals using nonlinear model (here we use the DNN model), nonlinear relationships can be discovered. In this paper, we built the model with the following input layers:

$$R_t^{\text{linear}} = f^{\text{nonlinear}}\left(R_{t-1}^{\text{linear}}, R_{t-2}^{\text{linear}}, R_{t-3}^{\text{linear}}, R_{t-4}^{\text{linear}}\right) + e_t, \quad (12)$$

where R_t^{linear} represents the residual at time t from the ARIMA model, $f^{\text{nonlinear}}$ is a nonlinear function determined by the DNN model, and e_t is the random error. And the combined forecast can be performed as

$$\widehat{Y_t} = \widehat{L_t} + \widehat{N_t} \,(13), \quad (13)$$

where $\widehat{N_t}$ is the forecast value of (12).

3. Results and Prediction

3.1. Data Set and the Process. Due to rapid economic growth and international tourism promotion, the number of tourists coming to Japan is greatly increasing year by year. Here we choose the inbound tourists from 2009:1 to 2015:12. And the process of data set is shown in Figure 3. The collected data were divided into two sets: the training data (data before 2015) and the testing data (data of 2015) [37, 38].

3.2. Evaluation Methods. Some quantitative statistical metrics such as normalized mean square error (NMSE), absolute percentage of error (APE), R (correlation coefficient), and program running time (PRT) are used to evaluate the forecasting performance of the forecasting models (Table 2). NMSE and APE are used to measure the deviation between the predicted and actual values. The smaller the values of NMSE and APE are, the closer the predicted values to the actual values are. The metric R is adopted to measure the correlation of the actual and the predicted values. The PRT can measure the running speed of the models.

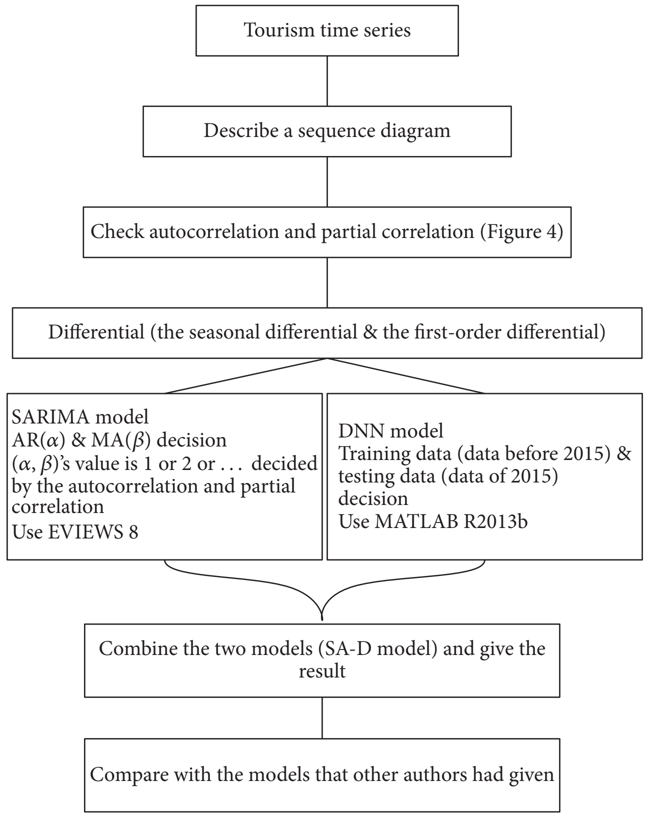


Figure 3: Process of data set.

Table 2: Calculations of the performance metrics.

Metrics	Calculation
NMSE	$\text{NMSE} = \frac{\sum_{i=1}^{n}(a_i - b_i)^2}{n\sigma^2}$; $\sigma = \frac{\sum_{i=1}^{n}(a_i - \bar{a})^2}{n-1}$
APE	$\text{APE} = \frac{\sum_{i=1}^{n}\lvert(a_i - b_i)/a_i\rvert}{n} \times 100\%$
R	$R = \frac{\sum_{i=1}^{n} a_i b_i}{\sqrt{\sum_{i=1}^{n} a_i^2} \times \sqrt{\sum_{i=1}^{n} b_i^2}}$
PRT	Decided by the actual operation

Note: a_i and b_i are the actual values and the predicted values.

3.3. Experimental Results. For the data having significant seasonal changes periodically, we use the SARIMA model in this paper to eliminate the linear trend. As Figure 4 shows, we can decide the possible generations of the ARIMA model and use the Akaike Information Criterion (AIC) to test which of the generations is the best.

Through the SARIMA model, we get the data that has no linear trend and train the data separately by the DNN model and the SA-D model. We can get the results of the DNN model and the SA-D model as follows.

Table 3: The compared results of the DNN model and the SA-D model.

Metrics	The DNN model	The SA-D model
NMSE	2.245	0.219
APE	0.87	0.78
R	0.32	0.89
PRT	The DNN model is rapider than the SA-D model	

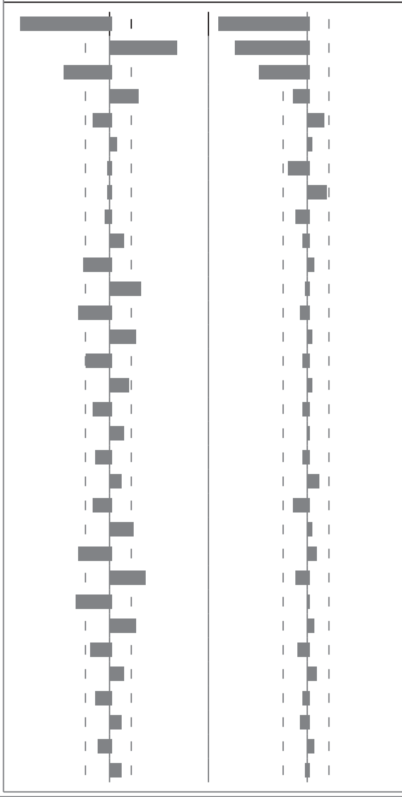
As Figures 5–7 show, we can see that the results of the SA-D model perform much better than those of the DNN model. In order to deeply evaluate the performance of the DNN model and the SA-D model, we calculate APE, NMSE, and R of the testing data set as Table 3 shows.

We can see that although the PRT of the DNN model is rapider than that of the SA-D model, the NMSE, APE, and R of the SA-D model are much better than those of the DNN model.

3.4. Models Comparison. To demonstrate the validity of the SA-D model, we train the same data that other authors had used in the other combination models and compare the results of the SA-D model and the other combination models. We collected the monthly outbound traveling population data of Taiwan to three areas (Americas, Europe and Oceania) from the Tourism Bureau, M.O.T.C. Republic of China

Correlogram of DX

Date: 01/11/17 Time: 14:40
Sample: 1 84
Included observations: 72



	AC	PAC	Q-Stat	Prob
1	−0.911	−0.911	62.260	0.000
2	0.701	−0.756	99.652	0.000
3	−0.468	−0.492	116.59	0.000
4	0.283	−0.131	122.87	0.000
5	−0.156	0.169	124.80	0.000
6	0.067	0.040	125.16	0.000
7	−0.007	−0.188	125.17	0.000
8	−0.007	0.203	125.17	0.000
9	−0.045	−0.098	125.34	0.000
10	0.150	−0.041	127.29	0.000
11	−0.259	0.074	133.14	0.000
12	0.320	−0.003	142.22	0.000
13	−0.317	−0.057	151.30	0.000
14	0.276	0.044	158.29	0.000
15	−0.231	−0.030	163.28	0.000
16	0.201	0.038	167.12	0.000
17	−0.179	−0.035	170.21	0.000
18	0.153	0.008	172.51	0.000
19	−0.127	−0.040	174.12	0.000
20	0.122	0.116	175.64	0.000
21	−0.160	−0.137	178.32	0.000
22	0.238	0.035	184.35	0.000
23	−0.319	0.081	195.39	0.000
24	0.357	−0.102	209.54	0.000
25	−0.332	0.022	222.05	0.000
26	0.262	0.050	230.02	0.000
27	−0.189	−0.088	234.23	0.000
28	0.142	0.079	236.68	0.000
29	−0.126	−0.032	238.63	0.000
30	0.120	−0.051	240.47	0.000
31	−0.110	0.070	242.03	0.000
32	0.099	−0.017	243.33	0.000

Figure 4: Autocorrelation and partial correlation.

Table 4: Results based on the orthogonal array factor assignment and statistical tests of the SA-D model.

Number	M	μ	k_{soma}	θ_{soma}	MSD	p
1	15	0.05	1	0	0.401 ± 0.169	0.1938
2	15	0.05	3	0.3	0.386 ± 0.170	0.2013
3	15	0.01	5	0.5	0.391 ± 0.171	0.1854
4	15	0.01	10	0.9	0.389 ± 0.167	0.191
5	25	0.05	1	0	0.392 ± 0.165	0.2563
6	25	0.05	3	0.3	0.395 ± 0.164	0.2742
7	25	0.01	5	0.5	0.398 ± 0.161	0.3011
8	25	0.01	10	0	0.390 ± 0.168	0.2916
9	30	0.05	1	0.9	0.402 ± 0.172	0.1928
10	30	0.05	3	0.3	0.399 ± 0.171	0.1897
11	30	0.01	5	0.5	0.394 ± 0.168	0.2001
12	30	0.01	10	0.9	0.397 ± 0.170	0.1936

Note: M means number of dendrites.

(Taiwan). The study time ranges from January of 1998 to June of 2009 [39]. The collected data were divided into two parts, training data (data from 1998 to 2007) and testing data (data after 2007), for each tourism demand time series. The

Table 5: Comparison of the SA-D model and the other combination models.

	Americas	Europe	Oceania
ARIMA + BPNN			
APE	13.41	12.95	13.46
NMSE	0.3992	0.8153	0.5327
R	0.9918	0.9917	0.9856
ARIMA + SVR			
APE	11.46	11.37	11.87
NMSE	0.2878	0.6316	0.5102
R	0.9923	0.9917	0.9871
The SA-D model (with data preset as other authors did)			
APE	9.61	9.73	9.89
NMSE	0.2788	0.4561	0.4968
R	0.9934	0.9921	0.9864
The SA-D model (without data preset)			
APE	10.34	10.51	10.87
NMSE	0.3458	0.5619	0.6027
R	0.9912	0.9906	0.9891

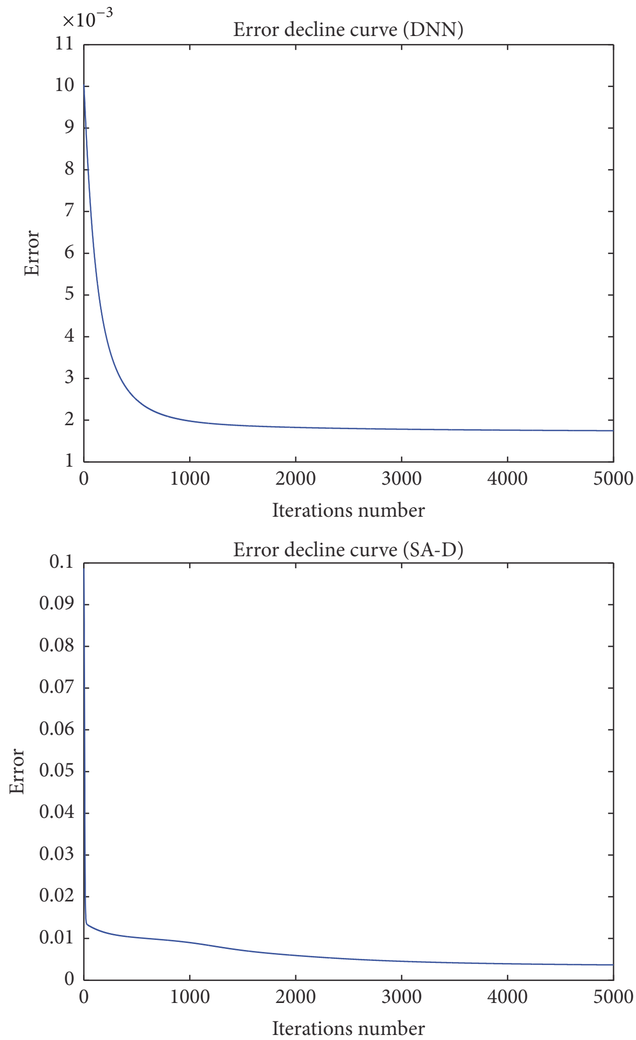


Figure 5: Error decline curve of the DNN model and the SA-D model.

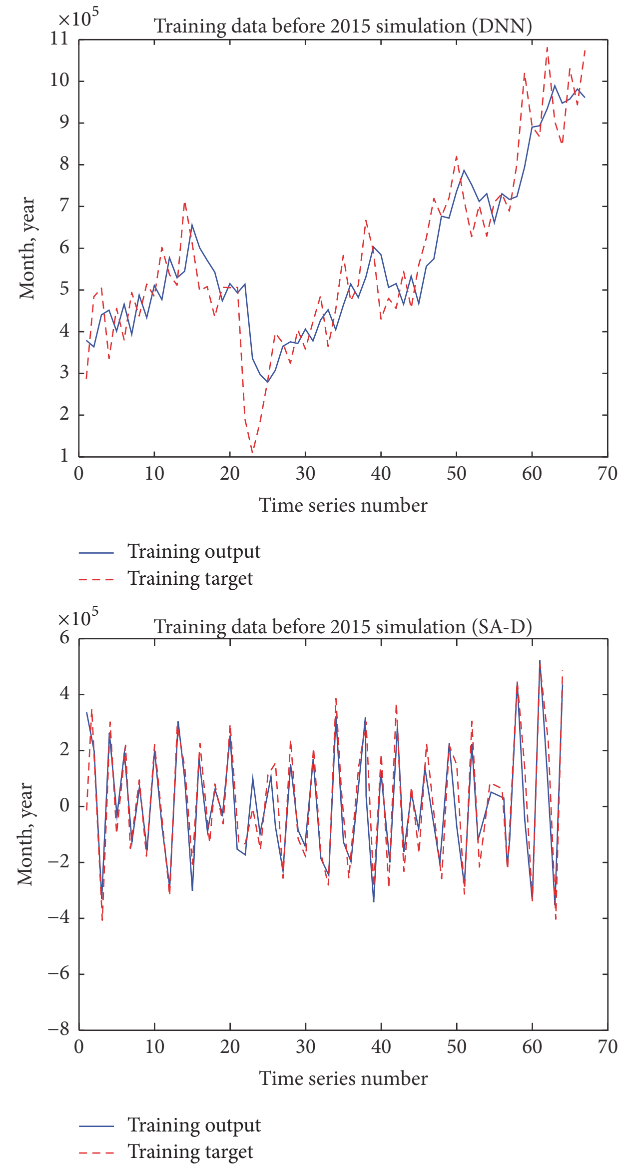


Figure 6: Training data before 2015 simulation of the DNN model and the SA-D model.

author scaled the data within the range of (0, 1) through the following formula:

$$\frac{x_t - x_{\min}}{x_{\max} - x_{\min}} \times 0.7 + 0.15. \tag{14}$$

So we use the data with the same preset as the author did and without the data preset separately and get our experimental results.

Before comparing with the models, we summarize the experimental results based on the orthogonal array, factor assignment, and statistical tests as Table 4 shows. Here the MSD values are calculated by $\overline{x} \pm s$, where $\overline{x}$ means the mean of the results over 20 runs and s means the standard deviation. It can verify whether the data is closer to reality or not. And p value can determine whether the residual is white noise sequence or not after the statistical test by using QLB statistic. Finally, we choose the result of number 7 to do the comparison.

As Table 5 shows, our model had much better results than other authors' models. But we have to say that the data preset by (14) made the results better and reduced the running time of program.

4. Conclusions

In this study, we proposed a new model, the SA-D model, which mixed the SARIMA model and the DNN model together. First, we used the data collected from Japan Tourism Agency Ministry of Land, Infrastructure, Transport and Tourism and Japan National Tourism Organization to compare the SA-D model and DNN model; the results showed that the SA-D model performed much better in fitting and forecasting the time series data. Then we verified the effectiveness of our model by comparing with other authors' models and got the expected result.

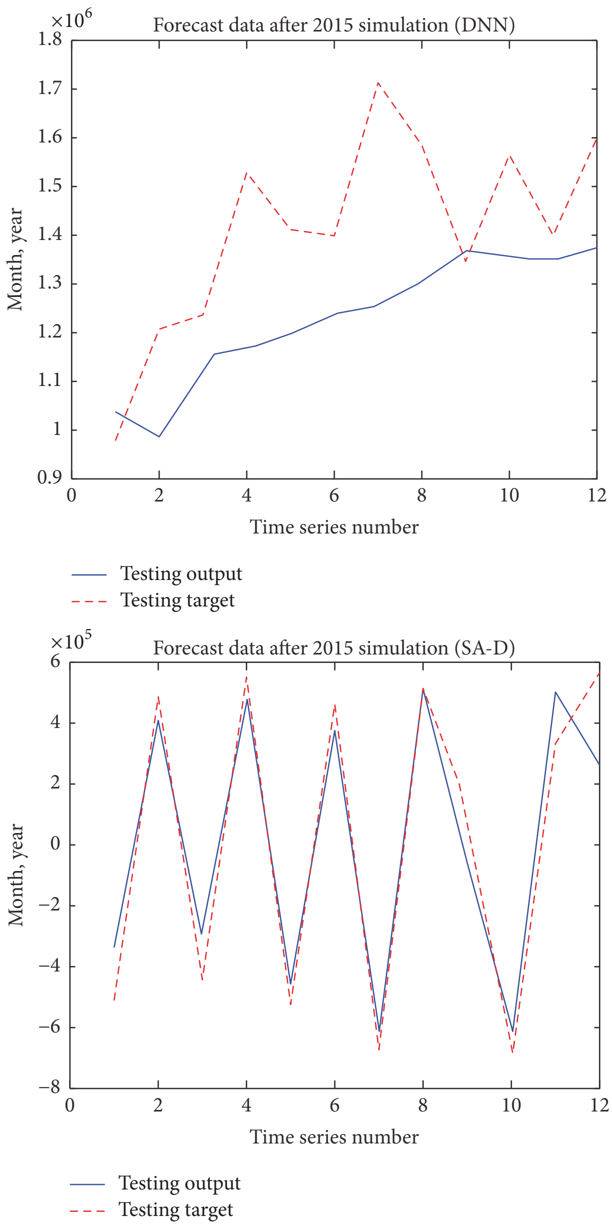


Figure 7: Forecast data after 2015 simulation of the DNN model and the SA-D model.

The contributions of this study lie in two aspects. Our study is based on neuron model with dendritic nonlinearity model and it theoretically strengthens the assumption that a neural network model performs better than linear models when forecasting nonlinear variables.

This study which mixed the linear model and the nonlinear model together opens the door for further combination models with different methods and models.

Acknowledgments

This research was partially supported by JSPS KAKENHI (Grant no. 15K00332).

References

[1] H. Song and G. Li, "Tourism demand modelling and forecasting—a review of recent research," *Tourism Management*, vol. 29, no. 2, pp. 203–220, 2008.

[2] C. J. S. C. Burger, M. Dohnal, M. Kathrada, and R. Law, "A practitioners guide to time-series methods for tourism demand forecasting—a case study of Durban, South Africa," *Tourism Management*, vol. 22, no. 4, pp. 403–409, 2001.

[3] R. Law, "Back-propagation learning in improving the accuracy of neural network-based tourism demand forecasting," *Tourism Management*, vol. 21, no. 4, pp. 331–340, 2000.

[4] R. Law, "Demand for hotel spending by visitors to Hong Kong: a study of various forecasting techniques," *Journal of Hospitality & Leisure Marketing*, vol. 6, no. 4, pp. 17–29, 1999.

[5] F.-L. Chu, "Forecasting tourism demand: a cubic polynomial approach," *Tourism Management*, vol. 25, no. 2, pp. 209–218, 2004.

[6] H. Qu and H. Q. Zhang, "Projecting International Tourist Arrivals in East Asia and the Pacific to the Year 2005," *Journal of Travel Research*, vol. 35, no. 1, pp. 27–34, 1996.

[7] V. Cho, "A comparison of three different approaches to tourist arrival forecasting," *Tourism Management*, vol. 24, no. 3, pp. 323–330, 2003.

[8] P.-F. Pai and W.-C. Hong, "An improved neural network model in forecasting arrivals," *Annals of Tourism Research*, vol. 32, no. 4, pp. 1138–1141, 2005.

[9] S. F. Crone and P. C. Graffeille, "An evaluation framework for publications on artificial neural networks in sales forecasting," in *Proceedings of the International Conference on Artificial Intelligence (IC-AI '04)*, pp. 221–227, Las Vegas, Nev, USA, June 2004.

[10] G. Zhang, B. Eddy Patuwo, and M. Y. Hu, "Forecasting with artificial neural networks: the state of the heart," *The International Journal of Forecasting*, vol. 14, no. 1, pp. 35–62, 1998.

[11] M. Nelson, T. Hill, W. Remus, and M. O'Connor, "Time series forecasting using neural networks: should the data be deseasonalized first?" *Journal of Forecasting*, vol. 18, no. 5, pp. 359–367, 1999.

[12] G. P. Zhang and D. M. Kline, "Quarterly time-series forecasting with neural networks," *IEEE Transactions on Neural Networks*, vol. 18, no. 6, pp. 1800–1814, 2007.

[13] J. Teixeira and P. Fernandes, "Tourism time series forecast with artificial neural networks," *Tékhne*, vol. 12, no. 1-2, pp. 26–36, 2014.

[14] G. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis: Forecasting and Control*, John Wiley & Sons, 2015.

[15] J. Shahrabi, E. Hadavandi, and S. Asadi, "Developing a hybrid intelligent model for forecasting problems: case study of tourism demand time series," *Knowledge-Based Systems*, vol. 43, pp. 112–122, 2013.

[16] X. Li, B. Pan, R. Law, and X. Huang, "Forecasting tourism demand with composite search index," *Tourism Management*, vol. 59, pp. 57–66, 2017.

[17] Y. Kawakubo and T. Kubokawa, “Modified conditional AIC in linear mixed models,” *Journal of Multivariate Analysis*, vol. 129, pp. 44–56, 2014.

[18] C.-F. Chen, M.-C. Lai, and C.-C. Yeh, “Forecasting tourism demand based on empirical mode decomposition and neural network,” *Knowledge-Based Systems*, vol. 26, pp. 281–287, 2012.

[19] O. Claveria and S. Torra, “Forecasting tourism demand to Catalonia: neural networks vs. time series models,” *Economic Modelling*, vol. 36, pp. 220–228, 2014.

[20] N. Davies, J. Pemberton, and J. D. Petruccelli, “An automatic procedure for identification, estimation and forecasting univariate self exiting threshold autoregressive models,” *The Statistician*, vol. 37, no. 2, pp. 199–204, 1988.

[21] H. Constantino, P. Fernandes, and J. Teixeira, “Tourism demand modelling and forecasting with artificial neural network models: the Mozambique case study,” *Tekhen*, vol. 14, no. 2, pp. 113–124, 2016.

[22] C. J. Lin, H. F. Chen, and T. S. Lee, “Forecasting tourism demand using time series, artificial neural networks and multivariate adaptive regression splines: evidence from taiwan,” *International Journal of Business Administration*, vol. 2, no. 2, article no. 14, 2011.

[23] J. M. Bates and C. W. J. Granger, “The combination of forecasts,” *Operational Research Quarterly*, vol. 20, no. 4, pp. 451–468, 1969.

[24] K.-Y. Chen, “Combining linear and nonlinear model in forecasting tourism demand,” *Expert Systems with Applications*, vol. 38, no. 8, pp. 10368–10376, 2011.

[25] S. Shen, G. Li, and H. Song, “Combination forecasts of International tourism demand,” *Annals of Tourism Research*, vol. 38, no. 1, pp. 72–89, 2011.

[26] W. Yan, “Toward automatic time-series forecasting using neural networks,” *IEEE Transactions on Neural Networks and Learning Systems*, vol. 23, no. 7, pp. 1028–1039, 2012.

[27] K. Lin, P. Pai, Y. Lu, and P. Chang, “Revenue forecasting using a least-squares support vector regression model in a fuzzy environment,” *Information Sciences*, vol. 220, pp. 196–209, 2013.

[28] D. Basak, S. Pal, and D. C. Patranabis, “Support vector regression,” *Neural Information Processing-Letters and Reviews*, vol. 11, no. 10, pp. 203–224, 2007.

[29] P.-F. Pai, K.-C. Hung, and K.-P. Lin, “Tourism demand forecasting using novel hybrid system,” *Expert Systems with Applications*, vol. 41, no. 8, pp. 3691–3702, 2014.

[30] H. Yang, L. Lu, and W. Zhou, “A novel optimization sizing model for hybrid solar-wind power generation system,” *Solar Energy*, vol. 81, no. 1, pp. 76–84, 2007.

[31] K. Bogner, F. Pappenberger, and H. L. Cloke, “Technical note: the normal quantile transformation and its application in a flood forecasting system,” *Hydrology and Earth System Sciences*, vol. 16, no. 4, pp. 1085–1094, 2012.

[32] E. B. Dagum, *The X-II-ARIMA Seasonal Adjustment Method*, Seasonal Adjustment and Time Series Staff, Statistics Canada, 1980.

[33] S. Hylleberg, R. F. Engle, C. W. Granger, and B. S. Yoo, “Seasonal integration and cointegration,” *Journal of Econometrics*, vol. 44, no. 1-2, pp. 215–238, 1990.

[34] J. Cunado, L. A. Gil-Alana, and F. P. de Gracia, “Is the US fiscal deficit sustainable?: a fractionally integrated approach,” *Journal of Economics and Business*, vol. 56, no. 6, pp. 501–526, 2004.

[35] W. S. McCulloch and W. Pitts, “A logical calculus of the ideas immanent in nervous activity,” *The Bulletin of Mathematical Biophysics*, vol. 5, no. 4, pp. 115–133, 1943.

[36] M. Minsky and S. Papert, *Perceptrons-Expanded Edition: An Introduction to Computational Geometry*, 1987.

[37] http://www.mlit.go.jp/kankocho/siryou/toukei/shukuhakutoukei.html.

[38] http://www.jnto.go.jp/jpn/statistics/data_info_listing/index.html.

[39] http://admin.taiwan.net.tw/statistics/year.aspx?no=134.

A Cold Start Context-Aware Recommender System for Tour Planning Using Artificial Neural Network and Case Based Reasoning

Zahra Bahramian,[1] Rahim Ali Abbaspour,[1] and Christophe Claramunt[2]

[1] School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran, North Kargar Ave., After Jalal Al Ahmad Crossing, Tehran 11155-4563, Iran
[2] Naval Academy Research Institute, Brest, France

Correspondence should be addressed to Rahim Ali Abbaspour; abaspour@ut.ac.ir

Academic Editor: Salvatore Carta

Nowadays, large amounts of tourism information and services are available over the Web. This makes it difficult for the user to search for some specific information such as selecting a tour in a given city as an ordered set of points of interest. Moreover, the user rarely knows all his needs upfront and his preferences may change during a recommendation process. The user may also have a limited number of initial ratings and most often the recommender system is likely to face the well-known cold start problem. The objective of the research presented in this paper is to introduce a hybrid interactive context-aware tourism recommender system that takes into account user's feedbacks and additional contextual information. It offers personalized tours to the user based on his preferences thanks to the combination of a case based reasoning framework and an artificial neural network. The proposed method has been tried in the city of Tehran in Iran. The results show that the proposed method outperforms current artificial neural network methods and combinations of case based reasoning with k-nearest neighbor methods in terms of user effort, accuracy, and user satisfaction.

1. Introduction

Nowadays, huge amounts of tourism information are available over the Web. Such information may be helpful for a given user who plans to visit an unknown region. However, it is often overwhelming and time consuming for the user to look through all the available information in order to find out some relevant places of interest and to organize them in a sort of well-defined tour. Hence, irrelevant information should be filtered and personalized options should be extracted according to the user's preferences.

Recommender systems (RSs) can be roughly defined as information filtering and decision support tools that provide products and services that match user's preferences [1–3]. Such recommender systems limit the information overload, provide personalized content, and increase systems usability as adapted to the problem [4–8]. Most of current recommender systems assume that user's preferences do not change whatever the context [9, 10]. However, in the case of a recommender system applied to the tourism domain, user's preferences can be affected by many contextual factors that should be particularly considered when providing recommendations. For instance, when considering the user interest for a given point of interest (POI), many additional contextual parameters such as user's own mobility, previous history, and the timing of a recommendation should be considered as important contextual information. Hence, in order to provide satisfactory services to the final users, a context-aware tourism recommender system should be used in order to automatically adapt the recommendations to changing contexts [11–13]. In other words, context-aware tourism recommender systems should incorporate contextual information into the recommendation process to appropriately model and predict the user preferences. Moreover, they should adapt these recommendations not only to the user's preferences but also to the contextual situation to generate more relevant suggestions.

However, and to the best of our knowledge, previous context-aware tourism recommender systems developed so far have not completely addressed these issues [9, 11–28]. One weakness of these researches is that they often suggest to a given user a list of POIs, which are specific tourist attractions that a user may find interesting such as a historical or cultural buildings or any places worth being visited, rather than a tour as an ordered set of POIs. Moreover, and despite the fact that collaborative recommendations are often provided based on other users, self-learning processes based on the context and assessment of a given user are not taken into account. Also, another common drawback of related context-aware tourism recommender systems is that they generally offer suggestions to a given user in one single session only. Indeed, most of the users rarely know all their needs at first. Therefore, initial recommendations are likely to be not always satisfactory. Moreover, most current context-aware tourism recommender systems often suffer from the cold start problem which occurs when a new user with little prior ratings has been registered to the system, making it difficult to suggest meaningful recommendations for that new user. They also assume that the user's preferences are stable and do not take into account user's preferences variations over time.

In order to overcome these problems, several researchers apply case based reasoning (CBR) [29–31] to develop case based recommender systems that present user's preference as a query item that he likes and each item case as a set of attributes [32–34]. These systems retrieve items that are similar to the user's query case. The main advantages of CBR is that (a) it can be directly applied to learn the user profile at the user modeling level, (b) it has the ability to learn the dynamic behavior of the system over time, and (c) it can provide effective explanation mechanisms when a sufficient number of previous cases are available.

However, an important issue still left for CBR is how to predict tours' ratings in order to recommend the most top rated tours to a user. In other words, some features are more important than the others, and then appropriate feature weighting should be executed before any rating prediction in order to take into account each feature relative importance. In existing case based recommender systems, the k-nearest neighbor (KNN) method [35] is widely used in rating prediction [32, 33], but it assumes that all selected features are equally important, this being not true in many cases as, for instance, each POI type is likely to have a specific interest value. Another open problem is how to progressively adapt the user model based on the information derived from the difference identified between a selected tour and the other tours in order to suggest a tour in a next cycle.

These problems lead us to proposing a hybrid method that combines an artificial neural network (ANN) [36, 37] with CBR. Our research develops a cold start context-aware recommender system applied to the tourism domain that offers personalized tours to the user based on his preferences and some contextual information. Our objective is to overcome the above-mentioned problems by considering user's feedback and applying CBR using an ANN. The contributions of this paper include (1) providing a tourism recommender system that considers contextual situations in the recommendation process; (2) proposing an interactive framework that considers user's feedback to (a) suggest tours to a user with limited knowledge about his own needs, (b) overcome the cold start problem which occurs when a new user with little prior ratings uses the system, and (c) take into account user's preferences variations; (3) recommending some tours to the users including both POIs and routes between them over the street network; and (4) proposing tours to the user taking into account only his own preferences and feedbacks without considering the preferences and feedbacks of other users.

The rest of this paper is as follows. Section 2 introduces several concepts from recommender to context-aware recommender systems. It also briefly reviews context-aware recommender systems applied to the tourism domain. Then it presents the principles behind CBR and ANN and a brief introduction to semantic similarity principles. The proposed method and its implementation results are explained in Sections 3 and 4, respectively. Finally, Section 5 provides conclusions and outlines future works.

2. Literature Review

This section describes several basic concepts on recommender and context-aware recommender systems with a specific focus on the tourism domain. The main principles behind CBR, ANN, and property-based semantic similarity are briefly discussed.

2.1. Recommender Systems. Recommender systems (RSs) select some items proven to better match user's preferences and reduce information overload [4, 5, 38]. Without loss of generality, let us categorize current recommendation approaches towards content-based recommender systems, collaborative recommender systems, knowledge-based recommender systems, and hybrid recommender systems. They are discussed below.

Content-based recommender systems derive the similarity of features with respect to user's preferences and select the ones that best match user's preferences [39]. *Collaborative recommender systems* make recommendations based on the preferences of similar users [3, 40]. *Knowledge-based recommender systems* apply reasoning mechanisms to make appropriate suggestions according to user's preferences as related to items properties [41–43]. An interactive recommender system can be also considered as a knowledge-based recommender system. Navigation-by-proposing is one form of interactive recommender systems that are based on preference-based feedback [44–46]. *Hybrid recommender systems* apply a combination of current recommendation techniques. The main idea behind hybrid recommender systems is to exploit the advantages of one technique to compensate for the shortcomings of another and improve the overall performance [47]. A metalevel hybrid recommender system is a class of hybrid recommender system that uses the model learned by one recommender system as an input for another [47].

2.2. Context-Aware Recommender Systems. Context may be defined as any additional information that can be used to characterize the location and properties of a given entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves [48]. In context-aware recommender systems (CARSs), the ratings are as a function of not only items and users, but also of contextual attributes whose role can be roughly formalized as follows [10, 49]:

$$R\colon \text{user} \times \text{item} \times \text{context} \longrightarrow \text{rating}, \qquad (1)$$

where user, item, and context denote the considered modeling dimensions while rating returns the value of the considered item for that user according to the context.

2.3. Context-Aware Recommender Systems in the Tourism Domain. Several context-aware recommender systems have been developed so far in the tourism application domain. One of the early mobile examples in the tourism domain is the Cyberguide project [14]. The Cyberguide offers several tour guide prototypes for handheld devices where contextual information on the user surroundings is provided on request. Contextual knowledge of the user's current and past locations are taken into account to generate user daily histories. GeoWhiz [22] proposes a mobile restaurant recommender system that uses a collaborative filtering approach based on user locations. Magitti [16] offers a mobile leisure guide system where a user context is detected. It infers current and possible future leisure activities of interest and recommends suitable venues to the users (e.g., stores, restaurants, parks, and cinemas). It offers a sort of context-aware system that considers time and location and additional context data such as weather and venues opening hours, as well as previous user patterns. It is also activity-aware and filters items not matching the users or explicitly specified activities. Reference [9] develops a location-based service recommendation model (LBSRM) that integrates location and user preferences to recommend the most appropriate hotels to the user. User preferences are taken into account thanks to an adaptive method including long-term and short-term preference adjustments.

Reference [15] proposes a hybrid mobile context-aware system to personalize POIs recommendations. POIs located within a radius around the user's location and based on the user's trajectory and speed are suggested. Contextually filtered POIs are filtered and selected according to the user's preferences. The mobile tourism recommendation system (MTRS) developed by [20] delivers several personalized recommendation services to mobile users, considering contextual information such as the user's location, current time, weather conditions, and POIs already visited by the users. The iTravel system [27] applies a collaborative filtering approach. The similarities between users are evaluated using the user rating lists. Nearby users are detected and rating data are exchanged using mobile peer-to-peer communications. I'm feeling Loco [13] is a ubiquitous location-based sites recommendation. It uses the user's preferences derived from the Foursquare location-based social network, the user's location, the used transport modes (e.g., walking, bicycle, or car), and the current user feeling in recommendation process. ReRex [11] assesses and models the relationship between contextual factors and item ratings. Using a predictive model based on matrix factorization, ReRex recommends POI and suggests a complete itinerary according to a particular itinerary's context.

SigTur/E-Destination [25] provides personalized recommendations applied to tourism activities. It considers different kinds of data including demographic information and travel motivations and takes into account user actions and ratings to generate recommendations. The approach is based on a tourism domain ontology that favors the classification of user activities. The reasoning process also combines content-based and collaborative recommendations. TRIPBUILDER [17] suggests personalized city sightseeing tours. POIs are derived from Wikipedia and illustrated by Flickr georeferenced photos. Tours are inferred from POI travel times as inferred from Google maps and a Traveling Salesman Problem algorithm that minimizes travel times and maximizes user's interests. POIs are categorized and semantically described by their popularity and average visiting time and further enriched by patterns of tourist movements.

In [26], tourist locations of interest are derived from their proximity to Flickr geotagged photos, semantically contextualized according to their related season and weather context, and finally rated in order to recommend some POIs. Travel histories are then derived and annotated in a sort of topic-based model, this favoring the search for user similarities. Reference [21] develops a probabilistic topic model to recommend POIs, based on user's interests as well as the ones of socially related users.

POST-VIA 360 [19] assists tourists in previsit, during-visit, and postvisit stages of their travels by means of a customer relationship management (CRM) approach. Geolocated POIs are classified and recommended thanks to an artificial immune system (AIS) that successively rates the POIs according to user rating. PlanTour [18] generates personalized oriented multiple-day tourist plans. The POIs are identified from a Minutube traveling social network and clustered over a daily basis. Tourist plans maximize the user utility and POIs travel distance. Reference [28] mines multiple periods in the time sequence to calculate the user's period of arriving at a certain area. Then they use item-based collaborative filtering for recommending locations based on users' preference and the periodic behaviors.

Table 1 summarizes such context-aware recommender systems as applied to the tourism domain according to a series of preselected criteria. The previous context-aware recommender systems in tourism domain apply single-shot recommendation strategy and return a single set of suggestions to a given user in one session only. They do not consider the user feedback in an interactive recommender system in tourism domain. Moreover, they are unable to propose recommendations to a user that has limited knowledge about his needs, or little prior ratings, or changing preferences during the time. In addition, none of the previous context-aware RSs in tourism domain recommend tours as sequences of POIs to the user.

Table 1: Context-aware recommender systems applied to the tourism domain.

Recommender system	Context-aware properties							Recommender System properties											
	Used context				Context-aware recommendation			Recommended Item						Recommendation technique				User feedback	
	User	Environment	Location	Time	Contextual prefiltering	Contextual postfiltering	Contextual modeling	POI	Hotel	Restaurant	Leisure	Route	Tour	Content-based	Collaborative	Knowledge-based	Hybrid	Yes	No
Cyberguide [14]	√		√	√		√		√						√				√	
GeoWhiz [22]	√	√	√		√					√					√				√
Magitti [16]	√	√	√	√			√				√						√	√	
LBSRM [9]	√	√	√		√				√					√				√	
MTRS [20]	√	√	√	√			√	√							√			√	
REJA [15]	√		√	√	√					√				√					√
I'm feeling Loco [13]	√		√	√	√			√						√					√
ReRex [11]	√	√	√	√			√	√							√			√	
iTravel [27]	√		√			√		√							√				√
SigTur/E-Destination [25]	√	√	√			√	√	√									√	√	
TRIPBUILDER [17]	√	√	√	√			√					√		√					√
[26]	√	√	√	√		√		√							√				√
SocoTraveler [21]	√	√	√				√	√							√				√
POST-VIA 360 [19]	√	√	√				√	√							√			√	
PlanTour [18]	√	√	√	√	√			√							√				√
[28]	√	√	√	√		√	√	√							√				√

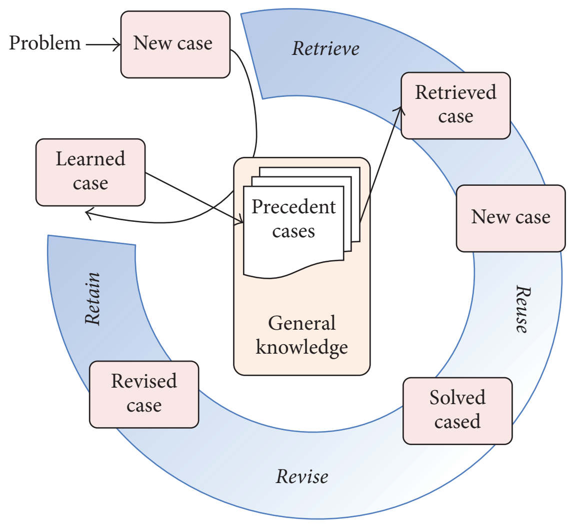


FIGURE 1: Case based reasoning cycle.

2.4. Case Based Reasoning. Case Based Reasoning (CBR) is a machine learning method that models human reasoning processes for learning and problem solving. A CBR stores past cases as a historical repository. Each case consists of two parts including the problem description and the solutions [29, 50, 51]. The problem description represents the context, that is, when the case takes place, while the solution part shows the methods applied to resolve the case. The objective of CBR is to solve new problems using solutions that were used to address similar problems [30, 31]. The structural CBR approach is one type of case representation that represents cases according to a common structured vocabulary using predefined attributes and values [52]. CBR generally involves four steps [53]: (1) retrieving similar previously experienced cases, (2) reusing cases by copying or integrating the emerging solutions from the retrieved cases, (3) revising or adapting the retrieved solutions to solve a new problem, and (4) retaining a new confirmed or validated solution (Figure 1).

2.5. Artificial Neural Network. Artificial Neural Network (ANN) [36, 37] is a branch of artificial intelligence inspired by the biological brain. It is a structure of connected nodes (i.e., artificial neurons) that are arranged in layers. The links between nodes have weights associated with them depending on the amount of influence one node has on another. A feedforward ANN is an ANN without any cycles in the network and propagates incoming data in a forward direction only. A multilayer perceptron (MLP) is one type of feedforward ANNs with full connection of each layer to the next one. The MLP consists of one input layer, one or more hidden layers, and one output layer. Nodes in the input layer respond to data that is fed into the network, while output nodes produce network output values. Hidden nodes receive the weighted output from the previous layer's nodes. Figure 2 shows the $n_{\text{input}}-n_{\text{hidden}}-n_{\text{output}}$ (n_{input} denotes input neurons, n_{hidden} denotes hidden neurons, and n_{output} denotes output neurons) architecture of a feedforward multilayer perceptron ANN.

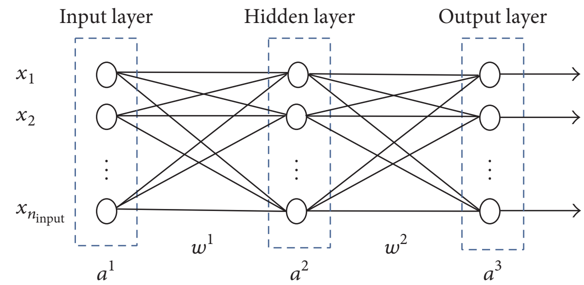


FIGURE 2: Structure of a feedforward neural network.

The output of unit i in layer $l+1$ is

$$a^{l+1}(i) = f^l\left(\sum_{j=1}^{n_l} w^l(i,j)\,a^l(j) + b^l(i)\right). \qquad (2)$$

The most common concrete algorithm for learning MLP is the backpropagation algorithm. In the backpropagation algorithm, the computed output values are compared with the correct output values to compute the value of error function. Then, the error is fed back through the network. The derivatives of the error function with respect to the network weights are calculated. The weights of each connection are adjusted using gradient descent method such that the value of the error function decreases. This process is repeated until the network converges to a state with small error.

Different training algorithms have been so far applied to train a backpropagation MLP. Each algorithm adjusts the ANN as follows:

$$w_k = w_{k-1} + \Delta w_k, \qquad (3)$$

where k is the index of iterations, w_k is the vector of weights in k iteration of training algorithm, and Δw_k is the vector of weights changes that is computed by each training algorithm including gradient descent with momentum and adaptive learning rate backpropagation (GDX), resilient backpropagation (RP), conjugate gradient backpropagation with Fletcher-Reeves updates (CGF), conjugate gradient backpropagation with Polak-Ribiere updates (CGP), conjugate gradient backpropagation with Powell-Beale restarts (CGB), scaled conjugate gradient backpropagation (SCG), BFGS quasi-Newton backpropagation (BFG), one-step secant backpropagation (OSS), and Levenberg-Marquardt backpropagation (LM) (Table 2).

2.6. Property-Based Semantic Similarity. The semantic similarity of two objects can be evaluated based on their common features or the lack of distinctive features of each object according to a domain ontology. A feature-based semantic similarity measure is one of the main approaches that evaluate the semantic similarity among concepts [54]. It considers the features of the concepts considered according to the ontology and evaluates the common and distinct features to derive a similarity measure.

Consider objects O_1 and O_2 with n_p properties (p_q, $q = 1, 2, \ldots, n_p$). Using Tversky's formulation, the similarity

TABLE 2: Algorithms for training backpropagation multilayer perceptron neural network.

Training algorithm	Description
GDX	It renovates weight and bias values conceding to the gradient descent and current trends in the error surface (ΔE_k) with adaptive training rate. $$\Delta w_k = p\Delta w_{k-1} + \alpha p \frac{\Delta E_k}{\Delta w_k}.$$
RP	It considers only the sign of the partial derivative to determine the direction of the weight update and multiplies it with the step size (Δ_k). $$\Delta w_k = -\operatorname{sign}\left(\frac{\Delta E_k}{\Delta w_k}\right)\Delta_k.$$
CGF	The vector of weights changes is computed as $$\Delta w_k = \alpha_k p_k,$$ where p_k is the search direction that is computed as $$p_k = \begin{cases} -g_0, & k = 0, \\ -g_k + \beta_k p_{k-1}, & k \neq 0, \end{cases}$$ where the parameter β_k is computed as $$\beta_k = \frac{g_k^T g_k}{g_{k-1}^T g_{k-1}}.$$
CGP	The vector of weights changes is computed as $$\Delta w_k = \alpha_k p_k,$$ where p_k is the search direction that is computed as $$p_k = \begin{cases} -g_0, & k = 0, \\ -g_k + \beta_k p_{k-1}, & k \neq 0, \end{cases}$$ where the parameter β_k is computed as $$\beta_k = \frac{g_{k-1}^T g_k}{g_{k-1}^T g_{k-1}}.$$
CGB	The search direction is reset to the negative of the gradient only if there is very little orthogonality between the present gradient and the past gradient as explained in this condition. $$\left|g_{k-1}^T g_k\right| \geq 0.2\left\|g_k\right\|^2.$$
SCG	It denotes the quadratic approximation to the error E in a neighborhood of a point w by $$E_{qw}(y) = E(w) + E'(w)^T y + \frac{1}{2} y^T E''(w)\, y.$$ To minimize $E_{qw}(y)$, the critical points for $E_{qw}(y)$ are found as the solution to the following linear system: $$E'_{qw}(y) = E''(w)y + E'(w) = 0.$$
BFG	The vector of weights changes is computed as $$\Delta w_k = -H_k^T g_k,$$ where H_k is the Hessian (second derivatives) matrix approximated by B_k as $$B_k = B_{k-1} + \frac{y_{k-1} y_{k-1}^T}{y_{k-1}^T \Delta x_{k-1}} - \frac{B_{k-1}\Delta x_{k-1}\left(B_{k-1}\Delta x_{k-1}\right)^T}{\Delta x_{k-1}^T B_{k-1} \Delta x_{k-1}}.$$
OSS	It generates a sequence of matrices $G^{(k)}$ that represents increasingly accurate approximations to the inverse Hessian (H^{-1}). The updated expression uses only the first derivative information of E as follows: $$G^{(k+1)} = G^{(k)} + \frac{pp^T}{p^T v} - \frac{\left(G^{(k)} v\right) v^T G^{(k)}}{v^T G^{(k)} v} + \left(v^T G^{(k)} v\right) uu^T,$$ where $$p = w^{(k+1)} - w^{(k)},$$ $$v = g^{(k+1)} - g^{(k)},$$ $$u = \frac{p}{p^T v} - \frac{G^{(k)} v}{v^T G^{(k)} v},$$ and g is the transfer function. It does not store the complete Hessian matrix and assumes that the previous Hessian was the identity matrix at each iteration.
LM	The vector of weights changes is computed as $$\Delta w_k = -\left(J_k^T J_k + \mu I\right)^{-1} J_k e_k,$$ where combination coefficient μ is always positive, I is the identity matrix, J_k is Jacobian matrix (first derivatives), and e_k is network error.

between two objects is given by a feature-based semantic similarity calculation method as follows [54, 55]:

$$\mathrm{SIM}(O_1, O_2) = \sum_{q=1}^{n_p} w_q \mathrm{SIM}_{p_q},$$
$$\mathrm{SIM}_{p_q} = \frac{\alpha \mathrm{CF}_{p_q}(O_1, O_2)}{\beta \mathrm{CF}_{p_q}(O_1) + \gamma \mathrm{CF}_{p_q}(O_2) + \alpha \mathrm{CF}_{p_q}(O_1, O_2)}, \quad (4)$$

where $\mathrm{CF}_{p_q}(O_1)$, $\mathrm{CF}_{p_q}(O_2)$, and $\mathrm{CF}_{p_q}(O_1, O_2)$ denote the common features of O_1 and O_2, distinctive features of O_1, and distinctive features of O_2 with respect to property p_q, respectively. w_q assigns the relevance amount of the property p_q and $\alpha, \beta, \gamma \in \mathbb{R}$ are constants that value the respective importance of the features considered.

3. Proposed Methodology

The objective of this paper is to consider the user feedbacks and develop a hybrid interactive context-aware recommender system applied to the tourism domain that offers personalized tours to a user based on his preferences. The proposed method combines an interactive tourism recommender system designed as a knowledge-based recommender system with a content-based tourism recommender system thanks to applying CBR and ANN.

The proposed method takes into account contextual information in the modeling process as a contextual modeling approach whose objective is to recommend the most appropriate tours to a user. It takes into account contextual information as follows:

(i) POIs locations in the user's environment

(ii) POIs opening and closing times

(iii) the street network

(iv) the tours already visited by the user denoted as his mobility history

(v) the distance traveled by the user on the street network.

Moreover, the rating assigned to the visited tours by the user and user's feedbacks are considered as user preferences and feedbacks, respectively. The following subsections develop the problem formulation and the proposed context-aware tourism recommender system.

3.1. Problem Formulation. In this paper, each tour is modeled as a sequence of POIs. A POI is a specific tourist attraction or place of interest that a user may find of value. Pois denotes the set of all POIs located in the case area as

$$\mathrm{Pois} = \left\{\mathrm{poi}_1, \mathrm{poi}_2, \ldots, \mathrm{poi}_{n_{\mathrm{poi}}}\right\}, \quad (5)$$

where n_{poi} is the total number of POIs that are located in the case area.

The proposed method considers n_{type} POI types such as restaurant and cultural place types. Each POI belongs to one of these types. Let Types denote the set of all POI types available in the case area as

$$\mathrm{Types} = \left\{\mathrm{tp}_1, \mathrm{tp}_2, \ldots, \mathrm{tp}_{n_{\mathrm{type}}}\right\}. \quad (6)$$

The function FuncType returns the type of a given POI as

$$\mathrm{FuncType}\colon \mathrm{Poi} \longrightarrow \mathrm{Type}. \quad (7)$$

A Tour_i is a nonempty nonrepetitive sequence of POIs that a user visits:

$$\mathrm{Tour}_i = \{\mathrm{tr}_{i1}, \mathrm{tr}_{i2}, \ldots, \mathrm{tr}_{in}\}, \quad (8)$$

where n is the number of POIs in Tour_i and tr_{ij} is a POI ($\mathrm{tr}_{ij} \in$ Pois, $j = 1, 2, \ldots, n$) in such a way that $\forall l \neq m$: $\mathrm{tr}_{il} \neq \mathrm{tr}_{im}$.

tm_{ij} ($j = 1, 2, \ldots, n$) denotes the time that a user starts visiting tr_{ij}. Without loss of generality, let us introduce a constraint to illustrate the potential of the approach. The proposed method also assumes that the dinning time is between 12 am and 2 pm. Therefore, if the start time of visiting a POI in a tour is between 12 am and 2 pm, the mentioned POI must be located in "Restaurant" type.

$$\begin{aligned} &\text{if} \quad 12\ \mathrm{am} \leq \mathrm{tm}_{ij} \leq 2\ \mathrm{pm}, \\ &\text{then} \quad \mathrm{FuncType}\left(\mathrm{tr}_{ij}\right) = \text{“Restaurant”}. \end{aligned} \quad (9)$$

Then Tours denotes the set of all possible tours considering the mentioned constraints that is given as

$$\mathrm{Tours} = \left\{ \bigcup_{\text{possible tours}} \mathrm{Tour}_i \right\}. \quad (10)$$

The user can assign a rating to each visited tour which is then stored in his history. The rating values are in the unit interval $[0, 1]$ and reflect the user's need. The tour with the highest rating will be the most interesting one. The FuncRank function returns Rating_i as the rating of Tour_i.

$$\begin{aligned} &\mathrm{FuncRate}\colon \mathrm{Tours} \longrightarrow [0, 1] \\ &\mathrm{Rating}_i = \mathrm{FuncRate}\left(\mathrm{Tour}_i\right). \end{aligned} \quad (11)$$

For each $\mathrm{Tour}_i = \{\mathrm{tr}_{i1}, \mathrm{tr}_{i2}, \ldots, \mathrm{tr}_{in}\}$, P_i is computed as

$$P_i = \left(p_{i1}, p_{i2}, \ldots, p_{in_{\mathrm{type}}}, \mathrm{TourDistance}_i\right), \quad (12)$$

where p_{ij} ($j = 1, 2, \ldots, n_{\mathrm{type}}$) denotes the number of POIs in Tour_i that are located in tp_j POI type; $\mathrm{TourDistance}_i$ denotes the distance traveled in Tour_i that is the sum of distances between each two consecutive POIs in Tour_i on the street network and computed as

$$\mathrm{TourDistance}_i = \sum_{j=1}^{n-1} \mathrm{Dist}\left(\mathrm{tr}_{ij}, \mathrm{tr}_{i(j+1)}\right), \quad (13)$$

where $\mathrm{Dist}(\mathrm{tr}_{ij}, \mathrm{tr}_{i(j+1)})$ is the shortest path between tr_{ij} and $\mathrm{tr}_{i(j+1)}$ on the street network.

3.2. Proposed Context-Aware Tourism Recommender System. Our objective is to develop a context-aware tourism recommender system that suggests the highest rated tours to a user based on his preferences. We assume that the user does not know a priori the types of POIs he would like to visit, and that he has little prior knowledge of possible recommended tours. The system asks the user to assign the starting time and the ending time of his requested tour. The proposed method first considers the user's mobility history and his interactions with the system to capture user's preferences. The proposed interactive tour recommender system is developed in three successive steps.

Step 1. The system learns the current user model and recommends n_{show} new tours to the user based on the current user model and some contextual information.

Step 2. The user selects (or rejects) a tour among the recommended tours and assigns a rating to it as a feedback. The feedback on the selected tour elicits the user's needs. This feedback is case based rather than feature-based.

Step 3. The system revises the user model for the next cycle using information about the selected tour and n_{similar} similar tours.

The recommendation process finishes either after the presentation of a suitable tour to the user or after some predefined iterations.

In order to implement this interactive tour recommender system, the system applies the CBR method as a knowledge-based filter. It develops a structural case representation that each case consists of a tour and its related rating. Each tour is considered as a problem description while its rating is the problem solution. CBR stores a history of the visited tours and their related ratings as previous cases. When applying the retrieval and reusing stages of a CBR cycle, the system uses the previously visited tours and recommends the n_{show} highest rated tours to the user. At the revising stage of a CBR cycle, the user selects or rejects one of the recommended tours and revises its rating by assigning a new rating to it as a feedback. In the retaining stage of CBR cycle, the system adapts the user model to use it in the next cycle.

To overcome the mentioned problems in an interactive case based recommender system, the proposed approach combines an ANN with CBR and actually takes into account the specific properties and values of each tour. We introduce a hybrid recommender system that applies ANN (as a content-based recommender) and CBR (as a knowledge-based recommender) in a homogeneous approach denoted as a metalevel hybrid recommender system. A feedforward multilayer perceptron ANN is used in the retrieval, reusing, and retaining phases of a CBR cycle as follows.

3.2.1. Learning Current User Model and Recommending New Tours. In this step, the proposed ANN is applied to the retrieval and reusing phases of a CBR cycle. The proposed multilayer perceptron neural network is made of 3 layers: an input layer, a hidden layer, and an output layer. For each visited Tour_i, the inputs of the proposed ANN are the elements of P_i. Therefore, the input layer has $(n_{\text{Type}} + 1)$ neurons. The proposed ANN output is the related rating of the tour (Rating_i) and therefore the output layer has one neuron. The system uses the history of the visited tours and their related ratings to train the ANN.

The ANN computes the ratings of all possible tours (Tours) and recommends the n_{show} best computed rated tours to the user, where n_{show} is a system specified constant.

3.2.2. Assigning the User Feedback. The user selects (or rejects) a tour from n_{show} recommended tours and assigns its rating as a feedback. This feedback is used to revise the user model.

3.2.3. Revising the User Model according to His Feedback. In this step, the proposed ANN is still used in the retaining phase of a CBR cycle due to its strong adaptive learning ability. The ANN adapts the user model based on the user's feedback. The similarity of the selected tours with all other tours is computed. Consider two tours $\text{Tour}_i = \{\text{tr}_{i1}, \text{tr}_{i2}, \ldots, \text{tr}_{in}\}$ and $\text{Tour}_j = \{\text{tr}_{j1}, \text{tr}_{j2}, \ldots, \text{tr}_{jn}\}$. The system computes $P_i = (p_{i1}, p_{i2}, \ldots, p_{in_{\text{type}}}, \text{TourDistance}_i)$ and $P_j = (p_{j1}, p_{j2}, \ldots, p_{jn_{\text{type}}}, \text{TourDistance}_j)$. In order to compute the similarity between Tour_i and Tour_j, $\text{SIM}(\text{Tour}_i, \text{Tour}_j)$, the similarity between P_i and P_j is computed using Tversky's feature-based semantic similarity method described in Section 2.6.

$$\text{SIM}\left(\text{Tour}_i, \text{Tour}_j\right) = \sum_{q=1}^{n_{\text{type}}+1} w_q \text{SIM}_{P_q},$$
$$\text{SIM}_{P_q} = \frac{\alpha \text{CF}_{P_q}\left(\text{Tour}_i, \text{Tour}_j\right)}{\beta \text{CF}_{P_q}\left(\text{Tour}_i\right) + \gamma \text{CF}_{P_q}\left(\text{Tour}_j\right) + \alpha \text{CF}_{P_q}\left(\text{Tour}_i, \text{Tour}_j\right)}$$
$$\sim \begin{cases} \min\left(p_{iq}, p_{jq}\right), & q = 1, 2, \ldots, n_{\text{type}}, \\ \min\left(\text{TourDistance}_i, \text{TourDistance}_j\right), & q = n_{\text{type}} + 1. \end{cases} \tag{14}$$

In this paper, we assume $\alpha = \beta = \gamma = 1$.

Therefore, the system determines the n_{similar} most similar tours to the selected tour, where n_{similar} is a system specified constant. It assigns their ratings the same as the selected tour rating. Using new ratings of the selected tour and its similar tours, the system adapts the proposed ANN and updates the weights of the proposed ANN. Therefore, the user model is updated for the next cycle. Accordingly, the system stores the user's feedbacks as new experiences in the memory.

This process is iterated until either a suitable tour is presented to the user or a predefined number of iterations is reached, where the number of iterations is a system specified constant. In fact, too few interaction stages might lead to inaccurate user modeling and recommendations, while on the other hand interacting in too many iteration stages is likely to be a cumbersome user task. In order to provide a good balance, we consider 20 iteration stages. This choice is relatively similar to the ones made by related works and that considered between 10 and 20 iteration stages [56–59].

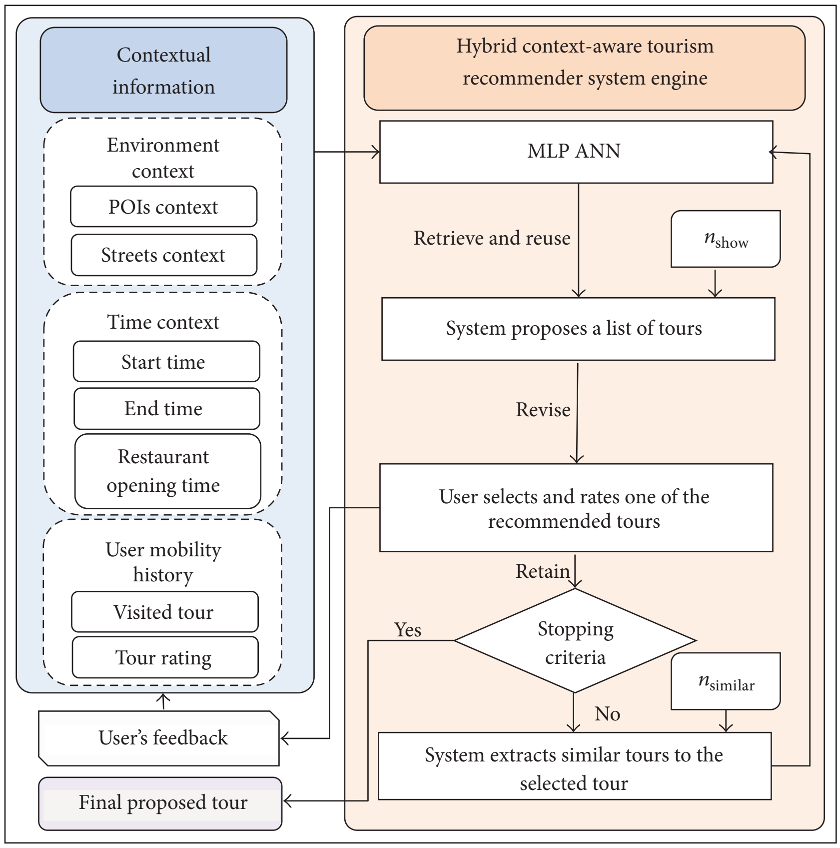


Figure 3: Architecture of the proposed hybrid context-aware recommender system applied to the tourism domain.

The proposed hybrid CBR-ANN approach is used as an interactional tour recommender system by combining content-based recommender system (using ANN) and knowledge-based recommender system (using CBR) (Figure 3). As shown in Figure 3, a supporting database represents the location and type of each POI, streets information, and restaurants' opening times. The system specifies the number of tours that the system recommends to the user at each cycle (n_{show}), the number of the most similar tours to the selected tour that is used in the retaining phase (n_{similar}), and the number of iterations. The user defines the starting and ending times of the required tour to the system and assigns a rating to the selected tour. Algorithm 1 shows the pseudocode of the proposed method.

4. Experimental Results and Discussion

The proposed hybrid context-aware tourism recommender system is evaluated according to the experimental context of a user that wants to plan a tour. The algorithm has been implemented by an Android-based prototype.

4.1. Data Set. The proposed hybrid context-aware tourism recommender system suggests tours to each user who wants to plan a tour in regions 11 and 12 of Tehran, the capital city of Iran. In order to develop the experimental setup, the role of the users has been taken by 20 students in the Surveying and Geospatial Engineering School of the University of Tehran. In the two regions considered, there are 55 POIs. Each POI belongs to one of the eleven POI types identified ($n_{\text{type}} = 11$) including hotel, cultural place, museum, shopping center, mosque, park, theater, cinema, cafe, restaurant, and stadium (Figure 4).

Without loss of generality, a series of assumptions have been considered as follows:

(i) Each tour is a sequence of two to five POIs. It is similar to the one made by several previous works in tourism recommender system [25, 60, 61] that recommend two to five POIs per tour. However, the proposed method can be extended and applied to situations with bigger number of POIs per tour with some minor adaptations.

(ii) The time that a user starts visiting a POI is either 8 am, 10 am, 12 am, 2 pm, or 4 pm ($\text{tm}_{ij} \in \{8\text{ am}, 10\text{ am}, 12\text{ am}, 2\text{ pm}, 4\text{ pm}\}$).

(iii) The user starts to visit a POI ($\text{tr}_{i(j+1)}$) 2 hours after he starts to visit a previous POI (tr_{ij}):

$$\text{tm}_{i(j+1)} = \text{tm}_{ij} + 2\text{ hours}. \quad (15)$$

Initially, each user visits 6 tours in the case area and assigns a rating to each of them by the unit interval. The system saves these ratings in the user's history. To evaluate the

Input: CB_initial is a set of visited tours and their ratings
Output: CB, net, recommendation
CB = CB_initial
net = Train_ANN(CB) //net is a trained ANN using CB
while ~termination criteria
    R = Reuse(CB, net, n_{show}) //System recommends the first n_{show} highest computed rated tours
    S = User_Select(R) //User selects and rates one of the recommended tours
    E = Extract(S, n_{similar}) //System extracts the first n_{similar} prior tours which have maximum similarities with tour S
    net, CB = Retain(net, CB, S, E) //System adapts CB and ANN
end

ALGORITHM 1: Pseudocode of the proposed hybrid context-aware tourism recommender system.

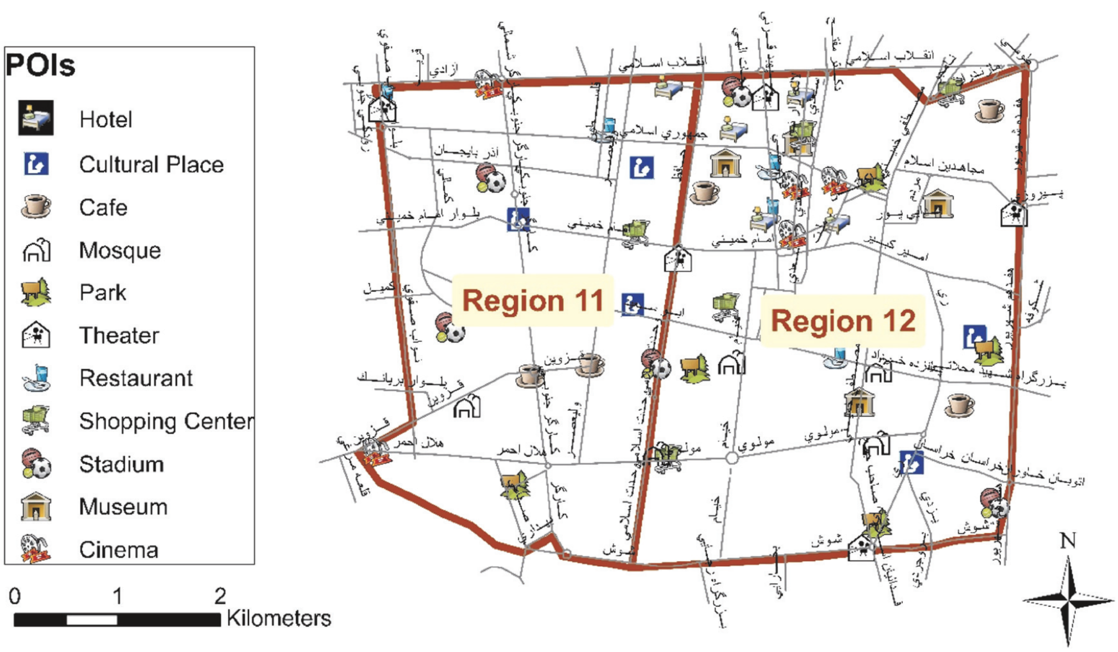


FIGURE 4: Synthetic view of the case study.

proposed context-aware tourism recommender system, some evaluation metrics and methods should be determined.

4.2. Evaluation Metrics and Methods. In order to evaluate the proposed method, the proposed system (CBR-ANN based recommender system) is compared to two other recommender systems including ANN based recommender system and CBR-KNN based recommender system:

(i) The ANN based recommender system is a single-shot content-based recommender system that uses an ANN to learn user profile.

(ii) The CBR-KNN based recommender system is an interactive recommender system that uses CBR method as a knowledge-based filter combined with KNN in the retrieving, reusing, and retaining phases of CBR.

On the other hand, three evaluation metrics are considered to compare CBR-ANN with ANN and CBR-KNN methods including user effort, accuracy_error, and user_satisfaction

(i) user effort: The system needs enough user feedbacks to generate valid recommendations, while without gathering enough user feedbacks this may lead to a poor user model and inaccurate recommendations. The number of user interactions with the system before reaching the final recommendation determines the user effort metric.

(ii) accuracy_error: The accuracy_error denotes the degree to which the recommender system matches the user's preferences. It is evaluated by the difference between the rating given by the system to the final selected tour denoted as $\hat{s}_{\text{final}}$ and the one of the user denoted as s_{final}. The lower the error of accuracy is, the better the method is performing; it is given as follows:

$$\text{accuracy\_error} = \left|\hat{s}_{\text{final}} - s_{\text{final}}\right|. \tag{16}$$

(iii) user_satisfaction: The user_satisfaction is evaluated by determining to which degree the final recommended tour is considered as valid by the user or not. The rating assigned by the user to the final recommended tour (s_{final}) is used as an indicator of user_satisfaction. It is valued by an interval $[0, 1]$, that is, 0 as not satisfied to 1 as satisfied.

$$\text{user\_satisfaction} = s_{\text{final}}. \tag{17}$$

Moreover, to evaluate the proposed method, two different types of evaluation methods are applied including per user and overall evaluation methods:

(i) The per user evaluation method only takes into account the recommendation process of a specific user and computes evaluation metrics for a specific user.

(ii) The overall evaluation method computes average, minimum, and maximum quality over all users. Let UE_i, AE_i, and US_i denote the user effort, accuracy_error, and user_satisfaction of a specific user, respectively. Let n_{user} denote the number of users considered (i.e., 20 in this paper). The mean, minimum, and maximum values of the user effort over all users are computed as follows:

$$\begin{gathered}\text{MeanUE} = \frac{1}{n_{\text{user}}}\sum_{i=1}^{n_{\text{user}}} \text{UE}_i, \\ \text{MinUE} = \min\left(\bigcup_{i=1}^{n_{\text{user}}} \text{UE}_i\right), \\ \text{MaxUE} = \max\left(\bigcup_{i=1}^{n_{\text{user}}} \text{UE}_i\right).\end{gathered} \tag{18}$$

The mean, minimum, and maximum values of the accuracy_error over all users are computed as follows:

$$\begin{gathered}\text{MeanAE} = \frac{1}{n_{\text{user}}}\sum_{i=1}^{n_{\text{user}}} \text{AE}_i, \\ \text{MinAE} = \min\left(\bigcup_{i=1}^{n_{\text{user}}} \text{AE}_i\right), \\ \text{MaxAE} = \max\left(\bigcup_{i=1}^{n_{\text{user}}} \text{AE}_i\right).\end{gathered} \tag{19}$$

The mean, minimum, and maximum values of the user_satisfaction over all users are computed as follows:

$$\begin{gathered}\text{MeanUS} = \frac{1}{n_{\text{user}}}\sum_{i=1}^{n_{\text{user}}} \text{US}_i, \\ \text{MinUS} = \min\left(\bigcup_{i=1}^{n_{\text{user}}} \text{US}_i\right), \\ \text{MaxUS} = \max\left(\bigcup_{i=1}^{n_{\text{user}}} \text{US}_i\right).\end{gathered} \tag{20}$$

After determining the evaluation metrics, an overall evaluation of the figures that emerge from a given user taken as an example is described in the next subsections.

4.3. Per User Evaluation of the Results. For each user, the system learns the current user model and recommends new tours accordingly (Section 4.3.1). Then the user selects one of the recommended tours and assigns a rating to it. The system revises the user model accordingly (Section 4.3.2). After 20 iterations, the final recommendation is presented to the user.

4.3.1. Learning Current User Model and Recommending New Tours. For each user, during the retrieval and reusing stage of a CBR cycle, the proposed ANN takes the history of a given user as an input to determine the relationship between the visited tours and their related ratings. This gives the rationale behind the learning process. The proposed feedforward multilayer perceptron neural network consists of three layers including one input layer, one hidden layer, and one output layer. Herein, eleven POI types are considered. Since the inputs of the proposed neural network are the number of POIs in the tour that are located in each POI type and the distance traveled in the tour, the input layer has twelve neurons. The output layer has one neuron that evaluates the rating of the considered tour.

The optimum number of hidden neurons depends on the problem and is related to the complexity of the input and output mapping, the amount of noise in the data, and the amount of training data available. Too few neurons lead to underfitting, while too many neurons contribute to overfitting. For each user, to obtain the optimal number of neurons in the hidden layer, different ANNs with different hidden neurons number between one and twelve are trained.

In order to train each of the ANNs, the data set is divided into three subsets including training, validation, and test sets. We do consider four tours and their related ratings as training data set, one tour and its related rating as validation data set, and one tour and its related rating as test data set. Then Mean Squared Error (MSE) is computed for training, validation, and test sets. MSE is given by the average squared difference between tour ratings computed by the ANN and assigned by the user. The training set is used to adjust the ANN's weights and biases while the validation set is used to prevent the overfitting problem. At execution, it appears that the MSE on the validation set decreases during the initial phase of

Table 3: Mean Square Error of different neural networks structures for a given user.

Number of neurons in hidden layer	MSE
1	0.018
2	0.022
3	0.067
4	0.029
5	**0.010**
6	0.018
7	0.014
8	0.011
9	0.044
10	0.032
11	0.045
12	0.038

the training. However, when the ANN begins to overfit the training data, the validation MSE begins to rise. The training stops at this point and the weights and biases related to the minimum validation MSE are returned. The MSE on the test data is not used during the ANN training, but it is used to compare the ANNs during and after training.

For ANNs with hidden neurons of a number between one and twelve, the network is trained and the Mean Square Error (MSE) value is computed. Table 3 shows MSE values related to ANNs with different number of hidden neurons for user 1. According to this experiment, it appears that the best multilayer perceptron neural network should have five hidden neurons as reflected by the MSE values for this user.

For each user, once the optimal number of hidden neurons is determined, the ANN is trained using several training algorithms that are used for training the backpropagation ANN. Table 4 shows Mean Square Error of different training algorithms used to train the ANN related to user 1. The results show that the Levenberg-Marquardt (LM) training method is the best training method for user 1 because it has the least MSE value. The trained ANN determines the relationship between the visited tours and their respective recommendation ratings and thus models the user's preferences.

Similar approaches are commonly used to determine the best number of hidden neurons and the best training algorithm for the other users. Table 5 shows the best number of hidden neurons, and the best training algorithm of ANN to learn the current user model. The results show that GDX and LM are most often the best training functions.

4.3.2. Revising the User Model Based on His Feedback. For each user, after training the ANN, the new ratings of the tours are computed using the trained ANN. Therefore, according to the current user model, new n_{show} best rated tours are recommended to the user.

In the revision stage of CBR cycle, the user reviews the recommendations and selects and rates a tour as a feedback. In the retaining stage of CBR cycle, the system revises the user model based on the user's feedback. The system computes the property-based semantic similarity between the selected tour and all other tours, determines the n_{similar} most similar tours to the selected tour, and assigns their ratings according to the selected tour rating. These values are used to adapt the user model for the next cycle by updating the weights of the proposed ANN. Therefore, the system learns from the current user's feedback and uses it to revise the user model. This process is iterated for 20 cycles in order to determine the final recommendation.

4.3.3. Experimental Results for One User. Figures 5 and 6 show the result of the proposed method for user 1 considering $n_{\text{show}} = 4$ and $n_{\text{similar}} = 2$. One can remark that the final selected tour is different from the tours which the user has previously rated. Similar approaches are used for the other users.

Figure 7 shows the rating that user 1 assigns to the selected tour at each cycle. In the first cycle, the proposed ANN recommends four tours and the user selects one of them. The user's rating of the first selected tour is 0.50. In the next cycles, the user selects one of the recommended tours and the system revises the recommendations according to the user feedbacks. The user's rating of the selected tour reaches 0.80 after eleven cycles.

To determine the best recommendation, the parameters of the proposed method should be set.

4.3.4. Setting the Proposed Method Parameters. To evaluate the impact of the proposed method parameters, the proposed system is tried using different n_{show} and n_{similar} values. Table 6 shows the number of iteration steps to reach a stable state of final selected tour for different n_{show} values. The results show that increasing n_{show} reduces the number of required iterations to reach the final selected tour.

Table 7 shows the number of iteration steps to reach a stable state of the final selected tour for different n_{similar} values. The results show that increasing n_{similar} reduces the rating of the final selected tour.

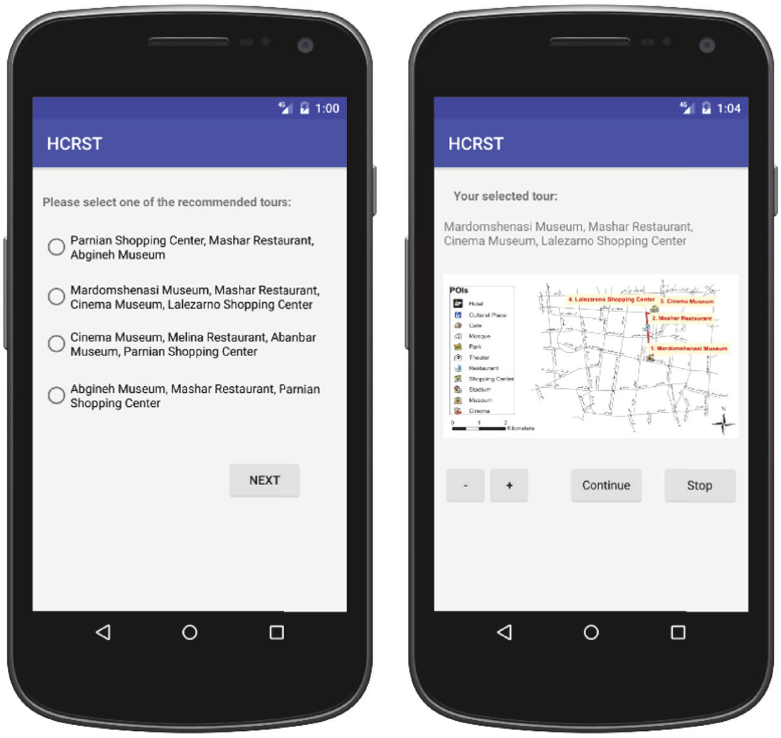
4.3.5. One User Result Evaluation. Table 8 shows the evaluation results of the proposed method for user 1. The experiments show that the user's rating of the selected tour reaches a good value of 0.80 after 11 cycles, 0.5 in one cycle, and 0.70 after 12 cycles in the CBR_ANN, ANN, and CBR_KNN methods, respectively. This indicates that CBR_ANN needs relatively less user effort compared to CBR_KNN. The experimental results show accuracy_error values of the CBR_ANN, ANN, and CBR_KNN methods are 0.01, 0.06, and 0.04, respectively; this outlines a better performance of the CBR_ANN method regarding the accuracy_error metric. Applying the CBR-ANN method increases the user's rating of the selected tour through the cycles by 60% and 14% relative to the ANN and CBR-ANN methods, respectively; this denotes an increasing user_satisfaction.

4.4. Overall Evaluation of the Results. Table 9 shows the overall evaluation results of the proposed method. The results show that the CBR_ANN method needs less user effort than the CBR-KNN method and decreases the mean,

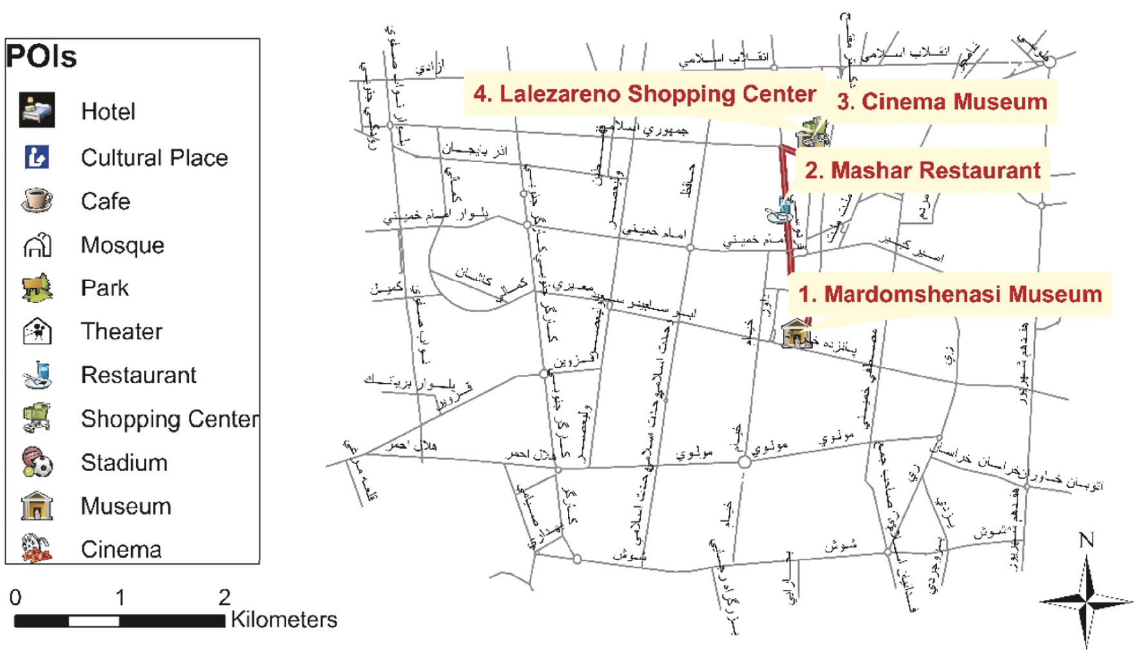
TABLE 4: Mean Square Error of different training algorithms for a given user.

Training algorithm	GDX	RP	CGF	CGP	CGH	SCG	BFG	OSS	*LM*
MSE	0.033	0.033	0.033	0.023	0.013	0.013	0.012	0.012	*0.010*

FIGURE 5: Proposed tour recommendation, (a) the first recommended tours, and (b, c) users' selected tour from the first recommended tours for a given user.



(a) (b)



(c)

Figure 6: Proposed tour recommendation, (a) final recommended tours, and (b, c) users' selected tour from final recommended tours for a given user.

minimum, and maximum values of the users' efforts (i.e., 17%, 33%, and 13%, resp.). Moreover, the results show that the CBR-ANN method outperforms the ANN and CBR_ANN regarding the overall accuracy_error and user_satisfaction metrics. Applying the CBR-ANN method increases the mean, minimum, and maximum values of users' satisfaction of the selected tour by 75%, 140%, and 23% compared to the ANN method, respectively. It also increases the mean,

Table 5: Best number of hidden neurons and training algorithm of ANN to learn the user model.

User number	Best number of hidden neurons	Best training function
1	5	LM
2	8	GDX
3	3	LM
4	5	CGB
5	2	CGB
6	4	BFG
7	5	GDX
8	9	RP
9	8	GDX
10	10	CGF
11	5	CGP
12	7	GDX
13	7	CGF
14	4	SCG
15	8	RP
16	3	LM
17	6	SCG
18	4	LM
19	11	OSS
20	10	RP

Table 6: Rating of the final selected tour and the number of iteration steps to reach the final selected tour considering different n_{show} values.

n_{show}	2	4	10
Final selected tour rating	0.80	0.80	0.80
Number of iterations to reach the final selected tour	19	11	5

Table 7: Rating of final selected tour and the number of iteration steps to reach the final selected tour considering different n_{similar} values.

n_{similar}	1	2	5
Final selected tour rating	0.80	0.80	0.75
Number of iterations to reach final selected tour	17	11	8

Table 8: Per user evaluation of the proposed method for a given user.

Method	UE	AE	US
CBR_ANN	11	0.01	0.80
ANN	1	0.06	0.50
CBR_KNN	12	0.04	0.70

minimum, and maximum values of users' satisfaction of the selected tour by 14%, 33%, and 14% compared to the ANN-KNN method, respectively. Moreover, the CBR-ANN method

Table 9: Overall evaluation of the proposed method.

Method	CBR_ANN	ANN	CBR_KNN
Overall UE			
MeanUE	10	1	12
MinUE	6	1	9
MaxUE	13	1	15
Overall AE			
MeanAE	0.02	0.10	0.08
MinAE	0.01	0.01	0.01
MaxAE	0.07	0.13	0.09
Overall US			
MeanUS	0.70	0.40	0.60
MinUS	0.60	0.25	0.45
MaxUS	0.80	0.65	0.70

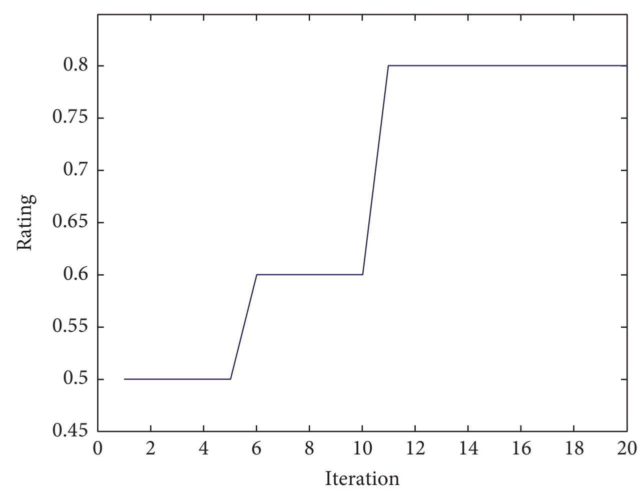


Figure 7: The rating that a given user assigns to the selected tour at each cycle.

has smaller mean and minimum values of accuracy_error relative to the ANN and CBR_KNN methods. This outlines a better performance of the CBR_ANN method regarding the accuracy_error metric.

4.5. Discussion. The proposed tourism recommender system has the following abilities:

(i) It considers contextual situations in the recommendation process including POIs locations, POIs opening and closing times, the tours already visited by the user, and the distance traveled by the user. Moreover, it considers the rating assigned to the visited tours by the user and user's feedbacks as user preferences and feedbacks.

(ii) It takes into account both POIs selection and routing between them simultaneously to recommend the most appropriate tours.

(iii) It proposes tours to a user who has some specific interests. It takes into account only his own preferences and does not need any information about preferences and feedbacks of the other users.

(iv) It is not limited to recommending tours that have been previously rated by users. It computes the ratings of unseen tours that the user has not expressed any opinion about.

(v) The proposed method takes into account the user's feedbacks in an interactive framework. It needs user's feedbacks to apply an interactive learning algorithm and recommend a better tour gradually. Therefore, it overcomes the mentioned cold start problem. The proposed method only needs a small number of ratings to produce sufficiently good recommendations. Moreover, it proposes some tours to a user with limited knowledge about his needs. Thanks to the available knowledge of the historical cases, less knowledge input from the user is required to come up with a solution. Also, it takes into account the changing of the user's preferences during the recommendation process.

(vi) The proposed method uses an implicit strategy to model the user by asking him to assign a rating to the selected tour. Such process requires less user effort relative to when a user assigns a preference value to each tour selection criteria.

(vii) The proposed method recalculates user predicted ratings after he has rated a single tour in a sequential manner. In comparison with approaches in which a user rates several tours before readjusting the model, the user sees the system output immediately. Also, it is possible to react to the user provided data and adjust them immediately.

(viii) The proposed method combines CBR and ANN and exploits the advantages of each technique to compensate for their respective drawbacks. CBR and ANN can be directly applied to the user modeling as a regression or classification problem without more transformation to learn the user profile. Moreover, a noteworthy property of the CBR is that it provides a solution for new cases by taking into account past cases. Also, the trained ANN calculates the set of feature weights, those playing a core role in connecting both learning strategies. The proposed method has the advantages of being adaptable with respect to dynamic situations. As the ANN revises the user model, it has an online learning property and continuously updates the case base with new data.

(ix) The results show that the proposed CBR-ANN method outperforms ANN based single-shot and CBR_KNN based interactive recommender systems in terms of user effort, accuracy_error, and user_satisfaction metrics.

5. Conclusion and Future Works

The research developed in this paper introduces a hybrid interactive context-aware recommender system applied to the tourism domain. A peculiarity of the approach is that it combines CBR (as a knowledge-based recommender system) with ANN (as a content-based recommender system) to overcome the mentioned cold start problem for a new user with little prior ratings. The proposed method can suggest a tour to a user with limited knowledge about his preferences and takes into account the user's preference changing during recommendation process. Moreover, it considers only the given user's preferences and feedbacks to select POIs and the route between them on the street network simultaneously.

Regarding further works, additional contextual information such as budget, weather, user mood, crowdedness, and transportation mode can be considered. Currently, the user has to explicitly rate the tours thus providing feedbacks which can be considered as a cumbersome task. One direction remaining to explore is a one where the system can obtain the user feedbacks by analyzing the user activity, such as saving or bookmarking recommended tour. Moreover, other techniques in content-based filtering (i.e., fuzzy logic) and knowledge-based filtering (i.e., critiquing) can be used. Also, collaborative filtering can be combined to the proposed method.

References

[1] C. C. Aggarwal, *Recommender Systems: The Textbook*, Springer, 2016.

[2] J. Bobadilla, F. Ortega, A. Hernando, and A. Gutiérrez, "Recommender systems survey," *Knowledge-Based Systems*, vol. 46, pp. 109–132, 2013.

[3] F. Ricci, B. Shapira, and L. Rokach, *Recommender Systems Handbook*, 2nd edition, 2015.

[4] J. Borràs, A. Moreno, and A. Valls, "Intelligent tourism recommender systems: a survey," *Expert Systems with Applications*, vol. 41, no. 16, pp. 7370–7389, 2014.

[5] D. Gavalas, V. Kasapakis, C. Konstantopoulos, K. Mastakas, and G. Pantziou, "A survey on mobile tourism Recommender Systems," in *Proceedings of the 3rd International Conference on Communications and Information Technology, ICCIT 2013*, pp. 131–135, June 2013.

[6] W.-J. Li, Q. Dong, and Y. Fu, "Investigating the temporal effect of user preferences with application in movie recommendation," *Mobile Information Systems*, vol. 2017, Article ID 8940709, 10 pages, 2017.

[7] K. Zhu, X. He, B. Xiang, L. Zhang, and A. Pattavina, "How dangerous are your Smartphones? App usage recommendation with privacy preserving," *Mobile Information Systems*, vol. 2016, Article ID 6804379, 10 pages, 2016.

[8] K. Zhu, Z. Liu, L. Zhang, and X. Gu, "A mobile application recommendation framework by exploiting personal preference with constraints," *Mobile Information Systems*, vol. 2017, Article ID 4542326, 9 pages, 2017.

[9] M.-H. Kuo, L.-C. Chen, and C.-W. Liang, "Building and evaluating a location-based service recommendation system

with a preference adjustment mechanism," *Expert Systems with Applications*, vol. 36, no. 2, pp. 3543–3554, 2009.

[10] G. Adomavicius and A. Tuzhilin, "Context-aware recommender systems," in *Recommender Systems Handbook*, pp. 217–253, Springer, 2011.

[11] L. Baltrunas, B. Ludwig, S. Peer, and F. Ricci, "Context relevance assessment and exploitation in mobile recommender systems," *Personal and Ubiquitous Computing*, vol. 16, no. 5, pp. 507–526, 2012.

[12] H. Huang and G. Gartner, "Using context-aware collaborative filtering for POI recommendations in mobile guides," in *Advances in Location-Based Services*, Lecture Notes in Geoinformation and Cartography, pp. 131–147, 2012.

[13] N. S. Savage, M. Baranski, N. E. Chavez, and T. Höllerer, "I'm feeling LoCo: a location based context aware recommendation system," in *Advances in Location-Based Services*, Lecture Notes in Geoinformation and Cartography, pp. 37–54, Springer, Berlin, Germany, 2012.

[14] G. D. Abowd, C. G. Atkeson, J. Hong, S. Long, R. Kooper, and M. Pinkerton, "Cyberguide: a mobile context-aware tour guide," *Wireless Networks*, vol. 3, no. 5, pp. 421–433, 1997.

[15] M. J. Barranco, J. M. Noguera, J. Castro, and L. Martínez, "A context-aware mobile recommender system based on location and trajectory," in *Management Intelligent Systems*, vol. 171 of *Advances in Intelligent Systems and Computing*, pp. 153–162, Springer, Berlin, Germany, 2012.

[16] V. Bellotti, B. Begole, E. H. Chi et al., "Activity-based serendipitous recommendations with the magitti mobile leisure guide," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '08)*, pp. 1157–1166, ACM, Florence, Italy, April 2008.

[17] I. R. Brilhante, J. A. Macedo, F. M. Nardini, R. Perego, and C. Renso, "On planning sightseeing tours with TripBuilder," *Information Processing and Management*, vol. 51, no. 2, pp. 1–15, 2015.

[18] I. Cenamor, T. de la Rosa, S. Núñez, and D. Borrajo, "Planning for tourism routes using social networks," *Expert Systems with Applications*, vol. 69, pp. 1–9, 2017.

[19] R. Colomo-Palacios, F. J. García-Peñalvo, V. Stantchev, and S. Misra, "Towards a social and context-aware mobile recommendation system for tourism," *Pervasive and Mobile Computing*, vol. 38, pp. 505–515, 2017.

[20] D. Gavalas and M. Kenteris, "A web-based pervasive recommendation system for mobile tourist guides," *Personal and Ubiquitous Computing*, vol. 15, no. 7, pp. 759–770, 2011.

[21] J. He, H. Liu, and H. Xiong, "SocoTraveler: Travel-package recommendations leveraging social influence of different relationship types," *Information and Management*, vol. 53, no. 8, pp. 934–950, 2016.

[22] T. Horozov, N. Narasimhan, and V. Vasudevan, "Using location for personalized POI recommendations in mobile environments," in *Proceedings of the International Symposium on Applications and the Internet (SAINT '06)*, pp. 124–129, IEEE, Phoenix, Ariz, USA, January 2006.

[23] M. Kenteris, D. Gavalas, and A. Mpitziopoulos, "A mobile tourism recommender system," in *Proceedings of the 15th IEEE Symposium on Computers and Communications (ISCC '10)*, pp. 840–845, IEEE, Riccione, Italy, June 2010.

[24] J. A. Mocholi, J. Jaen, K. Krynicki, A. Catala, A. Picón, and A. Cadenas, "Learning semantically-annotated routes for context-aware recommendations on map navigation systems," *Applied Soft Computing Journal*, vol. 12, no. 9, pp. 3088–3098, 2012.

[25] A. Moreno, A. Valls, D. Isern, L. Marin, and J. Borràs, "SigTur/E-Destination: ontology-based personalized recommendation of Tourism and Leisure Activities," *Engineering Applications of Artificial Intelligence*, vol. 26, no. 1, pp. 633–651, 2013.

[26] Z. Xu, L. Chen, and G. Chen, "Topic based context-aware travel recommendation method exploiting geotagged photos," *Neurocomputing*, vol. 155, pp. 99–107, 2015.

[27] W.-S. Yang and S.-Y. Hwang, "ITravel: a recommender system in mobile peer-to-peer environment," *Journal of Systems and Software*, vol. 86, no. 1, pp. 12–20, 2013.

[28] B. Xu, Z. Ding, and H. Chen, "Recommending locations based on users' periodic behaviors," *Mobile Information Systems*, vol. 2017, Article ID 7871502, 9 pages, 2017.

[29] Y. Guo, J. Hu, and Y. Peng, "Research of new strategies for improving CBR system," *Artificial Intelligence Review*, vol. 42, no. 1, pp. 1–20, 2014.

[30] M. M. Richter, "The search for knowledge, contexts, and Case-Based Reasoning," *Engineering Applications of Artificial Intelligence*, vol. 22, no. 1, pp. 3–9, 2009.

[31] C. K. Riesbeck and R. C. Schank, *Inside Case-Based Reasoning*, Psychology Press, 2013.

[32] L. Chen, G. Chen, and F. Wang, "Recommender systems based on user reviews: the state of the art," *User Modeling and User-Adapted Interaction*, vol. 25, no. 2, pp. 99–154, 2015.

[33] F. Ricci, D. Cavada, N. Mirzadeh, and A. Venturini, "Case-based travel recommendations," *Destination Recommendation Systems: Behavioural Foundations and Applications*, pp. 67–93, 2006.

[34] C.-S. Wang and H.-L. Yang, "A recommender mechanism based on case-based reasoning," *Expert Systems with Applications*, vol. 39, no. 4, pp. 4335–4343, 2012.

[35] D. T. Larose, *Discovering Knowledge in Data: An Introduction to Data Mining*, John Wiley & Sons, 2014.

[36] I. N. da Silva, D. H. Spatti, R. A. Flauzino, L. H. B. Liboni, and S. F. dos Reis Alves, *Artificial Neural Networks: A Practical Course*, Springer, 2016.

[37] J. Heaton, *Introduction to the Math of Neural Networks*, Heaton Research Inc, 2012.

[38] D. Gavalas, C. Konstantopoulos, K. Mastakas, and G. Pantziou, "Mobile recommender systems in tourism," *Journal of Network and Computer Applications*, vol. 39, no. 1, pp. 319–333, 2014.

[39] R. P. Biuk-Aghai, S. Fong, and Y.-W. Si, "Design of a recommender system for mobile tourism multimedia selection," in *Proceedings of the 2nd International Conference on Internet Multimedia Services Architecture and Applications (IMSAA '08)*, pp. 1–6, IEEE, Bangalore, India, December 2008.

[40] F. Martinez-Pabon, J. C. Ospina-Quintero, G. Ramirez-Gonzalez, and M. Munoz-Organero, "Recommending ads from trustworthy relationships in pervasive environments," *Mobile Information Systems*, vol. 2016, Article ID 8593173, 18 pages, 2016.

[41] T. Berka and M. Plößnig, "Designing recommender systems for tourism," in *Proceedings of the 11th International Conference on Information Technology in Travel & Tourism (ENTER '04)*, 2004.

[42] A. Hinze and S. Junmanee, "Travel recommendations in a mobile tourist information system," in *ISTA' 2005, 4th International Conference*, Lecture Notes in Informatics, pp. 89–100, GI edition, 2005.

[43] W. Husain and L. Y. Dih, "A framework of a Personalized Location-based traveler recommendation system in mobile application," *International Journal of Multimedia and Ubiquitous Engineering*, vol. 7, no. 3, pp. 11–18, 2012.

[44] L. McGinty and B. Smyth, “Comparison-based recommendation,” in *ECCBR 2002: Advances in Case-Based Reasoning*, Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), pp. 575–589, 2002.

[45] H. Shimazu, “ExpertClerk: Navigating shoppers' buying process with the combination of asking and proposing,” in *Proceedings of the 17th International Joint Conference on Artificial Intelligence (IJCAI '01)*, pp. 1443–1448, August 2001.

[46] H. Shimazu, “ExpertClerk: A conversational case-based reasoning tool for developing salesclerk agents in e-commerce webshops,” *Artificial Intelligence Review*, vol. 18, no. 3-4, pp. 223–244, 2002.

[47] R. Burke, “Hybrid recommender systems: survey and experiments,” *User Modelling and User-Adapted Interaction*, vol. 12, no. 4, pp. 331–370, 2002.

[48] A. K. Dey, “Understanding and using context,” *Personal and Ubiquitous Computing*, vol. 5, no. 1, pp. 4–7, 2001.

[49] P. M. P. Rosa, J. J. P. C. Rodrigues, and F. Basso, “A weight-aware recommendation algorithm for mobile multimedia systems,” *Mobile Information Systems*, vol. 9, no. 2, pp. 139–155, 2013.

[50] H. Ince, “Short term stock selection with case-based reasoning technique,” *Applied Soft Computing Journal*, vol. 22, pp. 205–212, 2014.

[51] I. Pereira and A. Madureira, “Self-Optimization module for Scheduling using Case-based Reasoning,” *Applied Soft Computing Journal*, vol. 13, no. 3, pp. 1419–1432, 2013.

[52] R. Bergmann, K.-D. Althoff, S. Breen et al., *Developing Industrial Case-Based Reasoning Applications: The INRECA Methodology*, Springer, 2003.

[53] A. Aamodt and E. Plaza, “Case-based reasoning: foundational issues, methodological variations, and system approaches,” *AI Communications*, vol. 7, no. 1, pp. 39–59, 1994.

[54] S. Likavec and F. Cena, “Property-based semantic similarity: what counts?” in *CEUR Workshop Proceedings*, pp. 116–124, 2015.

[55] A. Tversky, “Features of similarity,” *Psychological Review*, vol. 84, no. 4, pp. 327–352, 1977.

[56] K. Christakopoulou, F. Radlinski, and K. Hofmann, “Towards conversational recommender systems,” in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD 2016*, pp. 815–824, San Francisco, Calif, USA, August 2016.

[57] B. Kveton and S. Berkovsky, “Minimal interaction search in recommender systems,” in *Proceedings of the 20th ACM International Conference on Intelligent User Interfaces (IUI '15)*, pp. 236–246, ACM, Atlanta, Ga, USA, April 2015.

[58] T. Mahmood, G. Mujtaba, and A. Venturini, “Dynamic personalization in conversational recommender systems,” *Information Systems and e-Business Management*, vol. 12, no. 2, pp. 213–238, 2014.

[59] T. Mahmood and F. Ricci, “Improving recommender systems with adaptive conversational strategies,” in *Proceedings of the 20th ACM Conference on Hypertext and Hypermedia (HT '09)*, pp. 73–82, ACM, Turin, Italy, July 2009.

[60] E. R. Ciurana Simó, *Development of a Tourism Recommender System*, 2012.

[61] C.-C. Yu and H.-P. Chang, “Personalized location-based recommendation services for tour planning in mobile tourism applications,” in *Proceedings of the 10th International Conference on E-Commerce and Web Technologies (EC-Web '09)*, pp. 38–49, Springer, Linz, Austria, 2009.

Tourism Growth Prediction Based on Deep Learning Approach

Xiaoling Ren,[1] Yanyan Li,[2] JuanJuan Zhao,[3] and Yan Qiang[3]

[1]*College of Economics and Management, Taiyuan University of Technology, Jinzhong 030600, China*
[2]*College of History and Culture, Shanxi University, Taiyuan 030006, China*
[3]*College of Information and Computer, Taiyuan University of Technology, Jinzhong 030600, China*

Correspondence should be addressed to JuanJuan Zhao; zhaojuanjuan@tyut.edu.cn

Academic Editor: M. Irfan Uddin

The conventional tourism demand prediction models are currently facing several challenges due to the excess number of search intensity indices that are used as indicators of tourism demand. In this work, the framework for deep learning-based monthly prediction of the volumes of Macau tourist arrivals was presented. The main objective in this study is to predict the tourism growth via one of the deep learning algorithms of extracting new features. The outcome of this study showed that the performance of the adopted deep learning framework was better than that of artificial neural network and support vector regression models. Practitioners can rely on the identified relevant features from the developed framework to understand the nature of the relationships between the predictive factors of tourist demand and the actual volume of tourist arrival.

1. Introduction

Most countries depend on the tourism sector for economic growth as it creates jobs and contribute about 10.4% to the global gross domestic product (GDP) as at 2019 [1]. Prediction of tourism demand (TD) is one of the critical activities in the tourism sector due to the need for precise forecasts in making certain operational decisions, such as pricing, resources, staff, revenue, and capacity management [2, 3]. Precise TD prediction is also required by the governments to facilitate planning of destination infrastructure, operational flexibility, and environmental quality control [4]. Both quantitative and qualitative techniques are used in TD forecasting. The qualitative techniques depend on intuition, experience, and understanding of a specific destination market and exhibit poor adaptability [5]. They are used mainly in the prediction of tourist arrivals based on historical records and other determinants of tourism volume [6].

Most of the existing studies in TD prediction are based on the quantitative approach; they normally present a model using training data from historical tourist arrival volumes (TAVs) and other TD predictors [7, 8]. Web technology advancements have made search engines an essential tool for tourists when planning their trips, especially in getting relevant information on their areas of interest. Search Intensity Indices (SIIs) have been recognized as a potential TD indictor in the destination market [9, 10] and have been examined by many researchers for TD prediction [11]. SII data are important for accurate TD prediction even though some practitioners have reported some challenges in using them with the conventional prediction models. Two of the common practical barriers that exist are as follows: (i) issues related to feature selection. Rosselló-Nadal and He [12] stated that many factors are considered potential TD predictands, such as the exchange rate, travel cost, tourism prices, and several SII data. The increasing number of the potential influential predictands reduces the availability of training datasets in the feature space, meaning nonavailability of enough data for the building of accurate models.

According to Wang et al. [13], training of most prediction models on training data with numerous explanatory factors is a tedious task; hence, feature engineering is an essential step in building a prediction model as it provides the best set of relevant features that will improve the performance of the developed model [14]. Although some factors have established meanings, it is possible that numerous potential keywords are focused with end user in terms of tourism marketing. Selected feature to TD prediction is currently based mainly on the existing knowledge of the tourism of destination market with the selection of the effective features demand significant human efforts [15]. (ii) The second issue is related to lag order selection. Even though numerous TD prediction methods have adopted the SII data, few studies focus on the determination of the huge relation for series data of the time. Some of the current studies investigated unpredictability hypothesis using either the Granger causality test or Pearson correlation coefficients [16]; in these studies, the investigation of the less hypothesis is performed by examining the extent of the relationship between the lagged values of a factor and the volume of tourist arrival.

However, the reliability of both the Granger causality test and Pearson correlation coefficients is still in doubt in the face of nonlinear underlying relationships [17]. Therefore, the effective selection of the potential data relationships will enhance the development of highly accurate prediction models. The performance of time-series and AI models in prediction tasks is excellent as they rely less on feature selection depends on the existing information of market destination.

The performance of the existing prediction methods is not satisfactory in every destination market due to the impact of numerous real-world situations, especially when adopting numerous SII data as TD indicators that may demand significant field-related expertise to restrain ambiguity. In addition, each SII parameter has different numbers of lag effective; the complexity increases in the presence of the same problem, such as bias in platform and language [18].

The emergence of deep learning techniques has been the solution to most of the above barriers as they have provided the means for achieving accurate TD prediction [19]. Deep learning is an extension of the ANN techniques of two processing layers of nonlinear relationships; they have an influence on many methods due to its built-in feature selection capability. The deep learning network is also relevant in time-series analysis owing to its advantages of being flexible and ability to discriminate nonlinear relationships. Long-term dependencies can be specifically handled and learnt by the recurrent neural network (RNN), attention mechanism, and long short-term-memory (LSTM) models. Hence, deep learning is considered an alternative solution to TD prediction. This work proposes a deep learning technique for TD prediction that will simultaneously address the earlier mentioned practical issues.

Structure of this manuscript is as follows: introduction is mentioned before, and then related work shows the existing methods. The deep learning section comes with its properties, following by difference of deep learning and normal neural network, then continuing by the proposed method and detail regarding the main method. Result and discussion section comes with analysis and the given results followed by conclusion section to summarize the research.

2. Related Work

The need for accurate TD prediction is enormous as it provides the necessary tourism-related information to researchers and practitioners; such information aids in making decisions on certain activities, such as resource allocation, risks, and opportunity identification. A review of the existing literature on TD prediction was presented in this section; deep learning technique was also reviewed as it is the selected basis for this work.

2.1. Tourism Demand Prediction. The existing TD prediction-related studies can be classified into two approaches: qualitative and quantitative. The qualitative approach mainly depends on the experience and knowledge on a specific domain; hence, they are sometimes considered "artistic," and they exhibit low generalization potential [20]. The quantitative approach has been the method of choice for the estimation of the mount relation between many notes data in tourism. They develop models depending on historical data for prediction to potential tourist arrival volumes. The performance of the quantitative approach can be improved using two main approaches: the first plan is to introduce more related parameters that can motivate tourism-related travels and the second strategy is adoption of more complex models that can accurately generalize future trends.

The construction of TD prediction models mainly depends on input factors that are highly related to TD with no missing values. The available TD prediction models can be grouped in different ways using different criteria. They can be grouped into determinants and indicators based on the nature of their influence on TD. Determinants are the major prediction parameters. The traditional theory of economic, such as utility theory, and the theory of the behaviour of consumption estimate that TD is influenced by both qualitative and quantitative economic factors, but most of the TD prediction models do not consider the qualitative economic factors due to the difficulty of their quantification. Such models rely mainly on the quantitative economic factors because they can be measured and used feature to prediction methods. Considering TD nature, it could be stated that the consideration of only economic factors is not enough. Some works have previously focused on the impact of noneconomic determinants on travel motivations, as well as the impact of travel motivation on the destination choices. Kumar and Kumar [21], for instance, introduced qualitative noneconomic determinants such as climate index, special events, and leisure time index. These limits will have classified to pull, resistance, and push, considering their relationship with the specific domain; however, the pull factors are the only considered destination tourism market attributes [22] while the push factors have more influence on the source market [23]. The resistance factors on the other hand are comprised of factors restricting travel from source to the destination market, such as the relative prices and perceived corruption [24].

The determinants of economic theory mainly influence TD. The TD prediction accuracy can be improved by introducing some leading parameters that are seen as secondary factors into the prediction model [25]. The advancement of Web technology has made it possible for most tourists to search for important info before engaging on their trips; such information may be related to selection of the destination, hotel reservations, booking flights, and planning activities. The attention of tourist is reflected on the SII data; hence, they are effective TD indicators that need to be incorporated in TD prediction models. The study by [26] focused on the analysis of the relationship between the search words of tourists on US cities and the level of attractiveness of the cities. From the analysis, SII data were found as important tourism scale indicators in the destination market. Furthermore, Hilal et al. [27] predicted TD of Hong Kong from 9 source countries using the Google Trends Index; the study attested to the importance of SII data for such tasks.

Yang et al. [28] stated that data of SII portray choices to tourist and offer rapid data, which represents right on time variations to the choices of people. The relevance data of SII to prediction of motel residence were also presented by Li et al. [29]. These attributes made them better than the variable time-series of individual models as they can solve the problems associated with abrupt variations in econometric patterns [30].

Search engine selection is mainly based on their popularity in the targeted tourism market. Google and Baidu provide the SII data commonly used in the existing literature [31, 32]. However, the Baidu Index provides daily search volumes while Google company trends provide and normalize the index every week/month. Several prediction models are available in the field of TD prediction. In [8], the authors suggested that these methods are classified into time-series, AI, and econometric models, but TD prediction is usually done using time-series and econometric models [33].

Most of the common prediction methods are extensions of the AMA model [12] while the complex ones, such as Bayesian model, Markov-switching model, and generalized dynamic factor model, are developed for better performance [22, 24]. The existing techniques in this group rely on historical time-series patterns to determine the relationships between TD predictands and the tourist arrival volumes. When building a predictive model, the main task is to introduce the best set of features that will reduce the prediction errors based on the measured performance metrics, such as mean absolute errors (MAEs), root mean squared errors (RMSEs), or mean absolute percentage error (MAPE).

The AI models are the soft computing and machine learning methods used in TD prediction. The study by Law and Au [34] relied on multivariate regression analyses to build models for the identification of nonlinear relationships using neural networks. Furthermore, Zhang et al. [16] presented the improvement of the comprehensibility of TD prediction models using the rough set approach. According to Chakrabarty [35], evolutionary computing methods can be easily used to predict the monthly arrival of tourists at the Balearic Islands of Spain. Effectiveness and efficiency proved by machine learning were used to evaluate the distribution of people during tourism [34]. Hybrid models that integrate different models have recently been shown to provide better results [20, 36]. However, the "No Free Lunch" concept provides that no single technique can perform well in all scenarios as all methods are associated with certain limitations in certain scenarios [37]. Econometrics and time-series models normally depend on stabilizer economic structure and patterns of historical while AI models depend on the size with quality from the training data available.

2.2. Deep Learning (DL). Successful prediction of TD using AI models, such as SVR and neural networks, has been reported. The study by Chen et al. [38] succeeded in training deep network models through greedy layer-wise pretraining for wide range practical applications. Since the development of deep learning, it has found numerous practical applications, ranging from pattern recognition to natural language processing and image recognition [39]. It has also been used in predicting sequential data problems [40]. This section discussed two common deep network techniques that have shown great efficiency in time-series prediction.

The reviewed deep learning techniques are LSTM and RNN with mechanism of attention. Regarding the RNN, its popular deep networking [41] processes data elements through selective passage of information across the time steps. This is an important attribute for its suitability in TD prediction as its structure is included in the time-series data series provides important information of context. Presented in Figure 1, either of the x for input or y for output of RNN, it can be a singular point of data, but both are time-series data. The memory of the RNN is preserved in the neuron of the hidden layer that captures all information that has been previously processed. The neuron output is generated based on the state of the neuron of the previous hidden layer and the current input via a feedback loop mechanism. The RNN can establish relation between a range of loop elements; it is also being found efficient in data series of nontime [42].

LSTM was developed as an extension of the RNN; it was built with not just a recurrent learning unit, but with several gates for the capturing of the longer and shorter states from the starting and last units, respectively. This feature has enabled the use of LSTM in solving time-series prediction problems. Regarding the mechanism of attention, its feature selection technique works together beside other deep learning (DL) models. The model can assign different weights to different inputs to learn the relevance of the input without the need of doing it prior to model fitting.

The incorporated attention mechanism of LSTM made it ideal for TD prediction because it offers solution to both prediction and feature selection problems. Figure 2 shows the structure example of LSTM.

2.3. Rationale of This Work. Much progress has been made in the prediction of TD, but these developments are yet to reflect in the performance of feature selection processes for TD prediction. Although the prediction performance of TD

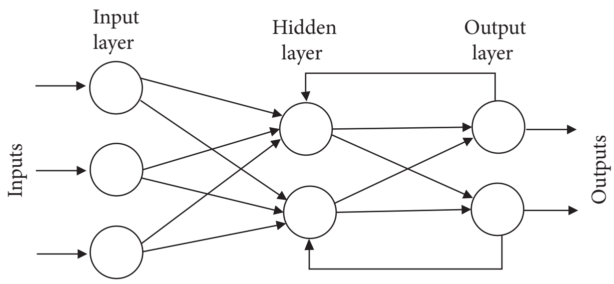


FIGURE 1: RNN structure.

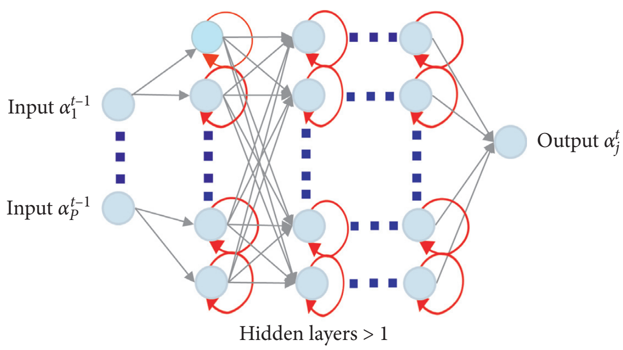


FIGURE 2: Structure example of LSTM.

prediction models is dependent on the selected features used as the training data, TD prediction is still facing two practical limitations; the first issue is associated with feature selection. For secondary TD prediction factors, feature selection is mainly aimed at query selection with the aim of collecting search engine keywords that are related to tourism. However, the issue of long tail in SII data means there are numerous search density small search queries, thereby reflecting travel experiences unique [22]. Some irrelevant and redundant features can be removed using common senses to arrive at a set of ideal subqueries related, but this demands much human effort. The second limitation is related to lag order selection. This lag order determines the nature of the relationship between time-series data. Hence, lag order selection is an important step of preliminary in TD prediction; it is done using methods such as Granger causality test [27].

Most times, some tests do not capture nonlinear relationships or explain the underlying effects of confounding [29]. A wrong lag order selection process will invalidate the subsequent steps of building a prediction model.

Deep learning is an aspect of artificial intelligence that is considered a potential alternative to the existing TD prediction models due to its two unique properties which are (i) ability to naturally learn from highly nonlinear correlations and (ii) ability to automatically select appropriate features at different network layers due to its built-in feature selection mechanism. Moreover, lag selection can be reduced by exploiting the temporally local correlation between TD and its predictands; this can carefully select the best feature of the raw data of input.

The properties made deep learning (DL) ability solution of the over-reliance in the field of expertise. Hence, the aim of the proposed work is to develop a model of deep learning for TD prediction via using the deep network framework for autoextraction of the relevant features with suitable lag orders from various potential features.

With the proposed method, deep learning used features extracted and structured as the neural network with variable nodes and layers. Taken features control the number of layers and nodes and control the system accordingly.

2.4. Deep Learning vs. Neural Network. The neural network works on the basis of entering the information that must be processed into the input layer and then into the hidden layers that are limited in number in the neural network. Also, the number of nodes is fixed in a normal neural network. As for deep learning, the number of hidden layers that are responsible for the process is variable. What distinguishes deep learning is the change in the number of hidden layers as well as the number of nodes in the concerned layer. As for the proposed method, deep learning also contains feedback between the hidden layers and the output layer as well.

3. Methodology

A deep learning-based conceptual framework for TD prediction is proposed in this study; the following subsections provide the detail of the adopted deep learning framework for addressing the abovementioned problems. The proposed conceptual model was used for TD prediction.

The proposed deep learning-based model for TD prediction was developed according to the steps shown as follows:

(1) The first step is the identification of the search engine platforms. While planning for travels, tourists normally use several search engines to get information about their potential destination. Hence, it is expected that different source marketing platforms have various search engines. So, that is why it is important to identify the search engine platforms first. Google, for instance, is the commonest search engine in most of the English-speaking regions of the world, while Baidu and Yandex are common in places such as Russia and China [29].

(2) The second step is the data collection phase. There is a need to get the volume of monthly tourist arrival volume from reliable sources. Most TD prediction variables can be sourced from various resource depends on data that are available. The collection of other factors, such as data of SII, involves the following substeps:

   (i) Identification of the initial search terms of the potential destination of the market and maximization of potential set of keywords searched in advance that will reflect the points of interest to tourist on the end user market using Google related to trends queries.

(ii) Translation of the tourism-related keywords into languages that can be carried by the other search engine platforms using Google Translate.
(iii) Extraction of the data per month of SII that corresponds to entered keywords comes from the final stage of a certain engine search. Monthly data can be obtained from Google Trends while the Baidu Index and other search engines may only provide daily data that require conversion into monthly data. Some search platforms may also not have the SII data of some relevant keywords.

Although the feature selection step is not required in the deep learning framework that was applied in the subsequent step, it is important to remove most of the irrelevant factors that relate loosely with the size of tourist arrivals; this will be done automatic by the deep learning framework. Regarding the limitation of the linear Pearson correlation coefficients (PCCs), factors with minor associations can be prefiltered using the maximal information coefficient (MIC). This MIC is based on the concept that if there are two related features, a scatter plot of the grid that divides the data can be made to understand the relation of related features. Provide the MIC generally:

$$MIC - p^2, \tag{1}$$

where ρ represents the PCC and can be used as a natural nonlinearity measure. For a high value of MIC, large equation (1) implies a nonlinear relationship while a linear relationship is denoted by small equation (1) [21].

(3) The training of the deep learning (DL) model is the third step. Being that deep learning techniques are developed with a built-in feature selection mechanism, this study proposes a deep network architecture for autoselection of the relevant factors and determination of the order delay time sequences of series.
(4) The model interpretation considers the last step. The trained model captures the relationship between the TD predictands and the tourist arrival volume. The most influencing factors on the lag orders can be determined from the weights of neural connections and degrees of attention. The proposed framework in this study requires no manual feature selection process as the deep learning model automatically performs the feature selection process.

3.1. Deep Network Structure. The proposed deep network architecture and its articulation with historical time-series TD data are presented in this section. The integration of the attention mechanism into the LSTM network is also detailed; the mechanism of attention gives the degrees of interest in the various factors. Tourism demand prediction is mainly aimed at predicting the tourist arrival volume based on historical multivariate factors.

The input is formally portrayed as the fully observed set of feature vector as follows:

$$(x_l)_{l=1^L} = x_1, x_2, \ldots, x_t. \tag{2}$$

The corresponding tourist arrival volume is represented as

$$(y_l)_{l=1^L} = y_1, y_2, \ldots, y_t, \tag{3}$$

where T represents the total length of time in steps, and say the week numbers or months with the gathered database. y_t represents the tourist arrival volume (TAV) with time of step t, while x_t of vector of multivariate factors.

The prediction of TD requires the use of the time-series of multivariate parameters $(x_l)_{l=1^L}$ and the real TAV $(y_l)_{l=1^L}$ as model inputs for the construction of a model F for the prediction of y at future time steps:

$$(\hat{y}_L)_{l=T+1}^{L+\Delta} = F\left((x_l)_{l=1}^{L}, (y_l)_{l=1}^{L}\right). \tag{4}$$

This expression differs from those of autoregressive models where the availability of $(x_l)_{l=L+1}^{L+\Delta}$ is normally assumed when predicting $(y_l)_{l=L+1}^{L+\Delta}$ as both are designed for the modelling of the relationship between conditions and their consequences. Long-term dependencies can be handled by the RNN, but the training is sensitive with the RNN of changing in gradient. So, the proposed LSTM and RNN can address this issue through the provision of block memory in their current connections. Cell memory is contained in each block for the storage of the temporal states of the network; there are three gates that control the network, which are called on the basis of data flow, and they are as follows: forget, remember, and inference; they ensure that weak signals are blocked from flowing through the network. Figure 3 depicts the LSTM framework.

Assuming the time-series as an input, this input is encoded by the LSTM into a set of hidden states $(y_l)_{l=1}^{L}$. LSTM is based on the concept that a few gates are implemented at each time step from the regulation of the flow of information through the sequences; this enables accurate capturing of any long-range dependency. For any time of step l in LSTM, the capturing of long-range dependencies requires updating of the hidden state H_l by the fixed data with the same current of time step x_l, at the preceding time step H_{l-1}, at the input gate z_l, at the forget gate f_l, at the output gate o_l, and at the memory cell c_l using the following equations [17]:

$$z_l = \sigma\left(W_{xi}X_l + W_{hi}h_{l-1} + b_z\right), \tag{5}$$

$$f_l = \sigma\left(W_{xi}X_l + W_{hi}h_{l-1} + b_f\right), \tag{6}$$

$$o_l = \sigma\left(W_{xi}X_l + W_{hi}h_{l-1} + b_o\right), \tag{7}$$

$$c_l = f_l * c_{l-1} + z_l * \tanh\left(W_{xi}X_l + W_{hi}h_{l-1} + b_c\right), \tag{8}$$

$$h_l = o_l * \tan h\left(c_l\right), \tag{9}$$

where σ and tan$h$ are frequent functions, while X indicates sage multiplication. The b and W are used with the LSTM as the parameters though framework training. The result of

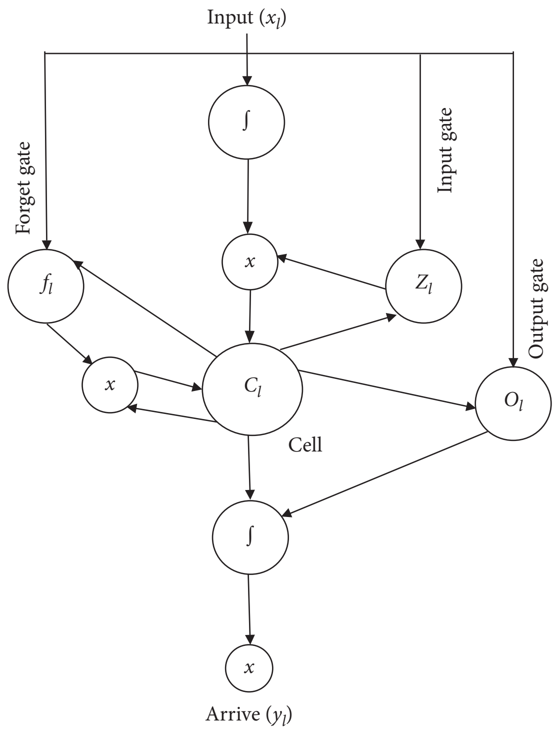


FIGURE 3: The LSTM framework.

equation (9) is utilized to estimate the results of the linear retreating layer:

$$\hat{y}_i = W_r h_i^L. \tag{10}$$

As mentioned in equation (7), W_r is indicated as the linear weight retreating layer.

The proposed method deep network (DN) structure of TD is seen in Figure 4. The framework used the LSTM parameters along with the concern technique. Identify the leg or lead relations among data series at time is important in TD expectation due to advantage effect varies depending on the periods of delay. The LSTM is used for the framework of long-term dependency in data series of the time, with attention technique which is indicated in which parts of the unit sequentially units of the framework are effective. This structure gives ability to authors to take two critical parts of data in TD expectation, called as follows:

(i) The relationship of temporal among different demand and factors

(ii) Significance of the factors depending on weights on TD

Therefore, the temporal of long-term dependency among different arrivals of tourist volumes and factors can be detected automatically via utilizing the LSTM of the alertness technology.Size of the input is $(m * d * n)$, while $(m * d)$ considers size of choosing data in training. The (n) is large tardiness arrangement specified by the users. All layers that are connected (dense) consider bullied according to attention technology with each attention. Then, the common relevant information is chosen in the lead series as seen in the following equation:

$$e_l = \left(W_e^1 \tan\, hW_e^2 \left(h_{l-1}; s_{l-1}\right) + W_e^3 x_l h_{l-1}\right), \tag{11}$$

where W_e^1, W_e^2, and W_e^3 are the weighing to be used by the framework. While the vector (e_l) represents as weighing that calculates the significance of feature of lead series on time l (x_l), and it was normalized e_l. Thus, lead series x_l is multiplied by attention weighing a_l: $\overline{x}_l * a_l$.

The LSTM utilizes $\overline{x}_l$ and h_{l-1} as input and updates the concealing case at time h_l. The vector c_l is presented by calculating up the multiplication:

$$c_l = \sum_{i=1}^{L} h_i w_i. \tag{12}$$

The final result is generated by the linear layer:

$$y_l = w_y^1\left(w_y^2 c_l + b_1\right) + b_2. \tag{13}$$

The LSTM and the identifier can be trained one by one.

4. Results and Discussion

4.1. Empirical Study. Implementation of the proposed imaginary framework was empirically evaluated through the prediction of the monthly TAV in Macau, an autonomous region of China that is located across the Pearl River Delta from Hong Kong. The economy of this region mainly depends on its gaming and tourism sectors. So, it is important to have an accurate and timely prediction of the TAV to sustain the economy of the region. The TAV of Macau in this study was predicted using secondary indicators such as SII data due to the lack of reliable data sources and expertise.

4.2. Performance Evaluation. To proposed model was evaluated for TD prediction performance by comparison with some conventional prediction models that included the SVR, ANN, ARIMA, and ARIMAX models [18, 20]. The predictions with the conventional models relied on the use of the TAVit dates back 12 months as an estimate of y_{k+1}, with the name of $\hat{y}_{k+1} = y_{k+11}$. For the ANN and SVR models, the input data used were the data from the past 12 months $(x_l, y_l)_{l=k-11^k}$ for the prediction of $\hat{y}_{k+1}$. The ANN model was built with a sigmoid activation function and one hidden layer; it was trained using the backpropagation algorithm. Stationary series are achieved in the ARIMAX and ARIMA using the AR order of (p, d) times of difference; they are trained on the MA order of q using the tourist data from the past 12 months for the prediction of the next 12-month TAV series; this is gradually increased during the process of model validation. ARIMA differed from ARIMAX by using only the TAV for the prediction task while ARIMAX requires other external factors, $x_{l=1^T}$. Features that contribute less to the TAV were eliminated using the MIC because such a large number of features cannot be handled by the SVR and ANN. The walk-forward model validation was employed to mimic a real-world scenario where new TAVs are made available monthly for the prediction of the TAV for the following month. The

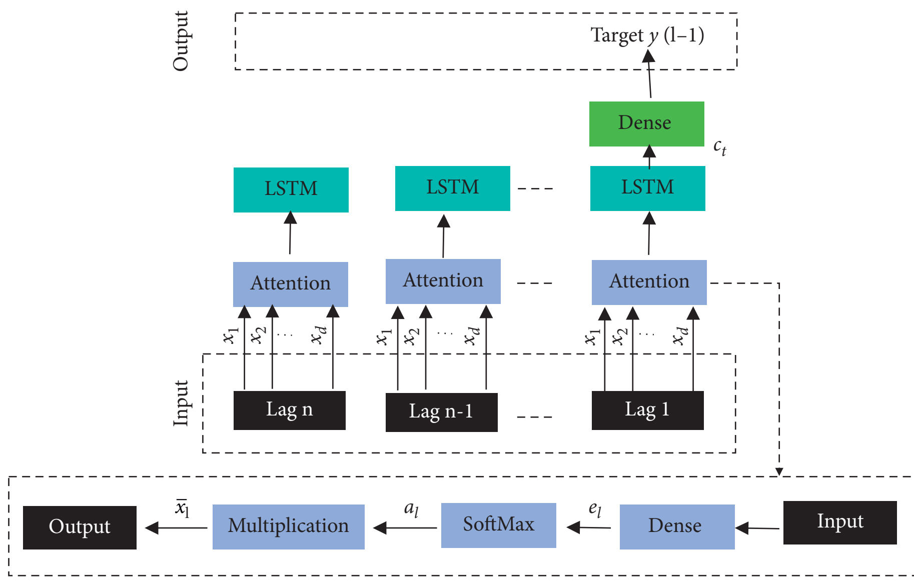


Figure 4: The deep network structure for tourism demand (TD).

prediction model is trained in each step and used to predict the TAV for the next month.

Three measures are used with this work of forecasting accuracy to the acquired predicted values (RMSE, MAE, and MAPE). They are defined as follows.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2},$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|, \quad (14)$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_i - \hat{y}_i\right|}{y_i}.$$

The best prediction model is determined as the model which achieved the lowest measurement values. The robustness of the developed model in this study was ensured by repeating the walk-forward validation process for the benchmarking models five times in the prediction of 12-month TAVs from 2016 to 2019. Note that the comparative models (SVR & ANN) have no expert-crafted features as their input features were automated from the MIC filtering process. Both models were further implemented using the features selected by the deep learning model; here, the models were recognized as SVR + F and ANN + F. Tables 1–3 summarize the global MAPE, MAE, and RMSE of the comparative models over a five-year period. The table shows that the performance of the deep network is better in terms of achieving low measurement errors for the 4 consecutive years.

Table 4 shows the result of the one-tailed l-test for the MAPE, MAE, and RMSE of the proposed and comparative models in this study at $\alpha = 0.05$. The results showed that the null hypothesis is rejected as it suggests the equality of the mean values of the proposed DLM and the comparative model. This is supported by the lower MAPE, MAE, and RMSE values of the DLM compared to the comparative models. The SVR and ANN with no feature selection performed comparatively with the conventional method. However, the proposed DLM which required no feature selection process performed better in terms of prediction than the other models. Note that the performance of SVR and ANN was improved by incorporating the DLM-selected features into their framework; the MAPE of SVR reduced to 5.086% from 6.482% while that of ANN reduced to 5.922% from 14.319%. Hence, the feature selection capability of the proposed approach is validated.

Although all DLM, ARIMA, and ARIMAX do not require preselected features, the ability of DLM to autoselect relevant features from the raw SII data improved its performance more than that of the ARIMA model. The comparison was made using only the Baidu keywords and Macau tourist arrival from Mainland China. Tables 5–7 show the MAPE, MAE, and RMSE of the comparative models within the studied five-year period. These tables also show similar improvements in performance; for instance, there were decreases in the MAPE. The results of

Table 1: The MAPE comparison for last 4-year prediction (global).

	DLM	SVR + F	ANN + F	ANN	SVR	ARIMA	NALVE
2016	0.925	7.441	5.474	7.656	8.718	5.31	7.177
2017	1.133	4.899	7.312	5.191	5.717	6.31	4.386
2018	2.434	4.564	4.981	30.051	4.298	6.93	2.958
2019	1.772	4.697	5.898	12.228	8.434	6.50	5.963

Table 2: The MAE comparison for last 4-year prediction (global).

	DLM	SVR + F	ANN + F	ANN	SVR	ARIMA	NALVE
2016	22,257	201,484	154,196	222,701	210,318	118,139	191,189
2017	29,479	122,697	178,699	128,183	148698	141,279	108,102
2018	64,598	114,743	122,549	607,331	113,690	182,658	77,967
2019	42,556	128,299	163,971	295,977	217,234	192,388	165,904

Table 3: The RMSE comparison for last 4-year prediction (global).

	DLM	SVR + F	ANN + F	ANN	SVR	ARIMA	NALVE
2016	27,102	269,194	211,419	279,121	276,138	162,255	208,665
2017	40,030	158,672	219,891	166,446	211,729	188,802	143,833
2018	88,811	154,531	134,545	632,044	135,048	234,939	95,596
2019	51,613	167,243	190,895	352,530	216,289	213,798	202,697

Table 4: The l-test results (global).

Comparison	MAPE		MAE		RMSE	
	p value	l-interval	p value	l-interval	p value	l-interval
DLM vs. SVR + F	0.0044	−5.22, ∞	0.0055	−143,255, ∞	0.0046	−194,018, ∞
DLM vs. ANN + F	0.0006	−5.48, ∞	0.0007	−143,121, ∞	0.0024	−188,382, ∞
DLM vs. ANN	0.0112	−24.27, ∞	0.0098	−501,812, ∞	0.006	−514,013, ∞
DLM vs. ARIMA	0.00003	−6.02, ∞	0.0002	−174,193, ∞	0.0003	−153,644, ∞
DLM vs. Naive	0.0042	−5.58, ∞	0.0097	−152,931, ∞	0.0094	−168,319, ∞

Table 5: The MAPE comparison for last 4-year prediction at China.

	DLM	SVR + F	ANN + F	ANN	SVR	ARIMA	NALVE
2016	1.846	6.86	9.45	12.62	14.1	8.39	12.11
2017	1.533	7.18	7.89	9.88	8.26	12.88	6.36
2018	1.658	4.59	5.18	6.78	6.39	8.31	3.21
2019	1.548	4.45	6.31	5.93	8.42	8.98	8.84

Table 6: The MAE comparison for last 4-year prediction at China.

	DLM	SVR + F	ANN + F	ANN	SVR	ARIMA	NALVE
2016	32,175	120,539	175,722	233,449	263,029	164,588	218,354
2017	27,316	118,491	136,835	160,881	136,998	203,611	104,771
2018	31,564	77,343	95,732	108,242	110,638	136,998	54,763
2019	28,944	75,383	109,944	109,874	165,568	156,299	168,568

Table 7: The RMSE comparison for last 4-year prediction at China.

	DLM	SVR + F	ANN + F	ANN	SVR	ARIMA	NALVE
2016	41,159	140,911	231,644	282,367	302,988	205,286	242,181
2017	29,873	151,186	168,883	182,485	171,184	230,795	142,591
2018	35,701	127,488	117,526	128,468	132,871	171,182	69,855
2019	31,454	113,514	134,952	134,222	205,288	190,473	193,677

Table 8: The l-test results at China.

Comparison	MAPE		MAE		RMSE	
	p value	l-interval	p value	l-interval	p value	l-interval
DLM vs. SVR + F	0.0007	−6.24, ∞	0.0018	−119,022, ∞	0.0004	−150,781, ∞
DLM vs. ANN + F	0.0015	−9.08, ∞	0.0019	−171,432, ∞	0.0015	−217,779, ∞
DLM vs. ANN	0.0148	−18.5, ∞	0.0121	−298,133, ∞	0.0074	−322,915, ∞
DLM vs. SVR	0.0019	−11.24, ∞	0.0033	−206,089, ∞	0.0022	−239,332, ∞
DLM vs. ARIMA	0.0015	−9.81, ∞	0.0006	−161,044, ∞	0.0003	−185,229, ∞
DLM vs. Naive	0.0068	−10.22, ∞	0.0093	−182,015, ∞	0.0059	−202,661, ∞

the l-test for the proposed DLM and the comparative models are shown in Table 8; the results further supported better performance of the proposed DLM compared to the benchmark models.

5. Conclusion

The tourism sector requires accurate and timely demand predictions for making informed sector-related decisions. Studies have previously focused on the time-series, econometrics, and AI models for this task in the previous years; however, the performance of these conventional models is dependent on the goodness of the selected features. The feature selection process and their lag order determination are domain specific and demand significant human effort. This study proposed a deep learning-based approach to the selection of the relevant features for better performance of the predictive models. The evaluations showed better performance of the proposed deep network framework compared to the conventional methods possibly due to two reasons; firstly, the ability of the deep network model is to mimic the natural biological system. The successive network layers extract low-level features from the initial input layer for the subsequent abstraction of the high-level features that will capture the semantic relationships between features in the succeeding layers. Secondly, the LSTM has an attention mechanism that automatically selects the relevant features at each time step.

This study made two important contributions to TD prediction; the first one is the development of a systemic conceptual framework of TD prediction and the validation of its TD prediction capability. The proposed model in this work considered all the available TD prediction factors and required no human intervention in terms of feature selection. The second contribution is the use of the attention score for the interpretation is the trained deep network architecture. This provides the practitioners a new way of updating their TD prediction based on a set of relevant indicators at different time steps. The outcome of this work also suggests the ability of the proposed DLM to select a set of relevant features and determine their suitable lag orders. With these contributions, this work can be extended in two directions: firstly, incorporation of different types of indicators, such as Blogs and Tweets into the TD prediction task;, which can address the issue of non-availability of training data as the DLM allows direct usage of these media data; secondly, feature sets with suitable lag orders can serve as inputs to other TD prediction models. The combination of DLM and the conventional prediction models can enable further theory development.

Future work can increase the features extracted and make the deep neural network more flexible in terms of the number nodes and layers. Prediction for a large variable number is required, and training should be made for the huge dataset.

Acknowledgments

The authors extend their appreciation to the National Natural Science Foundation of China, grant number 71701141, and Soft Science Research Project of Shanxi of China, grant number 2017041007-3, for funding and supporting this work.

References

[1] A. A. Peprah and A. F. Adekoya, "Entrepreneurship and economic growth in developing countries: evidence from Africa," *Business Strategy & Development*, vol. 3, no. 3, pp. 388–394, 2020.

[2] H. Li, M. Hu, and G. Li, "Forecasting tourism demand with multisource big data," *Annals of Tourism Research*, vol. 83, p. 102912, 2020.

[3] Y. Yao and Y. Cao, "A neural network enhanced hidden Markov model for tourism demand forecasting," *Applied Soft Computing*, vol. 94, p. 106465, 2020.

[4] V. Otrachshenko and F. Bosello, "Fishing for answers? impacts of marine ecosystem quality on coastal tourism demand," *Tourism Economics*, vol. 23, no. 5, pp. 963–980, 2017.

[5] J. Yu, J. Seo, and S. S. Hyun, "Attributes of medical tourism destination brands: case study of the Korean medical tourism market," *Journal of Travel & Tourism Marketing*, vol. 38, no. 1, pp. 107–121, 2021.

[6] X. Fu, J. Ridderstaat, and H. Jia, "Are all tourism markets equal? linkages between market-based tourism demand, quality of life, and economic development in Hong Kong," *Tourism Management*, vol. 77, p. 104015, 2020.

[7] K. Anurag, K. Venkataraghavan, and M. Sharma, "Bayesian BILSTM approach for tourism demand forecasting," *Annals of Tourism Research*, vol. 83, 2020.

[8] Y. Zhang, G. Li, B. Muskat, and R. Law, "Tourism demand forecasting: a decomposed deep learning approach," *Journal of Travel Research*, vol. 60, no. 5, pp. 981–997, 2021.

[9] L. Wen, C. Liu, H. Song, and H. Liu, "Forecasting tourism demand with an improved mixed data sampling model," *Journal of Travel Research*, vol. 60, no. 2, pp. 336–353, 2021.

[10] B. Ayaz, H. Ullah, M. K. Khan, and S. Jan, "The effect of google search volume index on the stock market excess returns. Evidence from listed firms in Pakistan stock exchange," *Review of Education, Administration & LAW*, vol. 4, no. 1, pp. 23–35, 2021.

[11] C. F. Tang and E. Lau, "Exploring the impact of political stability and climate change on inbound tourism demand: evidence from dynamic panel data analysis," *Regional Science Perspectives on Tourism and Hospitality*, pp. 403–419, 2021.

[12] J. Rosselló-Nadal and J. He, "Tourist arrivals versus tourist expenditures in modelling tourism demand," *Tourism Economics*, vol. 26, no. 8, pp. 1311–1326, 2020.

[13] X.-H. Wang, Y. Zhang, X.-Y. Sun, Y.-L. Wang, and C.-H. Du, "Multi-objective feature selection based on artificial bee colony: an acceleration approach with variable sample size," *Applied Soft Computing*, vol. 88, p. 106041, 2020.

[14] M. Spruit, T. Dedding, and D. Vijlbrief, "Self-service data science for healthcare professionals: a data preparation approach," in *Proceedings of the 13th International Joint*

Conference on Biomedical Engineering Systems and Technologies, pp. 724–734, Valletta, Malta, February 2020.

[15] K. Takahashi, "Comparing the determinants of tourism demand in Singapore and French Polynesia: applying the tourism demand model to panel data analysis," *Tourism Analysis*, vol. 25, no. 1, pp. 175–181, 2020.

[16] B. Zhang, X. Huang, N. Li, and R. Law, "A novel hybrid model for tourist volume forecasting incorporating search engine data," *Asia Pacific Journal of Tourism Research*, vol. 22, no. 3, pp. 245–254, 2017.

[17] A. De Rienzo, L. R. Chirieac, Y. P. Hung et al., "Large-scale analysis of BAP1 expression reveals novel associations with clinical and molecular features of malignant pleural mesothelioma," *The Journal of Pathology*, vol. 253, no. 1, pp. 68–79, 2021.

[18] T. Dergiades, E. Mavragani, and B. Pan, "Google Trends and tourists' arrivals: emerging biases and proposed corrections," *Tourism Management*, vol. 66, pp. 108–120, 2018.

[19] S. Pouyanfar, Y. Yang, S.-C. Chen et al., "Multimedia big data analytics," *ACM Computing Surveys*, vol. 51, no. 1, pp. 1–34, 2018.

[20] R. Law, G. Li, D. K. C. Fong, and X. Han, "Tourism demand forecasting: a deep learning approach," *Annals of Tourism Research*, vol. 75, pp. 410–423, 2019.

[21] N. Kumar and R. R. Kumar, "Relationship between ICT and international tourism demand: a study of major tourist destinations," *Tourism Economics*, vol. 26, no. 6, pp. 908–925, 2020.

[22] K. Zhang, Y. Chen, and C. Li, "Discovering the tourists' behaviors and perceptions in a tourism destination by analyzing photos' visual content with a computer deep learning model: the case of Beijing," *Tourism Management*, vol. 75, pp. 595–608, 2019.

[23] Y. Li and H. Cao, "Prediction for tourism flow based on LSTM neural network," *Procedia Computer Science*, vol. 129, pp. 277–283, 2018.

[24] Y. Ma, Z. Xiang, Q. Du, and W. Fan, "Effects of user-provided photos on hotel review helpfulness: an analytical approach with deep leaning," *International Journal of Hospitality Management*, vol. 71, pp. 120–131, 2018.

[25] M. W. Islam, L. Ruhanen, and B. W. Ritchie, "Adaptive co-management: a novel approach to tourism destination governance?" *Journal of Hospitality and Tourism Management*, vol. 37, pp. 97–106, 2018.

[26] E. E. Cust, A. J. Sweeting, K. Ball, and S. Robertson, "Machine and deep learning for sport-specific movement recognition: a systematic review of model development and performance," *Journal of Sports Sciences*, vol. 37, no. 5, pp. 568–600, 2019.

[27] K. Z. Hilal, A. O. Akyuz, M. Uysal et al., "An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain," *Complexity*, vol. 2019, Article ID 9067367, , 2019.

[28] X. Yang, B. Pan, J. A. Evans, and B. Lv, "Forecasting Chinese tourist volume with search engine data," *Tourism Management*, vol. 46, pp. 386–397, 2015.

[29] X. Li, B. Pan, R. Law, and X. Huang, "Forecasting tourism demand with composite search index," *Tourism Management*, vol. 59, pp. 57–66, 2017.

[30] P. F. Bangwayo-Skeete and R. W. Skeete, R. W. Skeete, Can Google data improve the forecasting performance of tourist arrivals? mixed-data sampling approach," *Tourism Management*, vol. 46, pp. 454–464, 2015.

[31] J. M. Stokes, K. Yang, K. Swanson et al., "A deep learning approach to antibiotic discovery," *Cell*, vol. 180, no. 4, pp. 688–702, 2020.

[32] S. L. Oh, Y. Hagiwara, U. Raghavendra et al., "A deep learning approach for Parkinson's disease diagnosis from EEG signals," *Neural Computing and Applications*, vol. 32, pp. 10927–10933, 2018.

[33] E. S. Silva, H. Hassani, S. Heravi, and X. Huang, "Forecasting tourism demand with denoised neural networks," *Annals of Tourism Research*, vol. 74, pp. 134–154, 2019.

[34] A. S. M. Arif and J. T. Du, "Understanding collaborative tourism information searching to support online travel planning," *Online Information Review*, vol. 43, no. 1, 2019.

[35] N. Chakrabarty, "A regression approach to distribution and trend analysis of quarterly foreign tourist arrivals in India," *Journal of Soft Computing Paradigm*, vol. 2, no. 1, pp. 57–82, 2020.

[36] X. Dong, Z. Yu, W. Cao, Y. Shi, and Q. Ma, "A survey on ensemble learning," *Frontiers of Computer Science*, vol. 14, no. 2, pp. 241–258, 2020.

[37] S. P. Adam, S.-A. N. Alexandropoulos, P. M. Pardalos, and M. N. Vrahatis, "No free lunch theorem: a review," *Approximation and Optimization*, vol. 145, pp. 57–82, 2019.

[38] J. Chen, L. Liu, J. Pei, and M. Deng, "An ensemble risk assessment model for urban rainstorm disasters based on random forest and deep belief nets: a case study of Nanjing, China," *Natural Hazards*, vol. 2021, pp. 1–22, 2021.

[39] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[40] W. Bao, J. Yue, and Y. Rao, "A deep learning framework for financial time series using stacked autoencoders and long-short term memory," *PloS One*, vol. 12, no. 7, p. e0180944, 2017.

[41] K. Cho, B. Van Merrienboer, C. Gulcehre et al., "Learning phrase representations using RNN encoder-decoder for statistical machine translation," arXiv preprint. arXiv preprint arXiv:1406.1078, 2019.

[42] F. Wang, Z. Xuan, Z. Zhen, K. Li, T. Wang, and M. Shi, "A day-ahead PV power forecasting method based on LSTM-RNN model and time correlation modification under partial daily pattern prediction framework," *Energy Conversion and Management*, vol. 212, p. 112766, 2020.

Fuzzy Neural Network-Based Evaluation Algorithm for Ice and Snow Tourism Competitiveness

Ying Zhao,[1,2] Qinghua Zhu,[3] and Jiujun Bai[4]

[1]*School of Economics and Management, Dalian University of Technology, No. 2 Linggong Road, Ganjingzi District, Dalian, Liaoning Province 116024, China*
[2]*School of Management, Anshan Normal University, No. 43 Pingan Street, Tiedong District, Anshan, Liaoning Province 114007, China*
[3]*Antai College of Economics and Management, Shanghai Jiaotong University, No. 1954 Huashan Road, Shanghai 200030, China*
[4]*University of Science and Technology Liaoning, No. 189 Qianshan Road, Anshan, Liaoning Province 114051, China*

Correspondence should be addressed to Jiujun Bai; baijiujun@ustl.edu.cn

Academic Editor: Zhihan Lv

This paper researches and analyzes the evaluation of the competitiveness of ice and snow tourism, uses the improved fuzzy neural network algorithm to process the system flow diagram of ice and snow tourism development through the function and characteristics of the power system of ice and snow tourism, and finally selects more than 40 indicators of the three subsystems of resources, economy, and culture. Based on the construction of cloud fuzzy neural network model, the above method is used for experimental comparison analysis, and experiments are conducted through University of California Irvine (UCI) dataset and engineering examples to compare with the traditional cloud model, fuzzy neural network, and BP neural network to analyze the operation efficiency, accuracy rate, and several rules of the algorithm. Through the experimental comparative analysis, the cloud fuzzy neural network can fully take into account the randomness and fuzziness of the data, optimize the generation of cloud rules, avoid multidimensional rule disasters, and ensure the operational efficiency of the algorithm; the accuracy rate of the algorithm is improved relative to that of the traditional technology, and it applies to a variety of datasets. And the software is used to test the ice and snow tourism industry system dynamics model to realize the correctness and robustness testing of the model. After the constructed model can reflect the real situation within the error range, the final policy simulation of the model is carried out.

1. Introduction

With the continuous improvement of the living standard of the residents, people are pursuing more spiritual life enrichment under the condition of material base satisfaction [1]. Ice and snow tourism as a new model of tourism development is gradually gaining popularity; in process of tourism, people can participate in ice and snow sports and deeper experience ice and snow culture and other rich connotations of ice and snow tourism activities to meet the diversified needs of tourists. Enhanced competitiveness can further improve the ice and snow tourism industry chain so that the regional economy accelerates development [2]. The development of ice and snow tourism and transportation industry, manufacturing, accommodation, catering, and other industries are closely related, and ice and snow tourism can enhance the economic effect, while the development of related industries will also play a driving role.

For snow and ice, ice tourism and winter tourism have always been popular for scholars to study; however, most of the current research results are only limited to a certain topic in the development of ice and snow tourism and rarely involve the intrinsic connection between the elements affecting the development of ice and snow tourism, lacking the systematic information research that integrates the whole situation and takes into account the elements [3]. By analyzing the time distribution characteristics of ice and snow tourism cities, we can understand the peak and low seasons of destination tourism network attention, make accurate predictions and corresponding reception measures for the real passenger flow, do a good job of peak season tourism warning, enrich off-season tourism products, implement refined management of ice and snow tourism destinations, and promote the sustainable development of ice and snow tourism destinations. It can also further verify the relationship between the information flow of network attention and the real tourism flow and provide a reference for passenger flow management [4].

The analysis of the ice and snow tourism market information by applying the system dynamics software has yielded relatively successful simulation data, so this method is generalizable and can be applied to ice and snow tourism market research, and the determination of some variables and parameters in the system can be adjusted appropriately according to the development status of different regions. The utility of ice and snow tourism market intelligence is that it is the foundation and basis for the investment decisions of the government and developers and is a precursor and prerequisite for decision-making. From the perspective of system science, we construct a system dynamics model for ice and snow tourism market information research and use the modeling software Genism PLE to realize simulation results based on existing market information, verify the validity of the model, and provide reliable predictions and feasibility recommendations through the analysis of multiscenario simulation results of system dynamics, so that the government and tourism developers can better grasp investment opportunities and directions. This will enable the government and tourism developers to better grasp the investment opportunities and directions, make decisions to avoid risks, improve the revenue, enhance the competitiveness of the tourism industry, and create higher value for the tourism economy. Our improved fuzzy neural network algorithm is the first research on the competitiveness of ice and snow tourism, which is in-depth analysis of ice and snow tourism, and it has strong accuracy.

2. Related Works

Wagner et al. analyzed more than 150 ski resorts in the European Alps consecutively, eventually defining 15 impact factors using Parandokan, Turkey, and Alps, Switzerland, as examples, and drawing statistical tables to analyze experimental innovation in the ski industry in economic development [5]. Bariscil used the Niseko region of Hokkaido, Japan; Allen and Daniel conducted interviews with regional government officials and residents who were already employed in the region, using the ski economy of Niseko, Hokkaido, Japan, as an example [6]. The rapid shift to a globalized tourism model in the region is examined, and the reasons for this shift, the positive and negative impacts on surrounding towns, and what other Japanese villages and cities can learn from the Niseko development experience are discussed [7]. Belonozhko et al. use system dynamics modeling to predict tourism demand for green ecology [8]. Bulatovic et al. argue that system dynamics is a method capable of capturing the dynamic behavior of complex systems over time and that tourism is a complex system with a large number of interactions between its various sectors, providing tourism policymakers and regulation managers with the opportunity to conduct strategic analysis and develop policies at different strategic analysis and policy formulation at different levels [8]. Therefore, it is recommended that the system dynamics model of sustainable development be applied to tourism to promote a comprehensive understanding of the complexities of tourism and to assist in the development of more effective policies [9]. The research on tourism cities started earlier, the research is more detailed and in-depth, the research method mostly adopts qualitative description and empirical analysis, and the research content focuses on exploring the theories related to tourism cities and analyzing the characteristics and influencing factors of the competitiveness of tourism cities through empirical evidence.

Fuzzy neural networks are an intelligent combination of fuzzy theory and neural networks to achieve the processing and representation of the ambiguity present in the data through the affiliation function and fuzzy neurons [10]. Tsuji combines evolutionary computation with neural networks and proposes a multicomponent class algorithm that effectively adapts the affiliation functions of fuzzified and DE fuzzifiers to the dataset and is successfully tested using real economic data [11]; Zhao proposes a new RL neurofuzzy model design for inline sequential learning evolution and develops a dynamic evolutionary fuzzy neural network (DENFIS) function approximation REL system [12]; Liu applied fuzzy neural networks to environmental safety assessment and achieved good results by using the feature that fuzzy neural networks can handle fuzzy phenomena [13]. Also, there are many improved algorithms of fuzzy neural networks that improve the performance of the algorithms [14]. Xu argued that the factors involved in the capacity of the tourism environment are complex and numerous, and the factors in the general environment have mutual checks and balances, which are difficult to quantify in terms of the overall impact on the whole body [15]. This kind of environment should use the principle of system dynamics to conduct a comprehensive study of the complex system [16].

Although the combination of fuzzy theory and neural network improves the situation, there is still the defect that it cannot handle the randomness and fuzziness of the data at the same time, and the process of determining the affiliation function needs to be determined artificially based on rich experience, which is influenced by subjective factors. The cloud model has great advantages in dealing with uncertainty and can realize the two-way conversion of qualitative data and qualitative concepts, but its method of finding numerical features is often determined according to the boundary of the data and cannot consider the whole data.

3. Fuzzy Neural Network Ice and Snow Tourism Competitiveness Evaluation Analysis

3.1. Improved Fuzzy Neural Network Algorithm Design. The interconversion between data and concepts is crucial in the expression of results. The cloud model reflects the distribution of data through the degree of certainty, and as the value of the degree of certainty approaches 1, the more likely the data belongs to this class or interval, and thus the uncertainty of the data can be expressed [17]. To use this property of cloud model in the fuzzy neural network, the fuzzy neural network algorithm based on cloud model is proposed to avoid the problems of overfitting and local optimal solutions by using numerical features to initialize the fuzzy neural network instead of the affiliation function with the degree of certainty [18]. At the same time, we propose a method to find the numerical features of the cloud model, introduce the concept of cloud rules to determine the boundary, and improve the traditional "soft and" algorithm, to establish a new network model structure, cloud fuzzy neural network.

The cloud model is introduced into the fuzzy neural network, and the cloud model is used to calculate the degree of certainty instead of the artificially determined affiliation function to reduce the interference of human factors. The accuracy of the cloud fuzzy neural network is ensured through Gaussian curve fitting and fuzzy clustering to obtain the numerical features of the cloud model, an improved "soft sum" algorithm is used for logical soft computation, and the conditional cloud generator is used to construct uncertainty inference, while the cloud rules are simplified by using the method of cloud rule determination to avoid the "rule disaster" due to a large amount of data. The paper constructs a cloud fuzzy neural network structure. The structure of the cloud fuzzy neural network is divided into six layers: the input layer, the clouded deterministic layer, the rule layer, the implicit layer, the inverse clouded layer, and the output layer. The topology of the network is shown in Figure 1.

The entry point of the cloud fuzzy neural network is responsible for passing the data to the clouding layer. The number of input nodes is determined by the number of conditional attributes that affect the output results.

$$\begin{aligned} f_i^1 &= x_i^2 + 2, \\ x_i^2 &= f_i^2, \quad (i = 1, 2, 3..., n). \end{aligned} \tag{1}$$

The data are processed for uncertainty and the conceptual cloud model is reduced approximately. Each node is a conditional cloud generator that represents the linguistic variable values and calculates the certainty of the quantitative values.

$$\begin{aligned} x_{ij}^2 &= \exp\left(-\frac{\left(x_i - Ex_{ij}\right)^4}{4\left(En_{ji}^{'}\right)^2}\right)(i, j = 1, 2, 3, \ldots, n), \\ \mu_{ij} &= \exp\left(-\frac{\left(x_i - 1\right)^4}{4\left(En_{ji}^{'}\right)^2} - \frac{\left(x_j - 1\right)^4}{4\left(En_{ji}^{'}\right)^2}\right). \end{aligned} \tag{2}$$

The executive function of each layer shows that CM-FNN is a network-type structure, and all nodes are uncertainty neurons, which is more suitable for dealing with data uncertainty than the traditional network-type fuzzy neural network.

The learning algorithm of CM-FNN adopts the more mature BP algorithm. In the process of network training that involves the initialization of weights and parameter adjustment, the traditional method initializes the weights by selecting random, as small as possible values, which easily leads to long network training time, too many iterations, and the existence of easy to fall into local optimal solutions [19]. In the current study, research scholars proposed optimizing the BP algorithm using genetic algorithm, particle swarm algorithm, annealing algorithm, and so on, but these algorithms are often too complicated in determining parameters and initialization. To address the above limitations, the BP algorithm is optimized using the cloud model in the network model to make the network converge quickly and obtain the global optimal solution.

Let the number of learning samples be R, the output of the network for the rth learning sample be r_t, the desired output be r_y, and the target learning function of the network be defined as

$$E = \frac{1}{2}\sum_{r=1}^{R}\left(t_r - y_r\right)^2\left(t_r + y_r\right)^2. \tag{3}$$

The initialization of the weights and thresholds of the BP algorithm generally uses a normal distribution with a mean of 0 and a variance of 1. It follows that the normal cloud model can be initialized for the BP algorithm, with the expectation (Ex) as the initial weight and the entropy (En) as the initial threshold. The steps of the algorithm are as follows: set the weights Ex and threshold En of the network; input the learned samples to each layer in turn; calculate the output of each layer; find the backpropagation error of each layer; record the learned samples until all samples are learned; calculate the error between the actual result and the output result; execute the step if it does not meet the requirement; and output the result if it meets the requirement; in the cloud fuzzy neural network, the cloud model in the determinacy function is used as the activation function of CFNN, while the expectation (Ex) and entropy (En) of the cloud model are used as the initial weights and threshold; then, the adjustment of the weights is different from the traditional BP algorithm, and the adjustment formula is as follows:

$$\begin{aligned} Ex_{ij}(k+1) &= Ex_{ij}(k) - \beta\frac{\partial^2 E}{\partial^2 Ex_{ij}}\ (i, j = 1, 2, 3, \ldots, n), \\ Ex_{ij}(k+1) &= Ex_{ij}(k) - \beta\partial^2\frac{\partial^2 E}{\partial^2 Ex_{ij}}\ (i, j = 1, 2, 3, \ldots, n). \end{aligned} \tag{4}$$

A fuzzy neural network based on a cloud model is the process of constructing a new network model by introducing the theory related to a cloud model in a fuzzy neural network. Firstly, to address the deficiencies in the current cloud model research, the use of Gaussian fitting and fuzzy clustering is proposed to calculate the numerical characteristics of the cloud model; secondly, to further reduce the

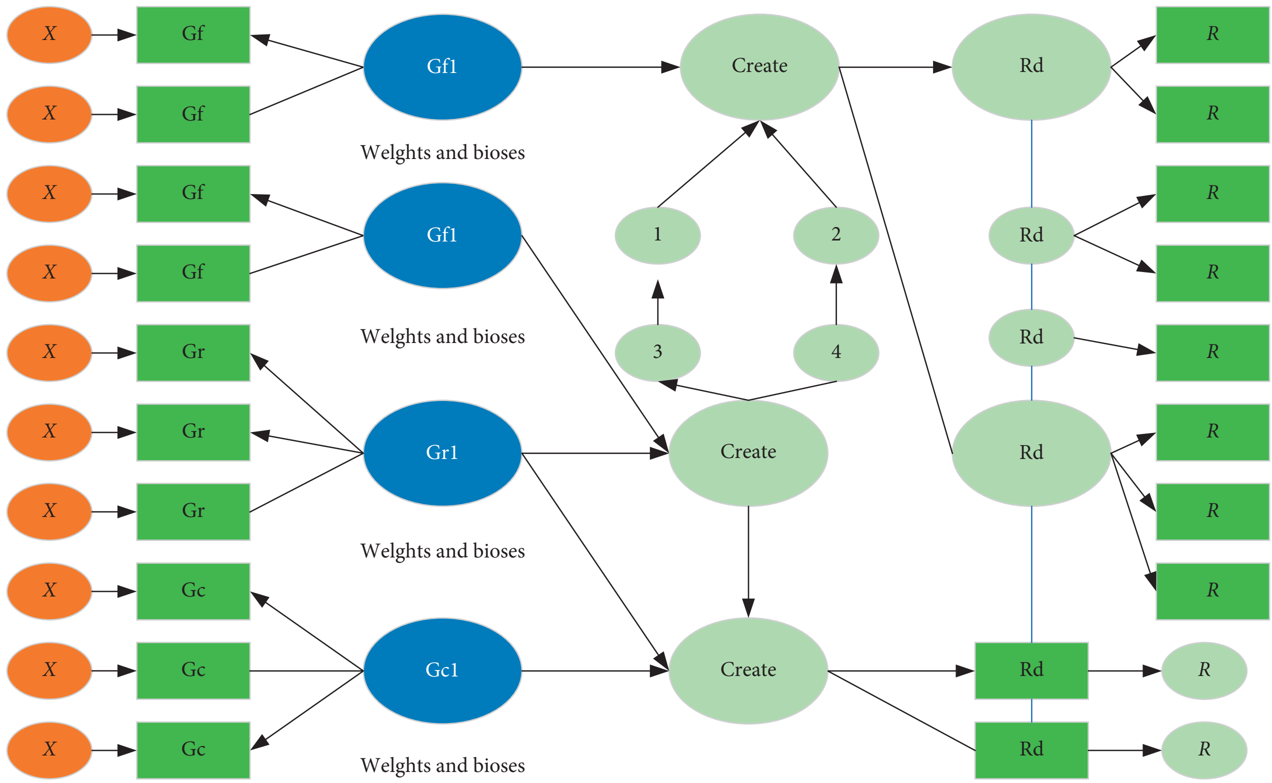


FIGURE 1: Topological model of cloud fuzzy neural network structure.

human influence in the cloud inference process, the method of projection mapping is used instead of the degree adjustment parameter; finally, to ensure the operational efficiency of the algorithm and reduce the number of rules, the rule simplification is performed using the cloud rule sure boundary. The initialization with cloud fuzzy neural network no longer uses random values, but the expectation and entropy of the cloud model; therefore, the dataset is preprocessed and normalized before performing the calculation of the cloud model numerical features. When error adjustment is performed, the adjustment of weights is converted to the adjustment of cloud model expectation and entropy, which reduces the number of error iterations to a certain extent and thus improves the operational efficiency of the algorithm.

The overall number of datasets and data dimensionality affect the running time of the algorithm. The introduction of rule simplification and the neural network has improved the efficiency of the algorithm. This section introduces how to build the cloud fuzzy neural network and gives the topology of the cloud fuzzy neural network, detailing the input and output of each layer and the role played by each layer; the learning algorithm of the fuzzy neural network is optimized by the cloud model, and the optimized weight adjustment formula is given; the algorithm idea and the operation process of the algorithm are introduced in detail, the flowchart of the algorithm operation is given, and the analysis of the cloud fuzzy neural network is given.

3.2. Ice and Snow Tourism Competitive Evaluation Analysis. With the rapid development of the Internet, the tourist city, as an important tourist destination, carries many tourists, which requires the transformation and upgradation of its tourism industry. The intelligent scenic spot through the destination information provided by the destination's network platform or a third-party platform, network platform, provides intelligent information to help tourists make decisions, help the destination to accurately measure the flow of tourists, and carry out accurate regulation within the destination. Through the interaction of intelligent information between tourists and destinations, tourist destinations can achieve joint growth of tourists and profitability, optimal use of scenic resources, and maximum ecological protection. Scenic areas can also give visitors an extraordinary information experience through on-site augmented reality (AR) virtual reality (VA) technology that gives the scenic area information content beyond reality [20].

Travel agents, as traditional providers of travel information and intermediary services, enable intelligent perception and easy use of travel information by human beings through technology updates that prompt service iterations. The new model facilitates time-saving for tourists, can provide clear travel guidance services, and facilitates the matching of tourists and suppliers. Not only can it provide a full range of services in multiple languages and currencies, but it also helps tourists solve the problem of information overload, and the whole design is entirely based on tourists' needs as the primary consideration. A smart travel agency can multimodel to adapt to market demand according to different users and different markets. The use of intelligent information to improve management efficiency and form core competitiveness can provide a sustainable space for the development of the hotel industry. Smart hotels directly provide information services and personalized services for customers. Smart hotels are the application of intelligent technology in the hotel industry, which can expand customer sources and increase market share through personalized and diversified services, thus establishing an efficient and intelligent market image of hotels, enhancing core competitiveness, and continuously stimulating innovation in hotel management mode.

Ice and snow tourism development emphasize the protection of ice and snow tourism resources while maximizing economic benefits, while also developing and holding a variety of ice and snow tourism projects and activities, which will bring the development of ice and snow tourism to its fullest potential. Playing economic benefits at the same time, the full use of ice and snow tourism resources will inevitably reduce the abundance of ice and snow resources, the resource environment to produce huge pressure, resulting in a certain number of tourist trips down, which is a negative feedback mechanism [21]. On the other hand, the resource subsystem continuously absorbs the white waste generated during travel, leading to the destruction of the ecological environment, affecting the travel experience of tourists, and reducing the number of tourist arrivals, which is also a negative feedback mechanism. On the other hand, the increase in government fiscal expenditures and the increase in investment in tourism promotion and ecological protection have improved the number of tourists to a certain extent, stimulating the increase in the proportion of residents participating in the ice and snow tourism industry, thereby increasing the total GDP. The construction of ice and snow tourism service facilities has been strengthened one after another, and the satisfaction of residents and tourists has increased, which is a positive feedback mechanism. The condition of infrastructure directly affects the condition of ice and snow tourism resources, the visibility of local ice and snow tourism, and tourism experience, which in turn affects the number of ice and snow tourism. Therefore, the infrastructure of ice and snow tourism requires continuous investment from the government to increase the number of tourism enterprises (accommodation, catering, and travel agencies), increase the number of people working in ice and snow tourism, and increase the national economic income, which in turn leads to the increase of total GDP. The causality diagram of the resource subsystem is shown in Figure 2.

The economic subsystem is a causal feedback purpose mainly reflected in several indicators such as total DGP and disposable income of residents and tourism employment rate. Higher government fiscal spending, more investment in tourism promotion, environmental protection, and ice and snow tourism service facilities, attracts tourists to spend, increases local employment, and raises the disposable income of residents, which in turn raises the total GDP and raises government fiscal spending, which is a positive feedback mechanism that is conducive to the development of the ice and snow tourism market. On the other hand, the residents are more satisfied, it will be better to receive and serve the visitors, the number of tourists further increased, the economic benefits created by related tourism enterprises such as catering, accommodation, travel agencies, and farmhouses will be improved, and the GDP contribution to local finances will achieve a quantitative breakthrough, so that the government has more sources of funding to serve the local infrastructure construction and so on, the conditions become better, and this is also a positive feedback mechanism. Of course, there is also a negative feedback mechanism; if the government does not make financial expenditure on snow and ice tourism, then the ecological damage to the environment will not be paid for; the residents and tourists will be less satisfied; the residents will reject the environmental pollution brought about by tourism; therefore, starting from the psychological resistance of lowering service standards, tourists will inevitably be reduced and the local economy will be depressed.

In the choice of variables of the economic subsystem, the main state variables of the system are selected as per capita ice and snow tourism consumption and ice and snow tourism income, which together reflect the state of the economic subsystem, the cumulative amount of ice and snow tourism income, and the fiscal revenue in time. Also, the auxiliary variables of the economic development subsystem include the number of relevant tourism employees, ice and snow tourism publicity investment, and ice and snow tourism service facilities investment. In the variable selection of the resource subsystem, the number of ice and snow tourism attractions and environmental protection expenditures are dominant, and the auxiliary variables include government infrastructure expenditures and capital investment in tourism. In the culture subsystem, the per capita disposable income of residents is selected as the main state variable reflecting this system, and the auxiliary variables include labor compensation of tourism services, business income of residents, related tourism employees, per capita labor compensation of related tourism enterprises, tourism-related industry employment ratio, and tourism investment rate. In this paper, the attributes of each variable are classified as shown in Table 1.

After the model is constructed, the simulation results of the model need to be compared with the actual results to check whether the model fits the historical values and future development trends and the actual, on this basis to ensure that the scenario analysis can simulate the future development trends. After the model is built, the simulation results and the actual results are analyzed to see how well the simulated values fit the historical values and whether the simulated scenarios match the actual development trend line.

4. Analysis of Results

4.1. Fuzzy Neural Network Algorithm Results in Evaluation Analysis. In this paper, we propose the use of Gaussian curve fitting and fuzzy clustering for the problem that the

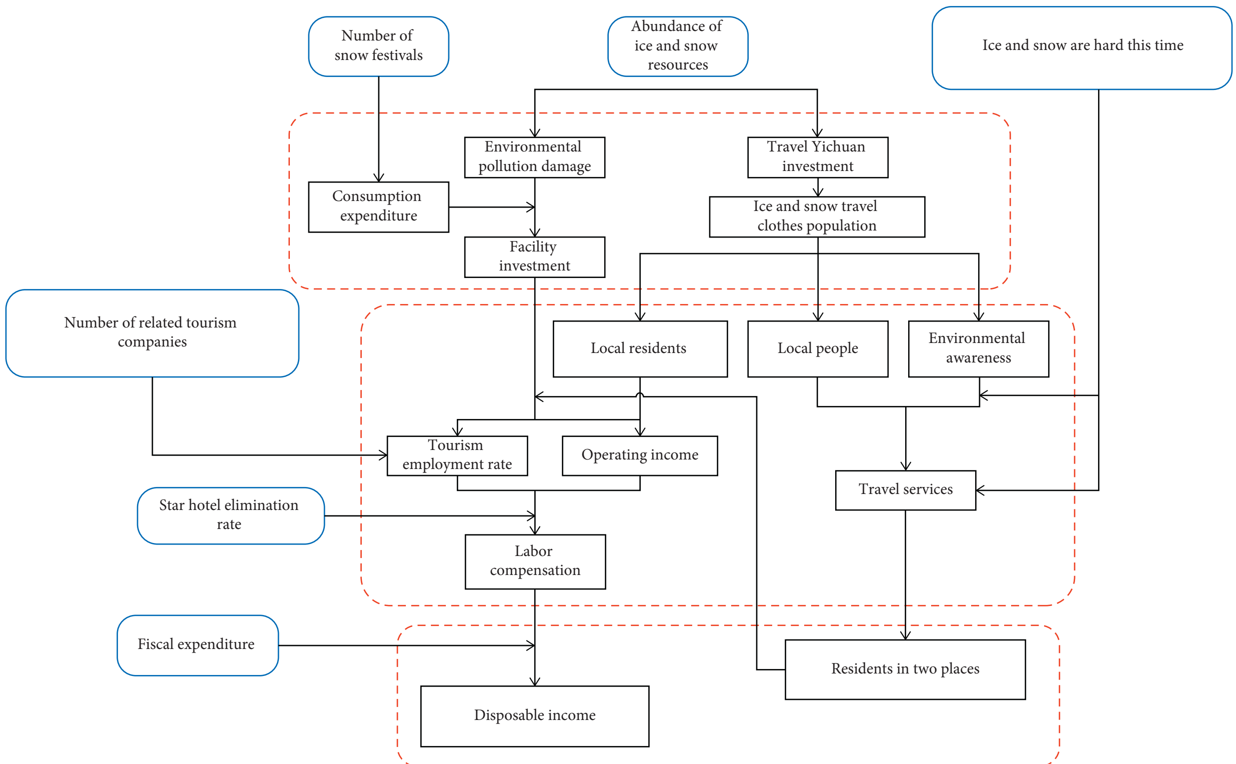


Figure 2: Ice and snow tourism market overall cause and effect diagram.

Table 1: Evaluation model main variables.

Variable type	Variable name	Number
State variables	Income from ice and snow tourism	6
Rate variable	Per capita consumption of ice and snow tourism	7
Constant	Operating income of residents	4
Auxiliary variable	Capital investment in tourism	6

method of determining the numerical characteristics of the cloud model is restricted by the type of data. Through the analogy of the degree of certainty and Gaussian function, the numerical characteristics of the cloud model are corresponding to the parameters of Gaussian function due to its similar formula structure and similar physical meaning, and the numerical characteristics of the cloud model are determined by finding the parameter values of Gaussian function. For small sample data, because the data are too small to reflect the distribution characteristics of the overall data, the clustering method is used to cluster the data into clusters, the center of each cluster is used as the expectation of the cloud model, and the entropy and superentropy of the cloud model are calculated by the matrix. To avoid the "rule disaster" in the cloud inference process, we propose the concept of cloud exact boundary rule and improve the "soft and" algorithm.

To verify whether CM-FNN has superiority, a comparative analysis with fuzzy neural network and BP neural network is conducted, the number of input nodes of all three neural networks is 5, the number of output nodes is 1, the maximum number of iterations is set to 1000, and the error is set to 0.0001. Through several experiments, ten of them are selected to compare the accuracy of the algorithm. The accuracy comparison of the Winequality-red dataset is shown in Figure 3.

The experimental comparative analysis of cloud fuzzy neural network through the dataset is compared with the traditional BP neural network and fuzzy neural network, and it can be seen from Figure 3 that the cloud fuzzy neural network has the advantage of expressing uncertainty compared to BP neural network and fuzzy neural network, BP neural network has the lowest accuracy and cannot handle uncertainty, and the fuzzy neural network has accuracy compared to BP neural network but cannot take into account the randomness of the data. Cloud fuzzy neural network has improved accuracy compared to both algorithms. The dataset is randomly divided and several experimental sessions are conducted to verify whether the algorithm has stability. As seen in Figure 3, the cloud fuzzy neural network has the least degree of difficulties, indicating that the algorithm operates with small fluctuations in results but remains stable.

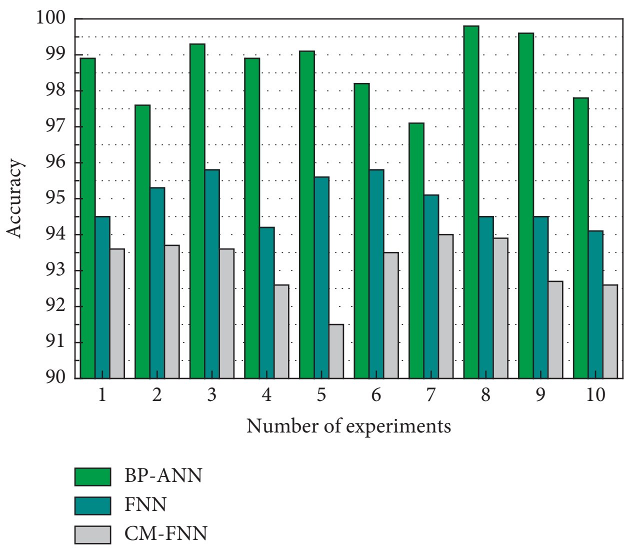


Figure 3: Accuracy comparison chart.

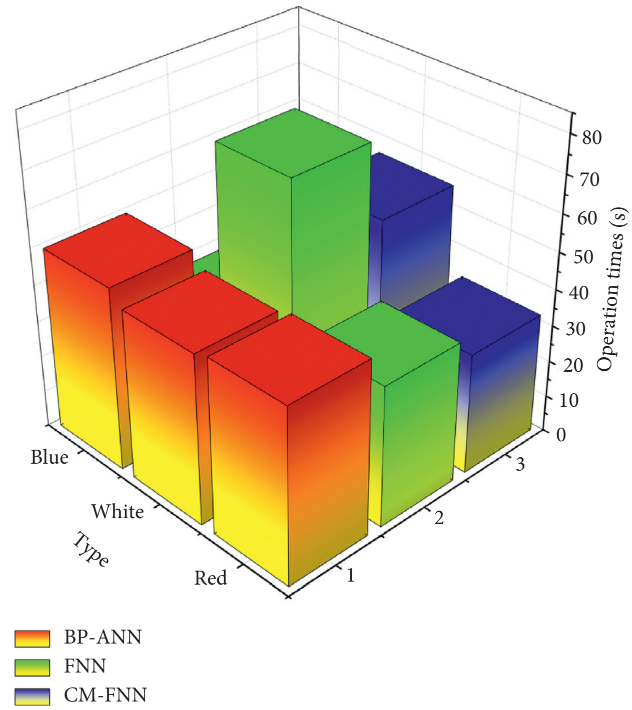


Figure 4: Comparison of algorithm running times for datasets.

The running efficiency of the algorithm is also an important indicator of the algorithm's excellence. The time taken varies with the method technique used, and a comparison of the running times of the dataset under different algorithms is shown in Figure 4.

The running time can measure whether the algorithm is efficient or not. As can be seen from Figure 4, BP-ANN has the shortest running time among all network models and CM-FNN has the longest running time, which is because the process of generating cloud rules is more time consuming, which increases the overall algorithm's time complexity, but the time consumption is acceptable when comparing the advantages of uncertainty representation and the improvement of result accuracy. Therefore, combining cloud models with fuzzy neural networks can improve the processing of uncertainty data.

As shown in Figure 5, when the data in the dataset are relatively standard and there is no need to consider uncertainty, the accuracy of the cloud fuzzy neural network algorithm under the three methods is relatively similar; as the amount of data continues to increase, the golden mean method and the mean method gradually lose their advantages; especially when dealing with uncertain data, the accuracy decreases, while Gaussian fitting has a greater advantage in large datasets, which can count the distribution characteristics of all data. The accuracy of fuzzy clustering is also improved with the increase of sample size for small data samples. Thus, it can be proved that the cloud numerical features are crucial for the cloud model-related algorithm, which indirectly affects the accuracy of the overall algorithm.

During the computation of the cloud model, one data may trigger one or more cloud rules, and as the amount of data increases, the number of cloud rules increases dramatically, causing a great burden to the algorithm operation. To solve this problem, the cloud model is improved by using an algorithm to first reduce the number of rules generated by a bounded approach to build a cloud rule base and then improve the "soft-with" algorithm to reduce the human influence. The runtime of the traditional cloud model and the improved cloud model is verified by the UCI dataset to prove the feasibility of the algorithm. The experimental results of the UCI dataset show that the improved cloud model and the related algorithms play a positive role in the accuracy of the CM-FNN, and the dataset is processed by numerical feature fitting and clustering, attribute simplification, and rule determination. The accuracy of the three methods is similar for small data samples with accurate data and no uncertainty expression. By comparing with the traditional "soft and" algorithm, it can be found that the cloud rules can reduce the running time of the algorithm, and the accuracy of the algorithm is relatively high with the increase of uncertainty and the number of data samples; by comparing with the traditional BP neural network and fuzzy neural network, it can be seen that the accuracy of CM-FNN in dealing with uncertain data is relatively high. It can be seen that CM-FNN can guarantee the accuracy of the algorithm when dealing with deterministic data, and the accuracy of BP neural network is lower when dealing with uncertain data, and CM-FNNN has the highest accuracy and can maintain relative stability, and it shows the goodness of the algorithm more with the increase of data samples.

4.2. Analysis of the Results of the Evaluation of the Competitiveness of Ice and Snow Tourism. The tourism flow represented by the network attention is the precursor effect of the real tourism flow, so the analysis of the precursor effect has important guiding significance for the forecast of passenger flow, network marketing, and tourism product creation in ice and snow tourism cities. According to the change of the network attention degree with before and after the holiday, it

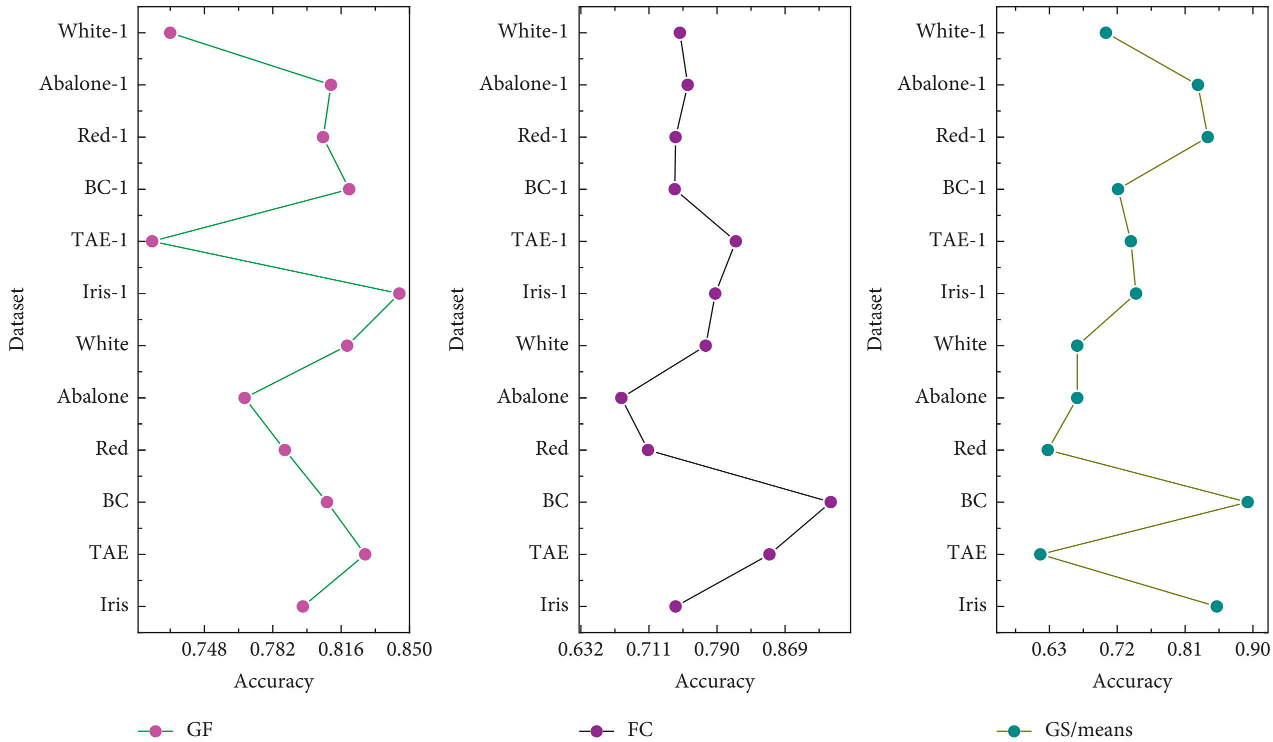


Figure 5: Effect of cloud digital feature determination method on accuracy.

can be learned that the network attention degree before the holiday is larger than that after the holiday, there will be a rapid rise before the holiday, a rapid decline during the holiday, and a slow rise after the holiday, but the peaks and troughs will not be higher than before the holiday, as shown in Figure 6. Specifically, the network attention starts to rise slowly from t1, reaches a peak at t2 on the eve of the holiday, declines rapidly during t2-t3, and gradually rises again during t3-t4. The changing trend of network attention is highly consistent with people's information demand before and after traveling, that is, people will search for information related to travel destinations before traveling, when the demand for travel information is high and the attention is high; people have gone out to travel during holidays, and the network attention drops rapidly; after the completion of travel activities, the demand for information is low, and the attention rises slowly, but the peak is lower than that before the holidays. This also indicates to a certain extent that the peak of real tourists is usually after the network attention.

In terms of time distribution characteristics, it has obvious seasonal characteristics and has different characteristics before and after different holidays, so climate comfort and holiday system are selected as the influencing factors of time distribution of network attention; in terms of spatial distribution characteristics, according to the above study, network attention is influenced by the level of economic development of the source place, the degree of network development, and the distance between two places, considering other possible related factors. In terms of spatial distribution characteristics, according to the above study, network attention is influenced by the level of economic development, the degree of network development, and the distance between two places, and other possible related factors such as population size and education level on network attention are also considered.

The portal layer of the ice and snow tourism platform needs to establish a unified data interface and realize rapid integration of various demands gathered from various channels through core algorithms; second, the ice and snow tourism platform resource gathering mechanism ensures that the ice and snow tourism platform can gather the required key core resources, take into account the reputation of the resource service provider, the cost of using resources, consumer preferences, and other factors, integrate different resources to form service modules, and sort them according to certain rules; third, consumers enter the entrance of the ice and snow tourism platform and find various resources that meet consumer requirements through different ways such as exact matching, fuzzy matching, and random matching. It should be noted that if there are no services on the ice and snow tourism platform that match the needs of tourists, that is, the core needs of tourists also cannot be met confirmed as matching failure, at this time, through the platform's early warning mechanism, early warning information is presented to the platform operator, resource service providers, and platform management subjects. According to the degree of urgency and importance of resources, the corresponding resource pooling scheme is formulated, the composite system synergy degree calculation is carried out sequentially according to the designed synergy degree calculation steps, and the entropy value and difference coefficient of each index are shown in Figure 7.

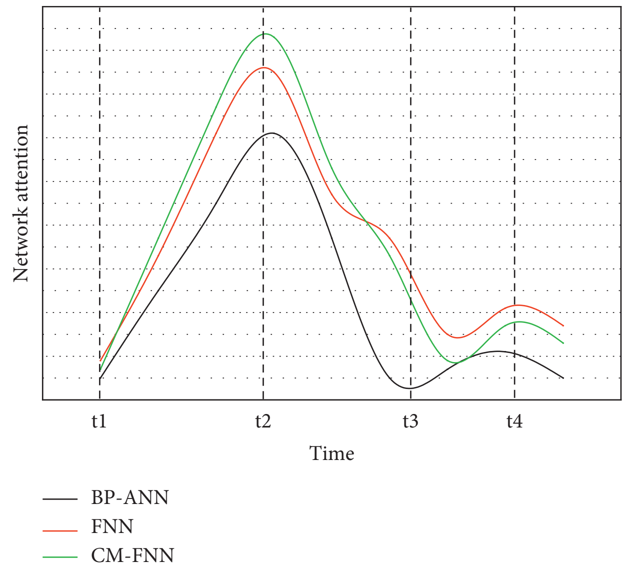


Figure 6: Ice and snow tourism network attention foreshadowing effect curve.

The orderliness between the three constituent dimensions of travelers, tourism elements, and supply and demand matchmakers is shown in Figure 8, which shows that the orderliness of traveler participation and synergy is the largest, indicating that the effect of traveler participation in ice and snow smart tourism is high, but the orderliness of the supply and demand matchmaker dimension is low.

Finally, the synergy degree of the composite system of the network platform is 0.868, which is in a moderate synergy state, especially in the supply-demand interface, which needs to be further strengthened, including the degree of platform interface and the provision of elemental synergy services by tourism intermediaries. For example, the management and cooperation of tourism service intermediaries should be strengthened, and the direct business cooperation of various travel agencies, service providers, and ground receiving organizations needs to be further improved. It should be noted that, affected by the network technology, the degree of element synergy and the degree of ice and snow tourism resources, the current ice and snow value joint service model has not yet been implemented, and the information interaction and element collaborative service model will be affected. This is the main service mode of the current ice and snow smart tourism. In the future, with the development of various information technologies such as artificial intelligence, the Internet of Things, and virtual reality, the network platform will carry out resource collection and element integration. The role of service innovation is further highlighted, and the value of various types of tourism participants will achieve common creation.

Strengthen leadership and planning, through the institutional reform of tourism and cultural administration, adhere to unified leadership and coordination, and complete smart tourism development planning based on all-area tourism planning. As an important reliance of the all-area tourism as the wisdom tourism, the related coordination work involves many levels of society and many interest

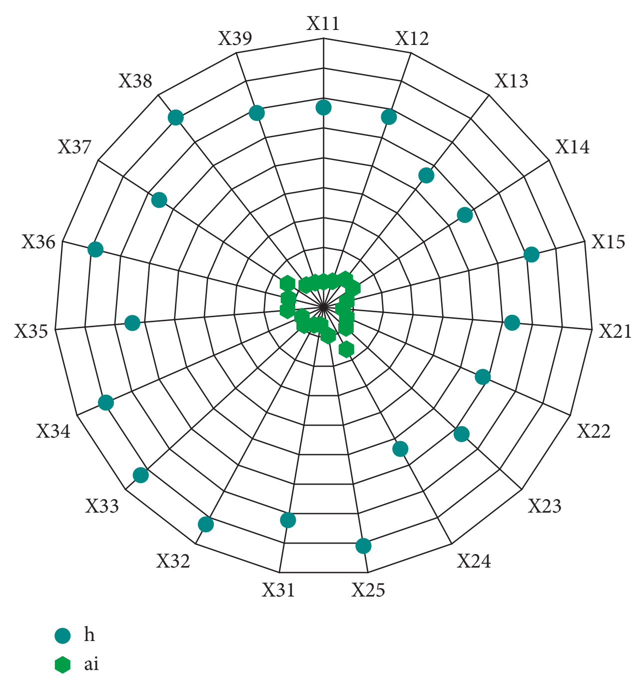


Figure 7: Entropy value and coefficient of variation of each index.

subjects, so it must be fully coordinated through the high-level organizations at the provincial or municipal level. It is recommended that wisdom tourism be included in the assessment of party and government officials at all levels of culture and tourism management, so that the entire tourism macro- and microadministrative agencies and public services can pay strategic attention to wisdom tourism and collaborate with multiple departments of development and reform, finance, transportation, urban and rural construction, market supervision, natural environment, emergency management, education, and human resources to solve real problems and potential conflicts in the development of

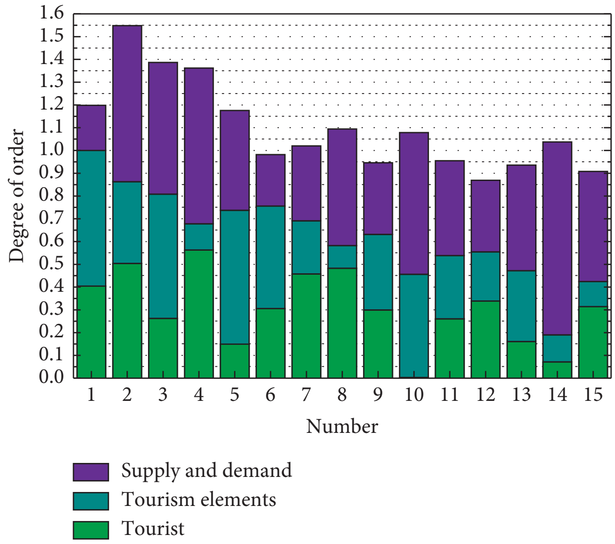


FIGURE 8: Orderliness score of each dimension.

wisdom tourism, with each department close collaboration, clear responsibilities, unified planning, and level-by-level implementation.

5. Conclusion

In this paper, we propose the use of Gaussian curve fitting and fuzzy clustering for the problem that the method of determining the numerical characteristics of the cloud model is restricted by the type of data. For small sample data, because the data are too small to reflect the distribution characteristics of the overall data, the clustering method is used to cluster the data into clusters, the center of each cluster is used as the expectation of the cloud model, and the entropy and superentropy of the cloud model are calculated by the matrix. Although the development history, development characteristics, and competitive advantages of the four characteristic towns are different, their methods of improving comprehensive competitiveness still have the same experience to follow, ice and snow tourism competitiveness improvement needs to rely on their environment, location, resources, and other advantages. The government needs to further regulate the development direction of the policy market industry, develop advantageous industries, rationally allocate resources, give play to the leading role of characteristic industries, and comprehensively improve the comprehensive competitiveness of the ice and snow tourism industry. This method is mainly used for predictive analysis in specific scenarios, and most other scenarios cannot be realized at present. In the future, we will further expand the applicability of this algorithm.

References

[1] W. Chen, P. Zhou, and K. Bae, "Research on development strategy of China ice-snow sports tourism industry based on SWOT-AHP model-case study on zhangjiakou," *International Journal of Contents*, vol. 16, no. 2, pp. 92–101, 2020.

[2] T. Bausch and C. Unseld, "Winter tourism in Germany is much more than skiing! Consumer motives and implications to Alpine destination marketing," *Journal of Vacation Marketing*, vol. 24, no. 3, pp. 203–217, 2018.

[3] A. Ianioglo and M. Rissanen, "Global trends and tourism development in peripheral areas," *Scandinavian Journal of Hospitality and Tourism*, vol. 20, no. 5, pp. 520–539, 2020.

[4] R. Steiger, D. Scott, B. Abegg, M. Pons, and C. Aall, "A critical review of climate change risk for ski tourism," *Current Issues in Tourism*, vol. 22, no. 11, pp. 1343–1379, 2019.

[5] P. M. Wagner, N. Hughes, P. Bourbonnais et al., "Sea-ice information and forecast needs for industry maritime stakeholders," *Polar Geography*, vol. 43, no. 2-3, pp. 160–187, 2020.

[6] A. Bariscil, "Some aspects of the competitiveness of Turkish regions and their tourism industry the example of Ardahan," *Journal of Advances in Humanities and Social Sciences*, vol. 3, no. 6, pp. 311–323, 2017.

[7] M. Woźniczko and D. Orłowski, "Unusual gastronomic establishments in the world as destinations of culinary tourism [J]," *Geography and Tourism Semi-annual Journal*, vol. 5, no. 1, pp. 113–127, 2017.

[8] M. L. Belonozhko, O. M. Barbakov, and A. L. Abramovsky, "Development of tourism in the arctic zone and its impact on environment," *Journal of Environmental Management and Tourism*, vol. 9, no. 8, pp. 1642–1650, 2018.

[9] J. Bulatovic, A. Mladenović, and G. Rajović, "The possibility of development of sport-recreational tourism on mountain area trešnjevik-lisa and environment," *European Journal of Economic Studies*, vol. 8, no. 1, pp. 19–42, 2019.

[10] J. Deng, T. Che, C. Xiao, S. Wang, L. Dai, and A. Meerzhan, "Suitability analysis of ski areas in China: an integrated study based on natural and socioeconomic conditions," *The Cryosphere*, vol. 13, no. 8, pp. 2149–2167, 2019.

[11] Y. Tsuji, "Sport tourism in Japan," *Journal of Global Tourism Research*, vol. 5, no. 2, pp. 107–112, 2020.

[12] R. X. Zhao, J. Q. Zeng, and J. L. Zhao, "Analysis of provincial tourism sustainable development model and countermeasure," *EURASIA Journal of Mathematics, Science and Technology Education*, vol. 13, no. 12, pp. 7671–7677, 2017.

[13] L. Liu and J. Chen, "Strategic coupling of urban tourism and regional development in Liaoning Province, China," *Asia Pacific Journal of Tourism Research*, vol. 25, no. 12, pp. 1251–1268, 2020.

[14] A. Aleksandrova and E. Aigina, "Modern aspects of cultural and historical heritage involvement in tourism activities in Russia," *Almatourism-Journal of Tourism, Culture and Territorial Development*, vol. 8, no. 7, pp. 244–254, 2017.

[15] H. Xu, D. Yang, and J. Weng, "Economic feasibility of an NSR/SCR-combined container service on the Asia-Europe lane: a new approach dynamically considering sea ice extent,"

Maritime Policy & Management, vol. 45, no. 4, pp. 514–529, 2018.

[16] A. Doran, P. Schofield, and T. Low, "Women's mountaineering tourism: an empirical investigation of its theoretical constraint dimensions," *Leisure Studies*, vol. 37, no. 4, pp. 396–410, 2018.

[17] E. Serrano, M. Oliva, M. González-García et al., "Post-little ice age paraglacial processes and landforms in the high Iberian mountains: a review," *Land Degradation and Development*, vol. 29, no. 11, pp. 4186–4208, 2018.

[18] M. Landauer, M. E. Goodsite, and S. Juhola, "Nordic national climate adaptation and tourism strategies - (how) are they interlinked?" *Scandinavian Journal of Hospitality and Tourism*, vol. 18, no. sup1, pp. S75–S86, 2018.

[19] H.-C. Liu, X.-Q. Chen, J.-X. You, and Z. Li, "A new integrated approach for risk evaluation and classification with dynamic expert weights," *IEEE Transactions on Reliability*, vol. 70, no. 1, pp. 163–174, 2021.

[20] X. Mou, Q. Z. Zhang, H. C. Liu et al., "Knowledge representation and acquisition using R-numbers Petri nets considering conflict opinions," *Expert Systems*, 2021.

[21] L.-J. Zhang, R. Liu, H.-C. Liu, and H. Shi, "Green supplier evaluation and selections: a state-of-the-art literature review of models, methods, and applications," *Mathematical Problems in Engineering*, vol. 2020, no. 4, Article ID 1783421, 25 pages, 2020.

Analysis of Complex Transportation Network and Its Tourism Utilization Potential: A Case Study of Guizhou Expressways

Sihong Chen[1,2] **Jianchao Xi**[1] **Menghao Liu**[1,2] **and Tao Li**[3]

[1]*Key Laboratory of Regional Sustainable Development Modeling, Institute of Geographic Sciences and Natural Resources Research, Chinese Academic of Sciences, Beijing 100101, China*
[2]*College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China*
[3]*Institute of Finance and Banking, Chinese Academy of Social Sciences, Beijing 100028, China*

Correspondence should be addressed to Jianchao Xi; xijc@igsnrr.ac.cn

Guest Editor: Wen-Ze Yue

Transportation is an example of a typical, open, fluid complex network system. Expressways are one form of complex transportation networks, and expressway service areas serve as infrastructure nodes in the expressway transportation network; hence, their construction has a significant impact on tourism development and utilization. Domestic and foreign studies on complex transportation networks have mostly been conducted from the perspective of railways, air transport, and urban transportation but seldom on expressway transportation networks. This study employed complex network theory, social network analysis, kernel density analysis, and bivariate autocorrelation to characterize the spatial structure of expressway transport networks in terms of geographical centrality. By innovating the coupling of geographical centrality and passenger flow centrality in clustering, the study also quantitatively analyzed the differences between the geographical advantage and actual passenger flow advantage of China's Guizhou expressway transportation network to analyze the tourism utilization potential of expressway service areas. We found that (1) the geographical centrality of the Guizhou expressway transportation network ranged from −1.28 to 3.33, and its distribution shows a single-core, polyconcentric dispersed spatial structure; (2) the passenger-car flow rate ranged from 15,000 to 3.66 million, and its distribution showed a dual-core, polycentric dispersed structure that is weakly concentric; and (3) there was a positive correlation of 0.22 between the geographical centrality and passenger flow of the Guizhou expressway transportation network, which showed seven cluster types—"high-high," "moderately high-high," "low-high," "moderately low-high," "high-low," "moderately high-low," and "low-low"—for which seven corresponding models of tourism development were proposed. This study broadens the practical application of traffic network complexity research and provides a scientific basis for upgrading and transforming the Guizhou expressway transportation network as well as for developing composite tourism uses for expressway service areas.

1. Introduction

Transportation is one of the six elements of tourism development and the most important intermediary component in the "three-body theory of tourism." [1] As the main transport corridor for self-driving tourism, expressways play an important role in improving interregional accessibility. With the gradual construction of the "fast forward, slow travel" expressway network, service areas have become part of their infrastructure, and their tourism service functions have expanded and matured. To enable tourists to receive high-quality, convenient, and efficient services, it is necessary to tap the development potential of expressway service areas by reviewing, upgrading, and shaping them into tourist destinations. Doing so will achieve integrated development between expressway service areas and the tourism and leisure industries, which is an important facet of the transportation-tourism relationship.

As the scale of transportation networks expands and their degree of complexity increases, research on transportation network complexity has become an important means to understand the spatial structure and organizational characteristics of transportation networks. A series of network analysis tools, such as multiple centrality assessment (MCA) [2], urban network analysis (UNA) [3], and spatial design network analysis (sDNA) [4], have been proposed, which have facilitated the computation and analysis of the morphological characteristics of complex transportation networks. Western scholars investigating complex transportation networks have mostly explored the centrality distribution of transportation hubs from the perspectives of railway [5, 6], air transport [7–10], and urban transportation [11–13] and have used transportation networks to analyze destination accessibility and the optimization of spatial structures [14, 15]. In contrast, scholars in China have primarily employed transportation network centrality, complexity, and other indicators to study the evolution of the structural characteristics [16] and spatial accessibility [17, 18] of high-speed rail [19], air [20, 21], subway [22, 23], and other traffic networks [24–26].

Transportation networks were first employed in tourism research in the 1920s. Western scholars initially explored them from the perspective of tourism transportation planning [27, 28] followed by an increasing research emphasis on the impact of transportation on tourism demand [29]. The emergence of different transportation modes, such as air transport and high-speed rail, led to changes in the accessibility of tourist destinations [30–33], which affected the spatial behavior and migration patterns of tourists [34–36]. Furthermore, continuous improvements to transportation conditions also resulted in a continual enhancement of tourists' tourism experience and transportation satisfaction [37]. Meanwhile, environmental [38–40], noise [41, 42], and congestion [43] problems in the transportation network have affected the sustainable development of tourism. In China, as the tourism industry developed, scholars in the 1980s began to explore the relationship between transportation and tourism [44]. The degree of transportation convenience became an important indicator for the development of the tourism industry [45], and changes in transportation facilities also affected the spatial structure of regional tourist destinations [46, 47]. Methods such as social network analysis, analytic hierarchy process, and TOP network were used to quantitatively investigate the relationship between tourism and complex transportation networks [48, 49], and the environmental impact of tourism transportation systems was calculated using ecological footprint, carbon emissions, and other indicators [50]. Furthermore, scenic byways were innovatively defined as tourist attractions for planning and evaluation [51].

As self-driving tourism has developed into an increasingly common phenomenon, expressways have become an indispensable and vital link in tourism development, making it crucial to perform timely complex network analysis on expressways and study their tourism utilization potential. Though several studies have been conducted in China and abroad on the impact of transportation networks on tourism [27–51], research on the relationship between expressway transportation networks and tourism is lacking. Thus, this study examined the expressway transportation network in Guizhou province using complex network theory, social network analysis, kernel density analysis, and bivariate autocorrelation to calculate the spatial clustering of geographical centrality and passenger flow centrality, quantitatively evaluate the difference between geographical advantage and actual passenger flow advantage, and analyze the tourism utilization potential of expressway service areas. Based on the results, seven models of tourism development were proposed, with a view of providing a scientific basis for optimizing the layout of expressway transportation networks and reshaping service areas for tourism.

2. Data and Methods

2.1. Study Area. Guizhou province is located in the inland southwestern region of China at a longitude of 103°36′–109°35′ and a latitude of 24°37′–29°13′ (Figure 1). It covers a total area of 176,200 km^2, and 92.5% is composed of mountainous and hilly areas including plateaus. Guizhou province is a world-famous mountain tourism destination, also known as the "Mountain Park Province" and the "Summer Capital of China." Due to its unique mountainous terrain, expressways have become the region's main transport corridor. The province has 6,450 km of expressways connecting 71 national and provincial scenic areas, and all 5A and most 3A and 4A scenic areas in the province are located within 30 minutes of expressway-connected areas. This has provided the facility guarantee and the tourist source needed for the integrated development of mountain tourism and expressway service areas.

2.2. Data Source. The first-hand data for this study came from field surveys and investigations of 65 pairs of expressway service areas in Guizhou that were randomly selected by our research team based on the principle of regional averaging. The manager of each expressway service area provided our team with basic information such as the passenger flow rate, deviations in different flow directions, and construction of service areas. Our second-hand data came from the passenger-car flow rate and vehicle registration data at each expressway section for February 3, May 1, June 9, August 1, October 1, and December 3, 2018, which were provided by the Guizhou Provincial Department of Transportation, and two schematic diagrams—one showing the distribution of expressway service areas and parking areas across Guizhou in 2019 and the other showing the expressway operation units across Guizhou in 2017. We also obtained the 2018 Google Earth images with a spatial resolution of 0.6 m, on which ArcGIS vectorization was performed to obtain a map of expressways in Guizhou.

2.3. Methods

2.3.1. Social Network Analysis. Social network analysis primarily consists of three basic centrality indicators—degree, closeness, and betweenness centrality [52]—which were used to measure the connectivity, accessibility, and intermediation, respectively, of expressway transportation networks. These were applied to the expressway network in

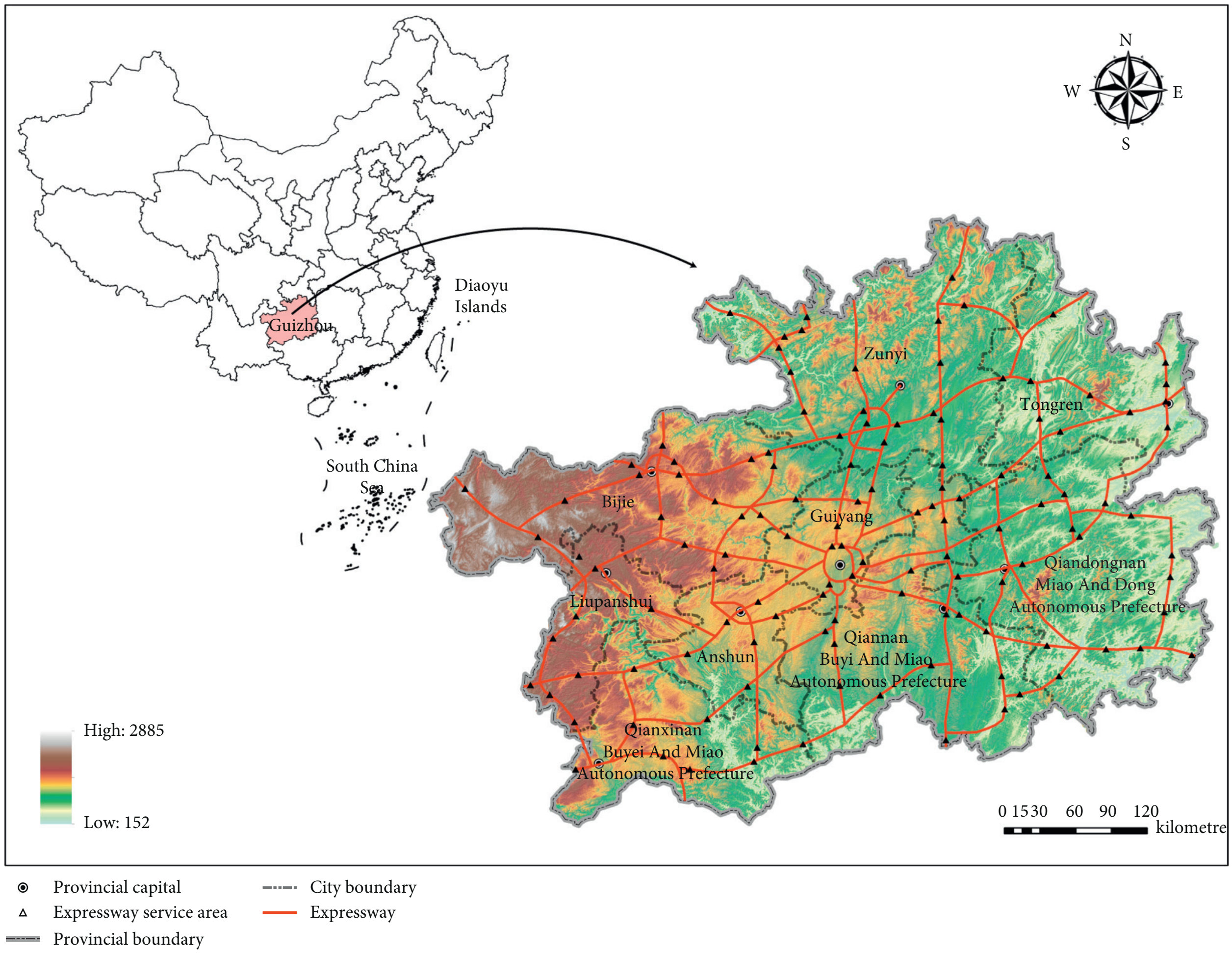


Figure 1: Location of the study area (Guizhou, China).

Guizhou province through Ucinet (Borgatti, S.P., Everett, M.G., and Freeman, L.C. Released 2002. Ucinet 6 for Windows: Software for Social Network Analysis. Harvard, MA: Analytic Technologies) calculations and then converted using factor analysis in SPSS (IBM Corp. Released 2017. IBM SPSS Statistics 25.0 for Windows. Armonk, NY: IBM Corp.) into geographical centrality, which provided a basis to quantitatively investigate the relationship between geographical centrality and passenger flow centrality.

Degree centrality (hereafter, D) measures the number of direct links to a node and is calculated by the following equation [52]:

$$D = \frac{x}{(n-1)}. \tag{1}$$

In (1), n is the number of nodes and x is the number of links between a given node and other nodes.

Closeness centrality (hereafter, C) measures the average length of the shortest distance between each node pair and is calculated by the following equation [12, 52]:

$$C = \frac{(n-1)}{\sum_{j=1}^{n} d_{ij}}. \tag{2}$$

In (2), d_{ij} is the shortest distance between nodes i and j.

Betweenness centrality (hereafter, B) measures the number of times a node is traversed on the shortest path between other nodes and is calculated by the following equation [12, 52]:

$$B = \frac{2\sum_{a}^{n}\sum_{b}^{n} g_{ab}(i)/g_{ab}}{n^2 - 3n + 2}. \tag{3}$$

In (3), g_{ab} is the shortest path between nodes a and b, and $g_{ab}(i)$ is the number of times i is traversed on the shortest path between a and b, where $a \neq b \neq i, a < b$.

In the network structure, degree centrality, closeness centrality, and betweenness centrality calculate the convenience, accessibility, and intermediary of network nodes from three perspectives [52]. Any centrality can only reflect one side of the network structure and cannot reflect the overall characteristics of the network space structure. To represent the geographical location features of the network structure in a unified way, this study puts forward the overall features of the geographical location of the network structure reflected by geographical centrality. Geographical centrality refers to the degree of a node's location center in the whole network, which is a unified indicator of network structure convenience, accessibility, and intermediation based on three network centricity characteristics: degree centrality, closeness centrality, and betweenness centrality. The higher the geographical centrality value, the better the location of the node in the network structure.

Considering that degree centrality, closeness centrality, and betweenness centrality are representative and there is a certain correlation among them that meets the calculation conditions of factor analysis, factor analysis in SPSS was used to calculate the weight index of the three types of centrality. Because the range of values for degree centrality, closeness centrality, and betweenness centrality is quite different, *Z*-score is used to standardize and obtain normalized values for the three indexes.

Geographical centrality (hereafter, *G*) is calculated as follows:

$$G = (w_D \times y_{Di} + w_C \times y_{Ci} + w_B \times y_{Bi}). \quad (4)$$

$$\begin{aligned} y_{Di} &= \frac{x_{Di} - \overline{x_D}}{s_D}, \\ \overline{x_D} &= \frac{\sum_{i=1}^{n} x_{Di}}{n}, \\ s_D &= \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_{Di} - \overline{x_D}\right)^2}, \end{aligned} \quad (5)$$

$$\begin{aligned} y_{Ci} &= \frac{x_{Ci} - \overline{x_C}}{s_C}, \\ \overline{x_C} &= \frac{\sum_{i=1}^{n} x_{Ci}}{n}, \\ s_C &= \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_{Ci} - \overline{x_C}\right)^2}, \end{aligned} \quad (6)$$

$$\begin{aligned} y_{Bi} &= \frac{x_{Bi} - \overline{x_B}}{s_B}, \\ \overline{x_B} &= \frac{\sum_{i=1}^{n} x_{Bi}}{n}, \\ s_B &= \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_{Bi} - \overline{x_B}\right)^2}. \end{aligned} \quad (7)$$

In (4)–(7), w_D, w_C, and w_B are the weights of degree centrality, closeness centrality, and betweenness centrality, which can be obtained by factor analysis. y_{Di}, y_{Ci}, and y_{Bi} are the normalized values for degree centrality, closeness centrality, and betweenness centrality, which can be obtained from a Z-score standardization calculation, where $\overline{x_D}, \overline{x_C}$, and $\overline{x_B}$ are the mean values and s_D, s_C, and s_B are the standard deviations [53].

2.3.2. Kernel Density Analysis. Passenger flow centrality is expressed by the total number of passenger cars passing through the expressway section where the service areas are located. It is an important factor affecting the reception and provision of tourism services by service areas. ArcGIS (Environmental Systems Research Institute (ESRI). Released 2014. ArcGIS 10.2 for Desktop. Redlands, CA: ESRI) was used to input the data on passenger-car flow rates for each expressway section into the vector database, and the kernel density plot of the passenger-car flow rate was computed using spatial kernel density analysis.

The kernel density is calculated as follows [54–56]:

$$\widehat{f(x)} = \frac{1}{nh^2\pi}\sum_{i=1}^{n}\left[1 - \frac{(x-x_i)^2 - (y-y_i)^2}{h^2}\right]^2, \quad (8)$$

$$h = 0.9 * \min\left(SD, \sqrt{\frac{1}{\ln 2}} * D_m\right) * n^{-0.2}. \quad (9)$$

In (8), n is the number of nodes in the service area of the expressway network, h is the bandwidth, and $(x-x_i)^2 - (y-y_i)^2$ is the deviation between (x_i, y_i) and (x, y).

In (9), SD is the standard distance, and D_m is the median distance.

2.3.3. Bivariate Spatial Autocorrelation Analysis. Tourism utilization potential was evaluated using the consistency in the spatial distribution between geographical centrality and passenger flow centrality, which was determined using coupling analysis spatial autocorrelation based on GeoDa (Luc Anselin. Released 2019. GeoDa 1.14 for Windows. Chicago, IL: Luc Anselin). This included both global and local spatial autocorrelation.

The equation for global spatial autocorrelation is given as follows [57]:

$$I_1 = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} C_{ij} z_i z_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} C_{ij}\sum_{i=1}^{n} z_i^2}. \quad (10)$$

In (10), C_{ij} is the spatial weight between i and j, and z_i and z_j are the deviations of attributes i and j from the mean.

The equation for local spatial autocorrelation is given as follows [57, 58]:

$$I_2 = \frac{X_k^i - \overline{X_k}}{\sigma_k}\sum_{j=1}^{n} C_{ij}\frac{\left(X_l^j - \overline{X_l}\right)}{\sigma_l}. \quad (11)$$

In (11), X_k^i is the value of attribute i at k; X_l^j is the value of attribute j at l; and σ_k and σ_l are the variances of attributes k and l.

3. Analysis of Results

3.1. Distribution Characteristics of Geographical Centrality

3.1.1. Degree Centrality. Based on calculations using formula (1), we can see from Figure 2 and Table 1 that the degree of the Guizhou expressway transportation network ranges from 0 to 0.07. Its distribution shows a clear polycentric clustered structure, with the expressway service areas around Guiyang (Area A), Bijie (Area B), and Zunyi (Area C) showing the highest levels of degree centrality and being primarily concentrically distributed. Area A is the primary

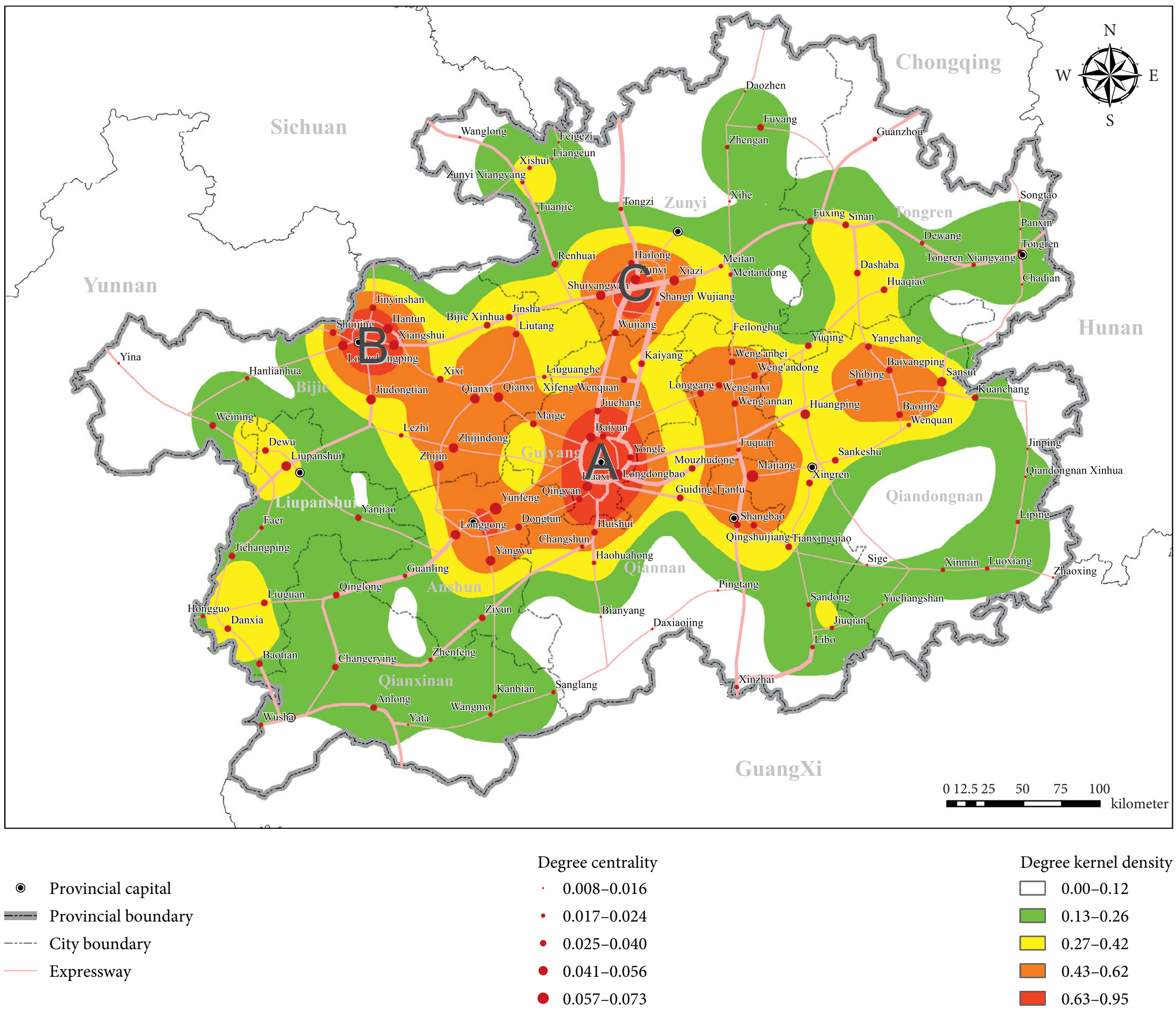


FIGURE 2: Kernel density plot of degree in the Guizhou expressway network.

core region of the overall network with respect to degree and is mainly distributed around Guiyang. The Longdongbao and Yunfeng service areas have the highest number of direct links to other nodes, both with a degree of 0.0726. These are the service areas with the best transportation accessibility and convenience in Guizhou province. Areas B and C are secondary core regions and are distributed around Bijie and Zunyi. The degrees of service areas within these regions, including Hantun, Xiangshui, Jiudongtian, and Shuiyangwan, are 0.05–0.07. Their transportation accessibility and convenience are second only to the Longdongbao and Yunfeng service areas. The degree of 50.4% of service areas ranges between 0.03 and 0.05 and that of 39.20% of service areas ranges between 0.01 and 0.03. These service areas have average transportation accessibility and are considered transitional service areas between the core and peripheral regions. The degrees of the Feigezi, Daxiaojing, Daozhen, and Songtao service areas are only 0.0081, and they have the lowest transportation convenience. These service areas have the fewest direct links with other service areas in the entire expressway transportation network.

The degree of the expressway transportation network in Guizhou province shows a polycentric distribution, with the three high-value areas (Guiyang, Bijie, and Zunyi) forming the core from which the degree gradually declines as we move outward to the periphery. The degree of Guiyang is far higher than that of Bijie and that of Zunyi; therefore, the core transportation hub is mainly located in the Guiyang urban area.

3.1.2. Closeness Centrality. Based on calculations using formula (2), we can see from Figure 3 and Table 2 that the closeness of the Guizhou expressway transportation network ranges between 9 and 25. Its distribution shows a "core-periphery-margin" spatial structure. Area A is the core

Table 1: Degree of expressway service areas in Guizhou province.

Name	Degree
Longdongbao	0.0726
Yunfeng	0.0726
Majiang	0.0645
Hantun	0.0565
Xiangshui	0.0565
Jiudongtian	0.0565
Zhijindong	0.0565
Shuiyangwan	0.0565
Huaxi	0.0565
Longchangping	0.0484
Liupanshui	0.0484
Zhijin	0.0484
Qianxi	0.0484
Zunyi	0.0484
Xiazi	0.0484
Baiyun	0.0484
Longgong	0.0484
Yangwu	0.0484
Huangping	0.0484
Sansui	0.0484
Shuijing	0.0403
Jinyinshan	0.0403
Maige	0.0403
Liutang	0.0403
Xifeng Wenquan	0.0403
Huoshipo	0.0403
Yongle	0.0403
Dongtun	0.0403
Changerying	0.0403
Huishui	0.0403
Shangbao	0.0403
Longgang	0.0403
Sinan	0.0403
Dashaba	0.0403
Yuqing	0.0403
Baiyangping	0.0403
Shibing	0.0403
Baojing	0.0403
Sankeshu	0.0403
Weining	0.0323
Dewu	0.0323
Jichangping	0.0323
Yanjiao	0.0323
Xixi	0.0323
Bijie Xinhua	0.0323
Jinsha	0.0323
Renhuai	0.0323
Hailong	0.0323
Wujiang	0.0323
Kaiyang	0.0323
Jiuchang	0.0323
Qingyan	0.0323
Qinglong	0.0323
Liuguan	0.0323
Danxia	0.0323
Baotian	0.0323
Ziyun	0.0323
Anlong	0.0323
Qingshuijiang	0.0323
Tianxingqiao	0.0323
Guiding Tianfu	0.0323
Mouzhudong	0.0323

Table 1: Continued.

Name	Degree
Weng'annan	0.0323
Weng'anxi	0.0323
Weng'andong	0.0323
Weng'anbei	0.0323
Fuxing	0.0323
Fuyang	0.0323
Huaqiao	0.0323
Yangchang	0.0323
Kuanchang	0.0323
Xingren	0.0323
Hanlianhua	0.0242
Faer	0.0242
Lezhi	0.0242
Liuguanghe	0.0242
Xishui	0.0242
Zunyi Xiangyang	0.0242
Tongzi	0.0242
Shangji Wujiang	0.0242
Guanling	0.0242
Hongguo	0.0242
Wusha	0.0242
Zhenfeng	0.0242
Kanbian	0.0242
Wangmo	0.0242
Sanglang	0.0242
Changshun	0.0242
Haohuahong	0.0242
Xinzhai	0.0242
Libo	0.0242
Jiuqian	0.0242
Sandong	0.0242
Xinmin	0.0242
Luoxiang	0.0242
Liping	0.0242
Fuquan	0.0242
Meitandong	0.0242
Meitan	0.0242
Zhengan	0.0242
Guanzhou	0.0242
Dewang	0.0242
Tongren Xiangyang	0.0242
Wenquan	0.0242
Tongren	0.0242
Yina	0.0161
Wanglong	0.0161
Tuanjie	0.0161
Liangcun	0.0161
Yata	0.0161
Bianyang	0.0161
Pingtang	0.0161
Sige	0.0161
Yueliangshan	0.0161
Zhaoxing	0.0161
Feilonghu	0.0161
Xihe	0.0161
Panxin	0.0161
Chadian	0.0161
Jinping	0.0161
Qiandongnan Xinhua	0.0161
Feigezi	0.0081
Daxiaojing	0.0081
Daozhen	0.0081
Songtao	0.0081

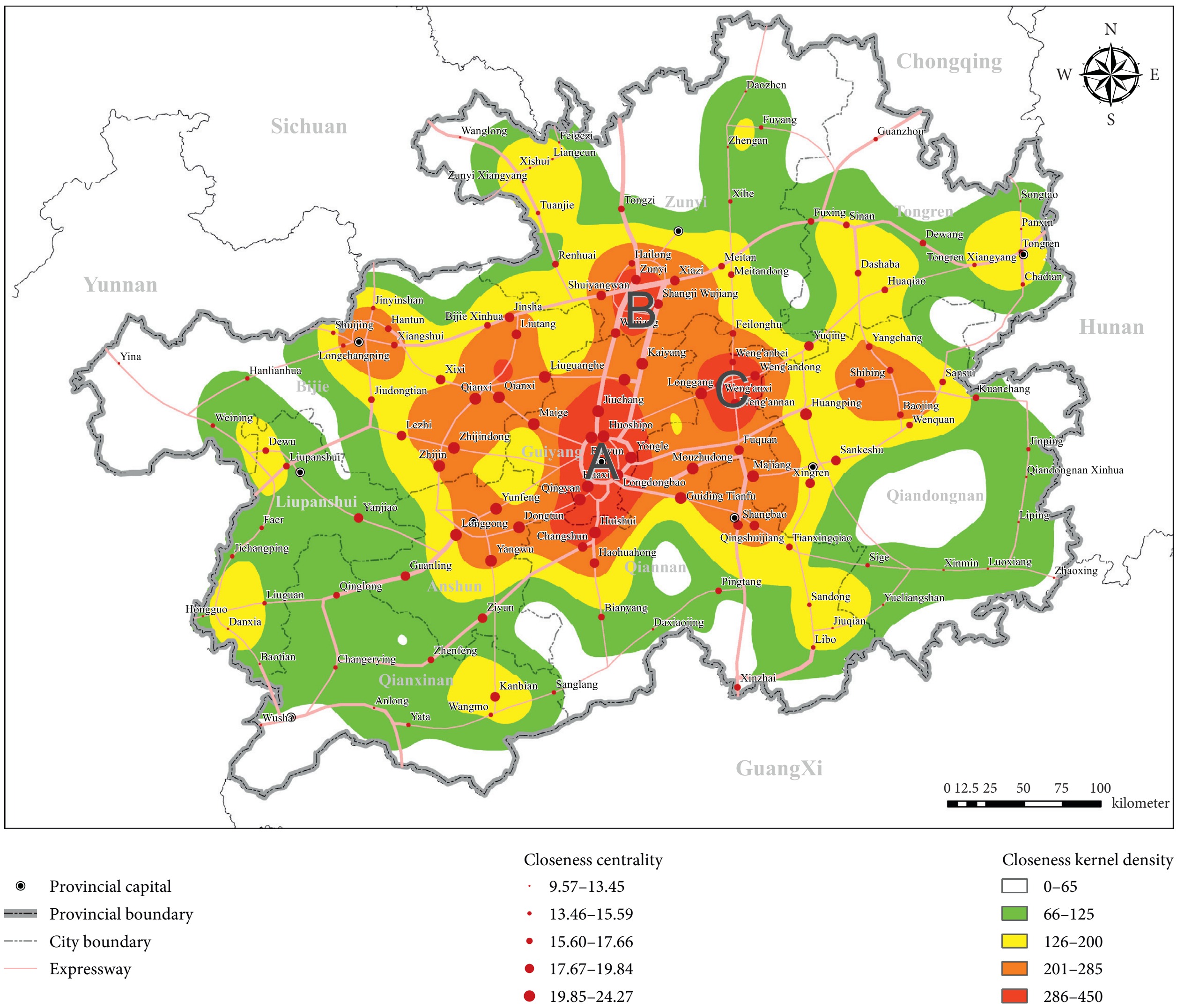


Figure 3: Kernel density plot of closeness in the Guizhou expressway network.

region with high values of closeness and is mainly located in the south of Guiyang and northwest of Qiannan. The closeness of the Longdongbao, Yunfeng, Yongle, Huoshipo, Huaxi, and Baiyun service areas is all above 20. Among them, the closeness of the Longdongbao service area is 24.2661; thus, this is the service area with the shortest average time needed to reach all other service areas within the network. Areas B and C are located at Zunyi and Weng'an and are small areas with relatively high closeness. The closeness of the Xiazi, Zunyi, Weng'anxi, and Weng'andong service areas ranges between 17 and 20, indicating that the paths to other service areas and the average time taken are relatively short. Regions that are far away from Areas A, B, and C but have high kernel densities include the areas around Bijie City, Qianxi County, and Sansui County, where the closeness of the service areas varies from 15 to 20. The closeness of the Weining, Sanglang, and Libo service areas is less than 15, indicating that their geographical locations are relatively marginal, where the average path to other service areas and the average time taken are comparatively long. The Songtao, Liangcun, and Feigezi service areas have the lowest closeness level, ranging between 11 and 9 and, accordingly, are the most remote service areas for travel.

The high values of closeness in the Guizhou expressway transportation network are primarily distributed around Guiyang city, where the closeness levels are far higher than those of other regions. Thus, we can conclude that the route from Guiyang to all other service areas is the shortest and takes the least time on average, which indicates that Guiyang occupies a core position in the expressway transportation network of the entire Guizhou province.

3.1.3. Betweenness Centrality. Based on calculations using formula (3), we can see from Figure 4 and Table 3 that the betweenness of the Guizhou expressway transportation network varies from 0 to 35. Its distribution shows a polycentric dispersed structure that is weakly concentric, where the overall layout is relatively concentrated, but the

Table 2: Closeness of expressway service areas in Guizhou province.

Name	Closeness
Longdongbao	24.2661
Yunfeng	23.3522
Yongle	23.0056
Huoshipo	22.7523
Huaxi	22.7106
Baiyun	22.1429
Kaiyang	21.9858
Zhijindong	21.9081
Guiding Tianfu	21.7926
Huangping	21.7544
Zhijin	21.6405
Mouzhudong	21.6405
Huishui	21.6028
Qingyan	21.4533
Longgang	21.4162
Jiuchang	21.3793
Maige	21.3425
Longgong	21.1244
Yangwu	20.8754
Qianxi	20.7705
Xifeng Wenquan	20.7358
Dongtun	20.5298
Majiang	20.5298
Liuguanghe	20.2946
Shangji Wujiang	19.8400
Liutang	19.6513
Wujiang	19.5893
Qingshuijiang	19.5893
Fuquan	19.4969
Shangbao	19.4662
Shuiyangwan	19.2547
Yuqing	19.2248
Lezhi	19.1654
Xiazi	19.1063
Weng'anxi	19.0476
Changshun	18.8450
Xingren	18.7311
Sankeshu	18.6747
Zunyi	18.6186
Shibing	18.6186
Yanjiao	18.4799
Weng'annan	18.4524
Haohuahong	18.4250
Guanling	18.3704
Ziyun	18.1287
Weng'andong	17.9971
Kanbian	17.9191
Xixi	17.8674
Jinsha	17.8674
Dashaba	17.6638
Renhuai	17.5887
Tianxingqiao	17.5637
Meitan	17.5637
Jiudongtian	17.3913
Weng'anbei	17.3913
Hailong	17.3184
Liupanshui	17.2943
Yangchang	17.2702
Huaqiao	17.1034
Bijie Xinhua	16.9399
Baiyangping	16.7794
Hantun	16.6443

Table 2: Continued.

Name	Closeness
Xiangshui	16.6443
Xinzhai	16.5997
Sinan	16.5775
Baojing	16.5554
Fuxing	16.5333
Pingtang	16.4238
Sansui	16.4021
Kuanchang	16.3804
Wenquan	16.2516
Qinglong	16.2304
Tongzi	16.2092
Dewu	16.1880
Zhenfeng	16.0207
Dewang	15.8771
Bianyang	15.8568
Feilonghu	15.8365
Meitandong	15.7560
Longchangping	15.5975
Wangmo	15.5975
Shuijing	15.5388
Jinyinshan	15.5388
Tongren Xiangyang	15.3276
Sige	15.1961
Tuanjie	15.1589
Faer	15.1220
Sandong	15.1220
Fuyang	15.1035
Guanzhou	15.0485
Weining	14.8681
Sanglang	14.6919
Libo	14.6054
Chadian	14.4860
Changerying	14.3519
Liuguan	14.3353
Jinping	14.3187
Xihe	14.0113
Hanlianhua	13.9483
Yata	13.8393
Tongren	13.7168
Jichangping	13.6414
Xinmin	13.4490
Jiuqian	13.3909
Yina	13.3765
Zhengan	13.3333
Zunyi Xiangyang	13.2905
Danxia	13.0115
Baotian	12.9436
Hongguo	12.8898
Daxiaojing	12.8232
Anlong	12.7835
Qiandongnan Xinhua	12.7703
Wusha	12.7049
Luoxiang	12.1450
Panxin	12.0976
Yueliangshan	11.9923
Xishui	11.7983
Wanglong	11.7759
Daozhen	11.7759
Liping	11.6105
Zhaoxing	11.0912
Songtao	10.8014
Liangcun	10.5802
Feigezi	9.5753

high-value areas are relatively scattered. Areas A, B, C, and D form the core areas of betweenness. Area A has the highest betweenness and is spatially located in the south of Guiyang city. In Area A, the betweenness of the Longdongbao service area is the highest at 34.8013, indicating that it is located on the greatest number of paths between pairs of service areas and is a "necessary path" for passenger flow between service areas. The betweenness of other service areas is also relatively high: for example, the betweenness of the Yunfeng, Yongle, and Guiding Tianfu service areas ranges between 10 and 20; thus, they occupy a core position. Areas B, C, and D are smaller areas concentrated around the Qianxi-Zhijin-Longgong region, distributed along the Zunyi-Xiazi route, and centered on Huangping, respectively. Their betweenness levels range from 10 to 25, forming small-scale "core-periphery" concentric structures. However, there are no transitional zones between these areas, and the betweenness drops to a low level in the intermediate areas—for example, that of the Maige service area is only 1.8884. This reflects the weak connectivity of the service areas in the intermediate concentric layers. As the Yina, Wanglong, Feigezi, and Tongzi service areas are not located between any node pairs, their betweenness is 0, which indicates that they are located in the marginal regions of the expressways connecting Guizhou with the surrounding provinces.

The core region with respect to betweenness in the Guizhou expressway transportation network shows a clear trend of dispersion and is centered around Guiyang, Zhijin, Zunyi, and Huangping. The service areas in these regions occupy a core position and are connected to a relatively large number of other service areas. However, upon expanding the scope, we observe a sharp drop in the effective "intermediary" connective function of the service areas, with the formation of large, discontinuous intermediate regions.

3.1.4. Geographical Centrality. Based on calculations using formulas (4)–(7), the result of the Kaiser–Meyer–Olkin test is 0.715 and the Bartlett test significance value is 0.000, which is below the significance level of 0.05 and is suitable for factor analysis. The weight coefficients calculated using factor analysis for degree, closeness, and betweenness are 0.388, 0.394, and 0.374, respectively. We can see from Figure 5 and Table 4 that the geographical centrality of the Guizhou expressway transportation network ranges from −1.28 to 3.33. Its distribution shows a single-core, polyconcentric dispersed spatial structure.

Area A is the core area of geographical centrality and is mainly concentrated in six municipal districts in the south of Guiyang city. Within this area, the geographical centrality of the Longdongbao, Yongle, and Guiding Tianfu service areas ranges between 1 and 3.33, while that of the Huaxi, Qingyan, Huoshipo, Baiyun, and Jiuchang service areas is all greater than 0. These service areas have highly convenient transportation conditions and complete transportation infrastructure, enabling them to occupy the most central geographical location in the Guizhou expressway transportation network. Areas B and C are the central regions of geographical centrality. Area B is centered around the Yunfeng service area and includes the Longgong, Yangwu, Qianxi, and Zhijin service areas, with the geographic centrality ranging from 0.74 to 2.11. However, a small low-value area is formed to the south of the Maige service area due to its lack of expressways in the north-south direction. Area C is centered around the Huangping service area, which has a geographical centrality of 2.0032, indicating that it has a high level of transportation convenience and accessibility. However, its long distance from Guiyang city resulted in its off-center position as a geographically central location. The geographical centrality of the transitional zones beyond Areas B and C ranges from 0 to 1, indicating that these areas have slightly inadequate transportation convenience, accessibility, and intermediation but are not considered remote locations; they account for 39.20% of all service areas. Service areas with geographical centrality ranging between −0.7 and 0 account for 38.40% and are marginal regions in the network with an average geographical location for transportation. Service areas with a geographical centrality of less than −0.7 account for 16% of all areas and are located in the outlying areas of the overall transportation network. These areas include the Yueliangshan, Wanglong, Liangcun, Daozhen, Zhaoxing, Songtao, and Feigezi service areas, which have poor geographical locations for transportation.

The core region with respect to the geographical centrality of the Guizhou expressway transportation network is concentrated in the southern urban area of Guiyang city, where its geographical location has the greatest advantages of centrality—high connectivity, convenience, and accessibility. This is followed by the central region, which is mainly distributed in the periphery of the core region and spreads in the north-south and east-west directions along the main transport corridors; this region has a superior geographical location and infrastructure for transportation as well as high accessibility. The transitional zones are located in the periphery of the central region and have less adequate transportation convenience, accessibility, and intermediation compared to the central region. The marginal regions have average transportation connectivity, while the outlying regions have poor geographical locations for transportation.

3.2. Distribution Characteristics of Passenger Flow Centrality. Based on calculations using formulas (8) and (9), as shown in Table 5 and Figure 6, the passenger flow rate of all sections in the Guizhou expressway network ranges between 15,000 and 3.66 million. Its spatial layout primarily exhibits a dual-core, polycentric dispersed structure that is weakly concentric and relatively dispersed. Zunyi city (Area A) is the cluster region with the highest passenger flow rate in the Guizhou expressway transportation network. Here, the Zunyi service area has the highest passenger-car flow rate at 3.66 million followed by the Xiazi service area at 2.43 million. These service areas primarily receive tourists coming from Chongqing and

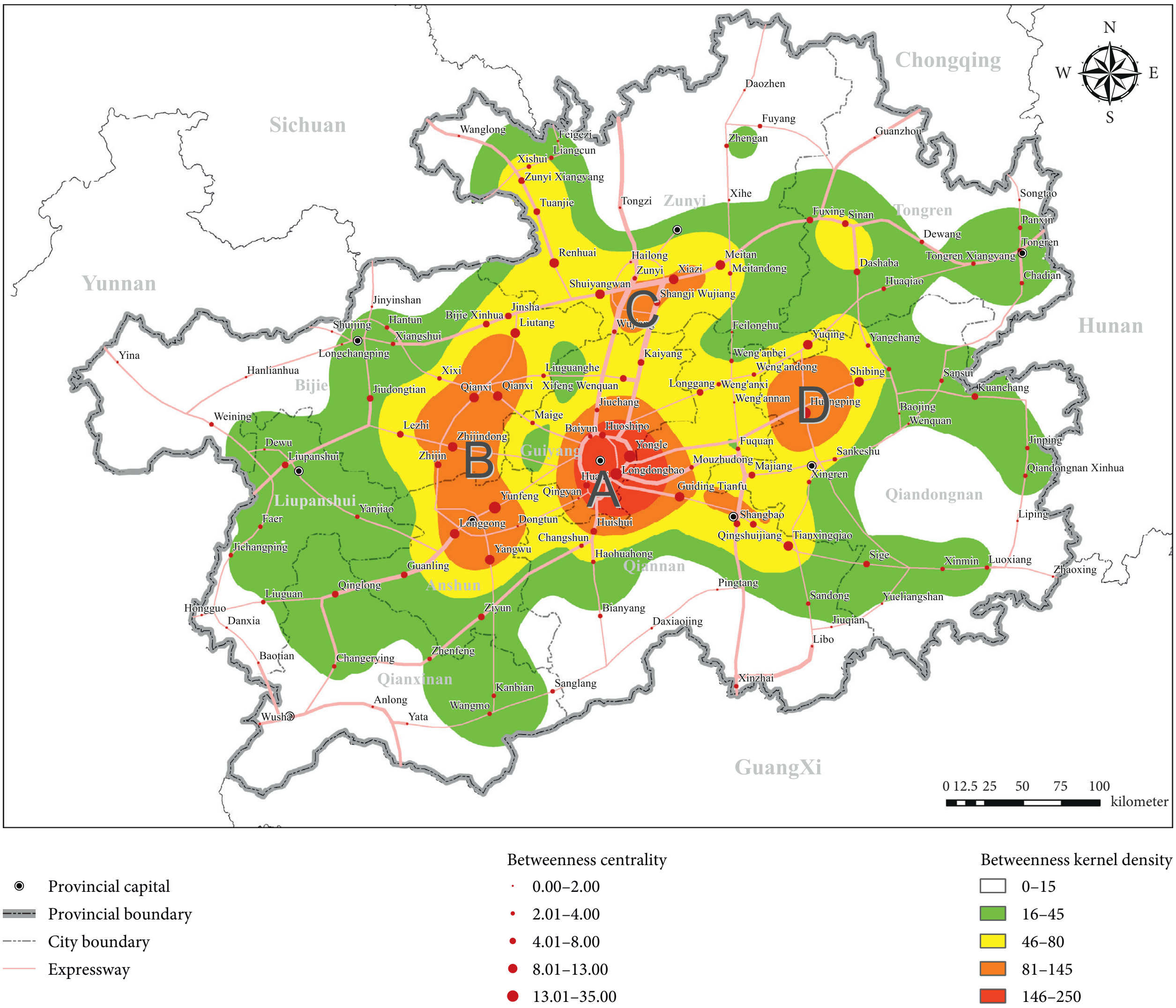


Figure 4: Kernel density plot of betweenness in the Guizhou expressway network.

Sichuan, forming the core region with the largest area with high flow rates. Guiyang city (Area B) attracts a large number of passenger-car transfers by virtue of its large population flow and convenient ring roads. Within this region, the passenger-car flow rate of the Longdongbao service area is 2.37 million, which is second only to the Zunyi and Xiazi service areas and a core region with high flow rates. The two major core regions are connected to each other by north-south expressways. Among them, the Wujiang, Kaiyang, and Shangji Wujiang service areas that are closely connected to Zunyi city have an average passenger-car flow rate of around 1.82 million, whereas that of the Jiuchang, Yongle, Baiyun, and Huoshipo service areas around Longdongbao gradually decreases to 1.4 million.

The "polycenters" are primarily distributed in Guiding (Area C), Xingyi (Area D), Sinan (Area E), and Bijie (Area F). Among them, the Guiding Tianfu, Mouzhudong, Fuquan, and Majiang service areas in Guiding County have an average passenger-car flow rate of about 900,000, receiving passenger cars mostly from Guiyang city. The Wusha, Changerying, and Anlong service areas in Xingyi city experience an average passenger-car flow rate of about 600,000 and receive passenger cars mostly from Yunnan. The Sinan service area in Sinan County has a passenger-car flow rate of up to 1.12 million, primarily from merging passenger cars from Hunan and Chongqing. The Longchangping and Xiangshui service areas in Bijie city experience an average passenger-car flow rate of 540,000, and they generally receive passenger cars from Yunnan and Sichuan.

The average passenger-car flow rate of median-value regions is about 650,000, which follows a zonal distribution along the expressway transport corridors. These regions are concentrated along the peripheries of the Lanhai, Hangrui, Hukun, and Shankun expressways. Other service areas beyond the regions above, such as the Daozhen, Yina, Xinmin, and Daxiaojing service areas, have an average passenger-car flow rate of about 100,000. In particular, areas such as southeast Qiandongnan, southwest Qiannan, southeast Qianxinan, northwest Bijie, and north Zunyi have low passenger-car flow rates, thus constituting the marginal regions.

Table 3: Betweenness of expressway service areas in Guizhou province.

Name	Betweenness
Longdongbao	34.8013
Huangping	22.3045
Yunfeng	20.1288
Yongle	18.6511
Guiding Tianfu	13.1280
Qianxi	11.7287
Shuiyangwan	11.3840
Longgong	11.3290
Xiazi	10.8608
Zhijindong	10.6430
Yuqing	10.5387
Tianxingqiao	9.4155
Meitan	9.3063
Renhuai	9.2840
Shibing	8.8271
Yangwu	8.8057
Liutang	8.5227
Tuanjie	7.8023
Lezhi	7.6282
Huishui	7.4428
Kaiyang	7.2087
Qingshuijiang	7.0535
Liupanshui	6.9696
Longgang	6.8019
Guanling	6.6514
Sinan	6.2995
Zunyi Xiangyang	6.2943
Zhijin	5.9361
Dashaba	5.8976
Qinglong	5.8694
Fuxing	5.6472
Huaxi	5.5953
Majiang	5.5557
Jiudongtian	5.3775
Huoshipo	5.0972
Shangbao	5.0533
Shangji Wujiang	4.8513
Ziyun	4.8175
Sige	4.8009
Xifeng Wenquan	4.7644
Jinsha	4.6453
Kuanchang	4.6282
Bijie Xinhua	4.3175
Kanbian	4.0857
Yanjiao	4.0442
Baiyun	3.8784
Changerying	3.8274
Xinmin	3.7398
Wujiang	3.5778
Tongren	3.5464
Xingren	3.5093
Sansui	3.4839
Haohuahong	3.3451
Zhenfeng	3.3341
Jinping	3.2033
Xishui	3.1996
Wangmo	3.1000
Tongren Xiangyang	3.0211
Weng'anxi	3.0122
Mouzhudong	2.9682
Meitandong	2.9068
Sankeshu	2.8848

Table 3: Continued.

Name	Betweenness
Faer	2.7247
Xixi	2.7239
Huaqiao	2.6556
Jiuchang	2.4818
Liuguanghe	2.4729
Fuyang	2.4458
Liuguan	2.2368
Changshun	2.1933
Hantun	2.1835
Xiangshui	2.1835
Xinzhai	2.1815
Weng'anbei	2.1618
Chadian	2.0497
Fuquan	2.0174
Zhengan	1.9616
Bianyang	1.9473
Weining	1.9296
Yangchang	1.9258
Luoxiang	1.8949
Maige	1.8884
Qiandongnan Xinhua	1.8308
Baiyangping	1.7890
Sanglang	1.7886
Sandong	1.7691
Weng'andong	1.7586
Dewang	1.7172
Jichangping	1.6521
Liangcun	1.6129
Panxin	1.6129
Zunyi	1.6079
Weng'annan	1.4250
Longchangping	1.4026
Feilonghu	1.1876
Dewu	1.1677
Jiuqian	1.1269
Xihe	1.0631
Libo	1.0068
Liping	0.8896
Yata	0.7684
Danxia	0.7096
Baotian	0.6217
Hanlianhua	0.6210
Anlong	0.5825
Baojing	0.5414
Qingyan	0.4819
Dongtun	0.3863
Wenquan	0.3309
Yueliangshan	0.2732
Hailong	0.1672
Yina	0.0000
Shuijing	0.0000
Jinyinshan	0.0000
Wanglong	0.0000
Feigezi	0.0000
Tongzi	0.0000
Hongguo	0.0000
Wusha	0.0000
Daxiaojing	0.0000
Pingtang	0.0000
Zhaoxing	0.0000
Daozhen	0.0000
Guanzhou	0.0000
Songtao	0.0000

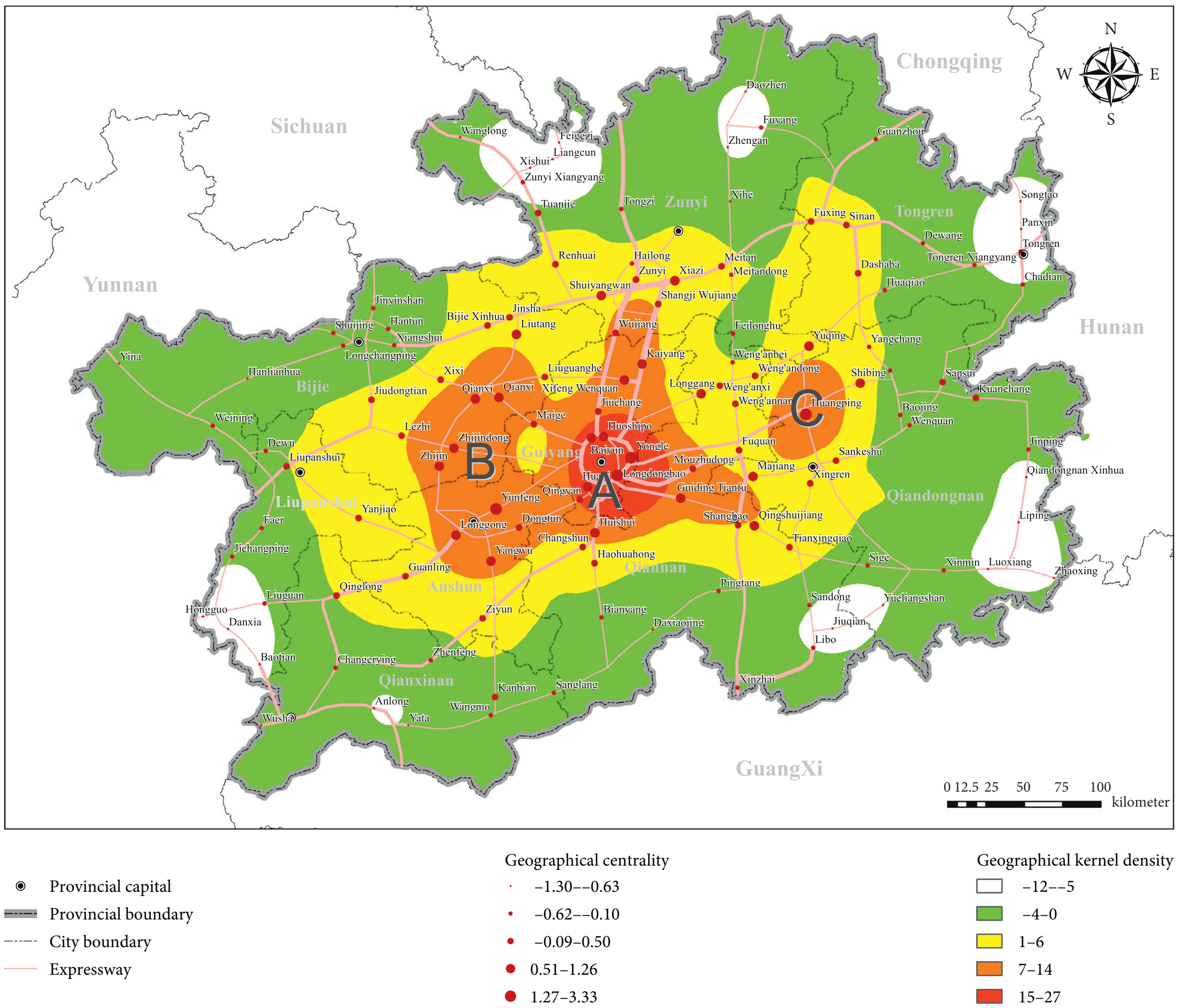


FIGURE 5: Kernel density plot of geographical centrality in the Guizhou expressway network.

The spatial distribution of passenger-car flow rates in the Guizhou expressway network is characterized by Zunyi city and Guiyang city as its dual-core, Guiding, Xingyi, Sinan, and Bijie as its secondary centers, and distribution along its transport corridors. However, the low passenger-car flow rates in the margins of the province are also highly significant.

3.3. Analysis of Tourism Utilization Potential of Expressway Service Areas. After calculations using formulas (10) and (11), based on the geographical centrality and passenger flow centrality, a coordinate plot for 125 geographical-passenger flow centrality pairs was created (Figure 7). As shown in Figure 8, there is a positive spatial correlation between the distribution of the geographical centrality and passenger flow centrality of expressway service areas. The bivariate global autocorrelation coefficient is 0.22, which indicates that expressway service areas tend to be built in areas with high passenger flow to a certain extent, thus providing transportation service facilities with high accessibility. Furthermore, the more complete the development of transportation conditions, the greater the passenger flow these areas will attract. To test whether Moran's I was significant, a Monte Carlo simulation was used in GeoDa. The P value was equal to 0.001, indicating that spatial autocorrelation is significant at 99.9% confidence interval.

The passenger-car flow rate is indicative of the potential tourist flow rate, and the accessibility of the transportation network will affect tourists' travel willingness and behaviors. Therefore, in Moran's I scatter plot, values along the geographical centrality y-axis >1, >0 and <1, >-1 and <0, and <-1 are defined as high, moderately high, moderately low, and low geographical centrality, respectively; values along the passenger flow centrality x-axis >0 and <0 are defined as high and low passenger flow centrality, respectively. As the difference between "low geographical centrality-low passenger flow centrality" and "moderately low geographical centrality-low passenger flow centrality" was of limited practical significance, these were merged into "low

Table 4: Geographical centrality of expressway service areas in Guizhou province.

Name	Geographical centrality
Longdongbao	3.3296
Yunfeng	2.1029
Huangping	2.0033
Yongle	1.8517
Guiding Tianfu	1.2610
Zhijindong	1.1585
Longgong	1.0921
Qianxi	1.0799
Shuiyangwan	0.8953
Huaxi	0.8710
Yangwu	0.8700
Kaiyang	0.8338
Huishui	0.8297
Xiazi	0.8133
Huoshipo	0.7897
Yuqing	0.7788
Longgang	0.7584
Zhijin	0.7438
Liutang	0.6768
Baiyun	0.6478
Majiang	0.6296
Shibing	0.5756
Qingshuijiang	0.5333
Xifeng Wenquan	0.5214
Lezhi	0.5017
Mouzhudong	0.4695
Tianxingqiao	0.4690
Renhuai	0.4620
Meitan	0.4364
Jiuchang	0.4010
Shangbao	0.3905
Maige	0.3756
Shangji Wujiang	0.3716
Guanling	0.3316
Liupanshui	0.2989
Wujiang	0.2687
Qingyan	0.2577
Liuguanghe	0.2454
Dashaba	0.2376
Jiudongtian	0.2137
Ziyun	0.1871
Yanjiao	0.1706
Dongtun	0.1634
Weng'anxi	0.1604
Xingren	0.1602
Jinsha	0.1426
Sinan	0.1373
Sankeshu	0.1301
Fuquan	0.1146
Haohuahong	0.0865
Kanbian	0.0819
Fuxing	0.0581
Zunyi	0.0504
Changshun	0.0495
Qinglong	0.0385
Tuanjie	0.0080
Bijie Xinhua	0.0059
Xixi	−0.0037
Weng'annan	−0.0321
Kuanchang	−0.0379
Weng'andong	−0.0615
Sansui	−0.0739
Huaqiao	−0.1009
Weng'anbei	−0.1038
Xiangshui	−0.1194
Hantun	−0.1194
Yangchang	−0.1364
Baiyangping	−0.1816
Zhenfeng	−0.2039
Sige	−0.2159
Xinzhai	−0.2219
Hailong	−0.2644
Meitandong	−0.2684
Wangmo	−0.2727
Baojing	−0.3036
Zunyi Xiangyang	−0.3076
Tongren Xiangyang	−0.3113
Changerying	−0.3189
Dewu	−0.3244
Longchangping	−0.3292
Dewang	−0.3443
Bianyang	−0.3535
Fuyang	−0.3578
Faer	−0.3586
Wenquan	−0.4047
Feilonghu	−0.4137
Weining	−0.4254
Sandong	−0.4313
Pingtang	−0.4334
Tongzi	−0.4350
Jinping	−0.4432
Tongren	−0.4653
Liuguan	−0.4662
Shuijing	−0.4672
Jinyinshan	−0.4672
Sanglang	−0.4816
Xinmin	−0.4829
Chadian	−0.5108
Libo	−0.5516
Guanzhou	−0.5748
Jichangping	−0.5943
Zhengan	−0.6321
Xihe	−0.6431
Hanlianhua	−0.6601
Yata	−0.6862
Jiuqian	−0.6887
Xishui	−0.7228
Qiandongnan Xinhua	−0.7342
Danxia	−0.7419
Baotian	−0.7568
Anlong	−0.7791
Luoxiang	−0.7804
Yina	−0.8005
Panxin	−0.8318
Hongguo	−0.8349
Wusha	−0.8571
Daxiaojing	−0.8914
Liping	−0.9213
Yueliangshan	−0.9464

Table 4: Continued.

Table 4: Continued.

Name	Geographical centrality
Wanglong	−0.9933
Liangcun	−1.0146
Daozhen	−1.0175
Zhaoxing	−1.0758
Songtao	−1.1349
Feigezi	−1.2826

geographical centrality-low passenger flow centrality" for the analysis. This produced seven major categories, as shown in Table 6.

3.3.1. High-High Cluster. Service areas in the "high-high" cluster type are geographically located at the center of the expressway transportation network. These service areas have complete expressway transportation facilities, high transportation convenience, accessibility, and intermediation, as well as a high number of core scenic areas and large passenger-car flow rate. This type of the service area is generally distributed around Guiyang city, as well as in Anshun (Longgong), Bijie (Jinsha and Qianxi), Qiannan (Guiding Tianfu, Mouzhudong, and Fuquan), and Qiandongnan (Majiang). They account for 13.6% of all service areas, with an average geographical centrality of about 0.90 and an average passenger-car flow rate of up to 1.17 million. Service areas in the "high-high" cluster type have the greatest potential for tourism utilization and can rely on major transportation hubs and passenger-car flow rates to enhance the focus of the transportation hub-type service areas.

3.3.2. Moderately High-High Cluster. Service areas in the "moderately high-high" cluster type are supported by high-quality scenic areas and large passenger flow, but their geographical locations are not sufficiently central, and they do not have adequate transportation convenience, accessibility, and intermediation. Hence, the geographical centrality of these service areas is slightly lower than that of the "high-high" cluster type. These service areas are mainly distributed in Zunyi, as well as Bijie (Xiangshui and Jiudongtian), Anshun (Guanling and Ziyun), Qiannan (Shangbao), and Qiandongnan (Huangping). They account for 9.6% of all service areas, with an average geographical centrality of about 0.44 and an average passenger-car flow rate of up to 1.26 million, far exceeding those of the "high-high" cluster type. The rapid development of red tourism in such service areas, including Zunyi, has resulted in large passenger flows from Chongqing, Sichuan, and Hunan. Their potential for tourism utilization is also high, and these regions can rely on the concentrated transfer of large passenger flows. Therefore, the construction of service areas relying on tourist attraction can be improved.

3.3.3. Low-High Cluster. Service areas in the "low-high" cluster type have extremely marginal geographical locations.

Table 5: Passenger-car flow rates of expressway service areas in Guizhou province.

Name	Flow
Zunyi	3,661,081
Xiazi	2,431,688
Longdongbao	2,369,429
Wujiang	1,892,692
Kaiyang	1,791,420
Shangji Wujiang	1,790,814
Jiuchang	1,692,232
Yongle	1,473,084
Baiyun	1,362,797
Majiang	1,283,252
Hailong	1,143,308
Sinan	1,118,963
Qinglong	1,085,028
Huoshipo	1,075,324
Longgong	1,065,735
Fuquan	1,022,454
Shuiyangwan	986,808
Guanling	962,574
Huishui	901,144
Liupanshui	869,839
Shangbao	825,564
Mouzhudong	791,746
Huangping	789,166
Xinzhai	763,012
Jiudongtian	728,219
Renhuai	702,210
Qianxi	701,471
Tongren	685,608
Wusha	668,470
Anlong	637,520
Zhenfeng	606,424
Xifeng Wenquan	601,833
Xiangshui	592,971
Fuxing	587,794
Jinsha	585,045
Dewang	578,103
Guiding Tianfu	555,510
Tuanjie	546,301
Tongren Xiangyang	543,816
Zunyi Xiangyang	517,868
Ziyun	511,282
Longchangping	494,850
Changshun	483,479
Changerying	480,507
Yuqing	471,780
Bijie Xinhua	462,451
Tongzi	443,813
Meitan	437,170
Sankeshu	423,887
Dashaba	418,023
Libo	413,940
Zhijindong	403,976
Yata	379,674
Hanlianhua	362,812
Haohuahong	347,559
Maige	331,908
Chadian	322,606
Yanjiao	312,802
Zhijin	309,954

Table 5: Continued.

Name	Flow
Jinyinshan	302,366
Liping	297,774
Baotian	287,978
Weng'annan	287,713
Xingren	285,228
Yangchang	272,377
Liutang	270,751
Wanglong	268,958
Guanzhou	268,172
Lezhi	256,067
Sansui	253,625
Weng'andong	253,225
Liuguanghe	252,862
Panxin	251,448
Baojing	249,026
Qiandongnan Xinhua	237,566
Faer	235,737
Huaqiao	231,525
Baiyangping	226,532
Yunfeng	222,684
Liuguan	218,770
Bianyang	208,504
Dongtun	203,993
Yangwu	201,454
Huaxi	196,867
Shuijing	194,059
Weining	186,973
Jichangping	178,594
Kuanchang	177,358
Jinping	177,358
Hantun	177,178
Danxia	167,605
Luoxiang	164,756
Meitandong	161,945
Wenquan	154,567
Xixi	150,893
Weng'anxi	141,313
Tianxingqiao	125,982
Weng'anbei	125,768
Qingyan	124,219
Qingshuijiang	112,417
Wangmo	109,460
Shibing	108,028
Sanglang	100,589
Dewu	96,270
Yina	90,703
Fuyang	87,313
Feilonghu	80,973
Xishui	80,198
Liangcun	80,198
Zhaoxing	74,444
Longgang	67,238
Songtao	66,075
Daxiaojing	61,475
Xinmin	58,972
Zhengan	54,161
Xihe	53,562
Sige	49,865
Hongguo	49,457
Pingtang	45,500

Table 5: Continued.

Name	Flow
Yueliangshan	43,302
Kanbian	40,921
Feigezi	40,099
Sandong	35,431
Jiuqian	28,868
Daozhen	14,934

They are typically distributed at the intersections between Guizhou and other provinces but have high passenger-car flow rates. For example, the Tongren, Xiangyang, Tuanjie, Wusha, and Xinzhai service areas account for 4.8% of all service areas and have an average geographical centrality of about −0.36, but their average passenger-car flow rate is 620,000. Although such service areas are not the core nodes in terms of geographical location, they are situated at crucial gateway positions in Guizhou province, receiving a large volume of tourists from other provinces. These areas have great potential for tourism utilization and development and can serve as "image windows" for external publicity. Therefore, they can be improved by the construction of tourism gateway-type service areas.

3.3.4. Moderately Low-High Cluster. Service areas in the "moderately low-high" cluster type are similar to those in the "low-high" cluster type in that they have high passenger flow but are located at relatively marginal areas in the overall network. For example, the Tongren area (Dewang, Sinan, and Fuxing) receives tourists coming from Dewang and Xiangyang; the Bijie area (Longchangping) receives tourists coming from northwestern Yunnan; and Qianxinan (Anlong, Qinglong, and Zhenfeng) receives Yunnan tourists coming from Wusha. These service areas account for 6.4%, with an average geographical centrality of about −0.14 and an average passenger-car flow rate of 750,000. These types of service areas are located at internal connections with "low-high" service areas and function as secondary gateways for Guizhou province. They can be upgraded through the construction of secondary gateway-type service areas.

3.3.5. High-Low Cluster. Service areas in the "high-low" cluster type have low passenger flow but are geographically situated at core nodes in the overall transportation network. They are generally distributed in the west of Guiyang city, northeast of Anshun city, west of Bijie, north of Qiannan, and west of Qiandongnan. These service areas account for 16.8%, with an average geographical centrality of about 0.41 and an average passenger-car flow rate of 240,000. This type of service area, such as Huaxi and Qingyan, experiences a high level of infrastructure construction but an extremely low passenger flow due to insufficient attractiveness. However, given their proximity to city suburbs and the leisure needs of large urban populations, they can be improved via the construction of urban leisure-type service areas.

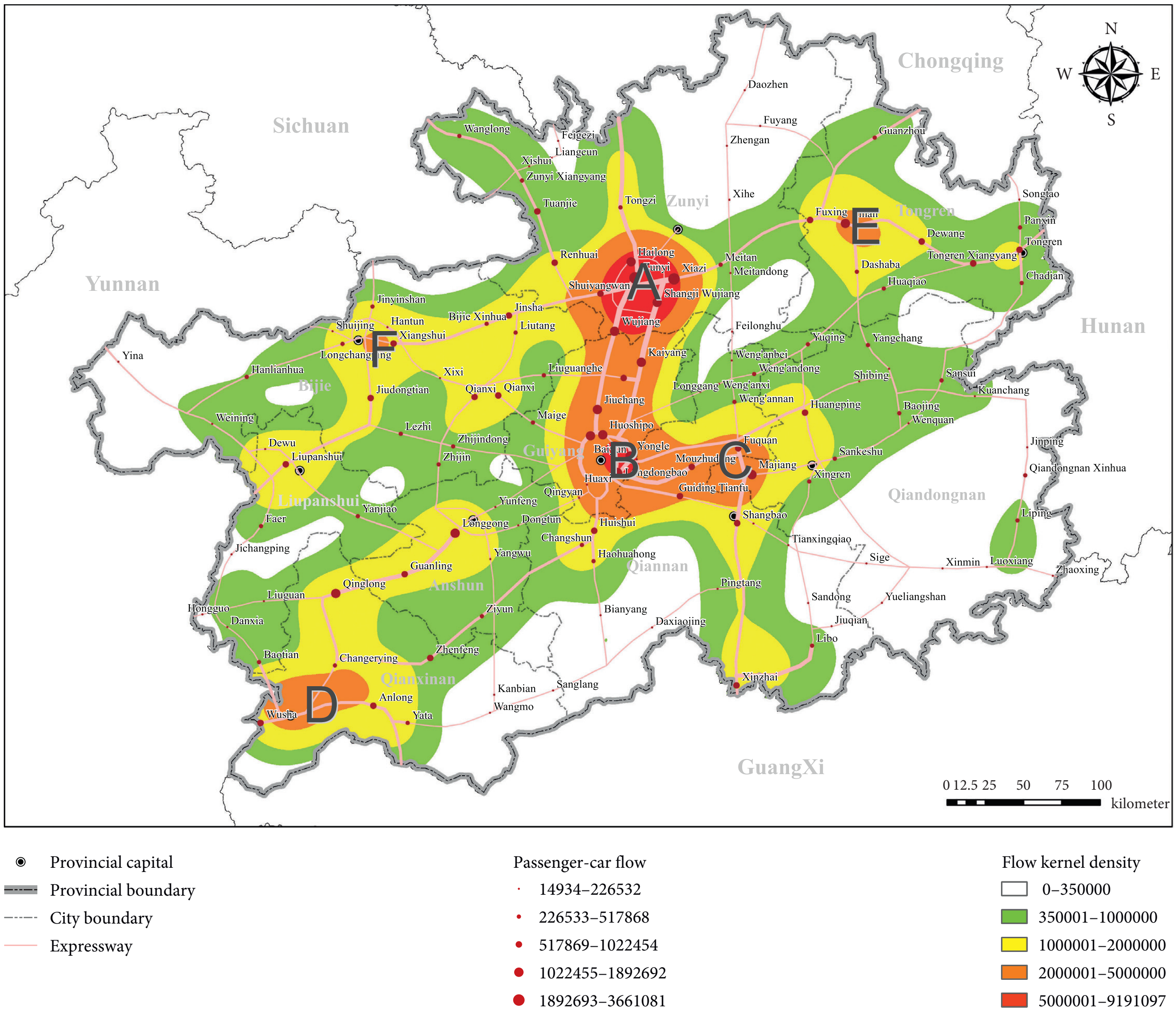


FIGURE 6: Kernel density plot of passenger-car flow rates in the Guizhou expressway network.

3.3.6. Moderately High-Low Cluster. Service areas in the "moderately high-low" cluster type have low passenger flows and insufficiently central geographical locations. They are mostly distributed in northwestern Qiandongnan, as well as Qiannan (Qingshuijiang and Pingtang), Tongren (Huaqian), Zunyi (Meitandong and Yuqing), Bijie (Xinhua), and Liupanshui (Yanjiao). These service areas account for 10.4%, with an average geographical centrality of about 0.03 and an average passenger-car flow rate of 240,000. They are situated neither on the periphery of cities nor at the intersections between provincial borders. To improve, they can be linked with the surrounding villages through the construction of rural leisure-type service areas.

3.3.7. Low-Low Cluster. Service areas in the "low-low" cluster type have extremely low passenger flows and are located in the marginal zones, which are distributed in the northwest of Bijie, north of Zunyi, west of Liupanshui, southeast of Qianxinan, south of Qiannan, northwest of Qiandongnan, and west of Tongren. These service areas account for 39.2%, with an average geographical centrality of about −0.54 and an average passenger-car flow rate of 170,000, indicating their low tourism utilization potential. In such service areas, the construction of comprehensive community service centers and agricultural product trade show centers can be undertaken to develop and upgrade them as community co-construction and sharing-type service areas.

4. Conclusions and Discussion

4.1. Conclusions. This study performed a comprehensive analysis of the complexity of the expressway transportation network in Guizhou province, which enabled us to understand the differences between its geographical

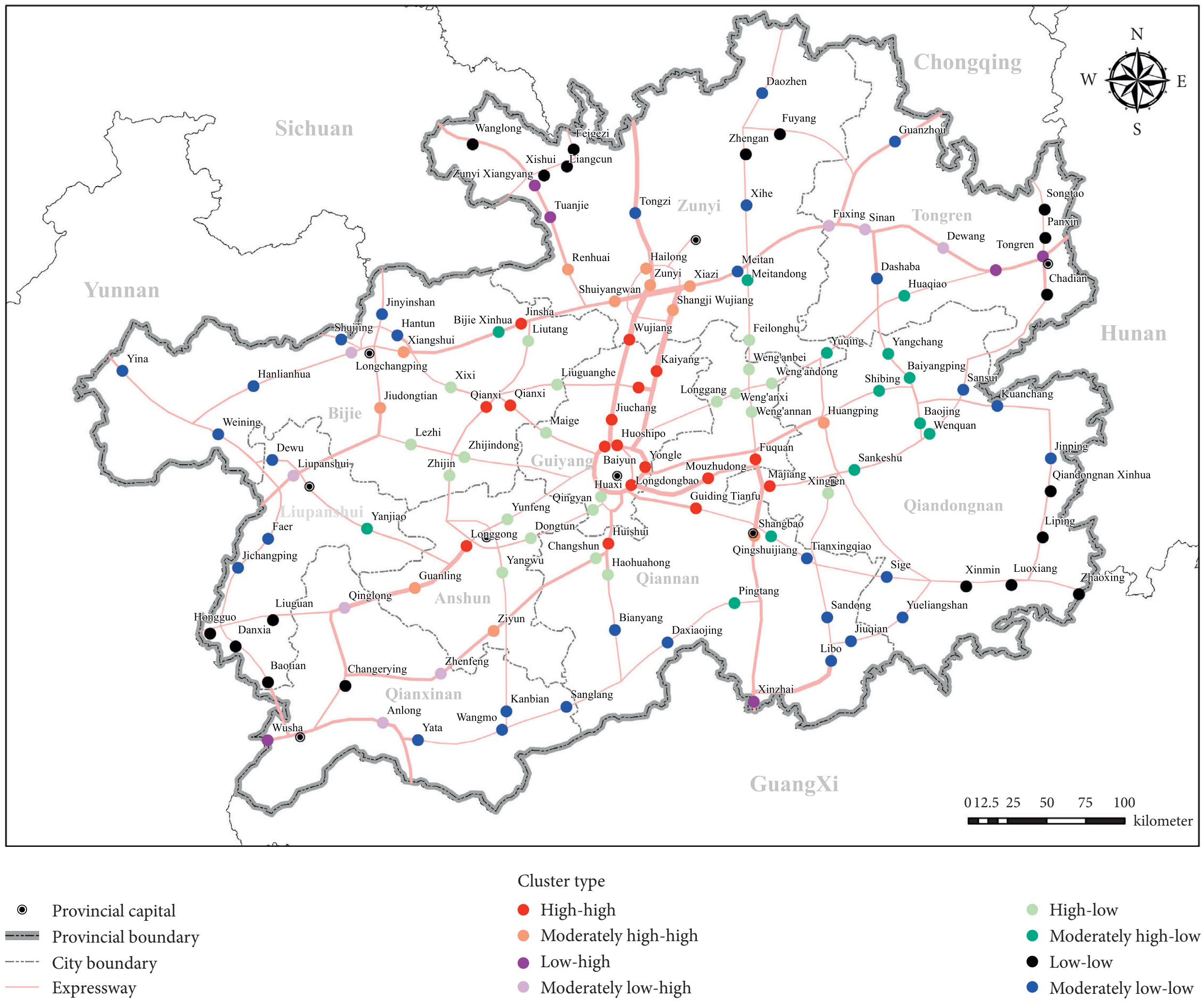


FIGURE 7: Distribution of the bivariate local cluster of expressway service areas in Guizhou province.

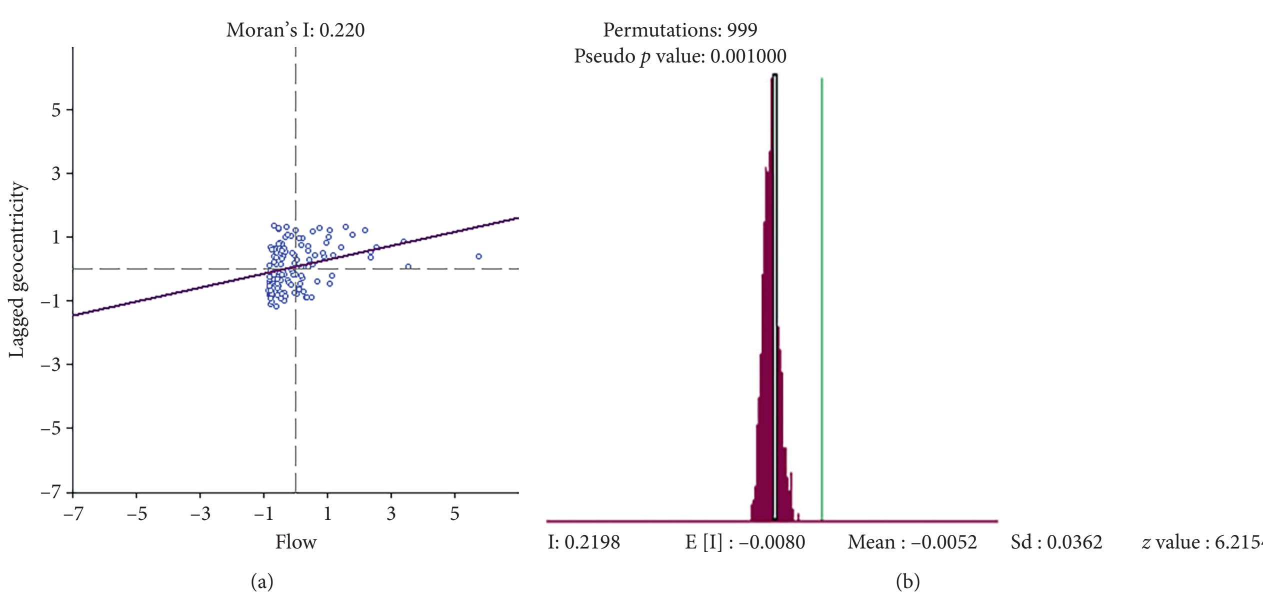


FIGURE 8: Moran's I scatter plot and test plot.

Table 6: Cluster types of geographical centrality-passenger flow centrality and tourism development models of expressway service areas in Guizhou province.

Cluster type	Expressway service area	Tourism development model
High-high	Qianxi, Jinsha, Wujiang, Kaiyang, Xifeng Wenquan, Jiuchang, Baiyun, Huoshipo, Yongle, Longdongbao, Longgong, Huishui, Guiding Tianfu, Mouzhudong, Fuquan, Majiang	Transportation hub-type service areas
Moderately high-high	Xiangshui, Jiudongtian, Renhuai, Hailong, Shuiyangwan, Zunyi, Xiazi, Shangji Wujiang, Guanling, Ziyun, Shangbao, Huangping	Tourist attraction relying-type service areas
Low-high	Zunyi Xiangyang, Tuanjie, Wusha, Xinzhai, Tongren Xiangyang, Tongren	Tourism gateway-type service areas
Moderately low-high	Longchangping, Liupanshui, Qinglong, Zhenfeng, Anlong, Fuxing, Sinan, Dewang	Secondary gateway-type service areas
High-low	Lezhi, Zhijin, Zhijindong, Xixi, Maige, Liuguanghe, Liutang, Huaxi, Qingyan, Yunfeng, Dongtun, Yangwu, Changshun, Haohuahong, Weng'annan, Weng'anxi, Longgang, Weng'andong, Weng'anbei, Feilonghu, Xingren	Urban leisure-type service areas
Moderately high-low	Yanjiao, Bijie Xinhua, Pingtang, Qingshuijiang, Meitandong, Huaqiao, Yangchang, Yuqing, Baiyangping, Shibing, Wenquan, Baojing, Sankeshu	Rural leisure-type service areas
Low-low	Yina, Weining, Hanlianhua, Shuijing, Dewu, Faer, Jichangping, Jinyinshan, Hantun, Wanglong, Xishui, Liangcun, Feigezi, Tongzi, Liuguan, Hongguo, Danxia, Baotian, Changerying, Kanbian, Wangmo, Yata, Sanglang, Bianyang, Daxiaojing, Tianxingqiao, Libo, Jiuqian, Sandong, Sige, Yueliangshan, Xinmin, Luoxiang, Zhaoxing, Liping, Meitan, Xihe, Zhengan, Daozhen, Fuyang, Guanzhou, Dashaba, Songtao, Panxin, Chadian, Sansui, Kuanchang, Jinping, Qiandongnan Xinhua	Community co-construction and sharing-type service areas

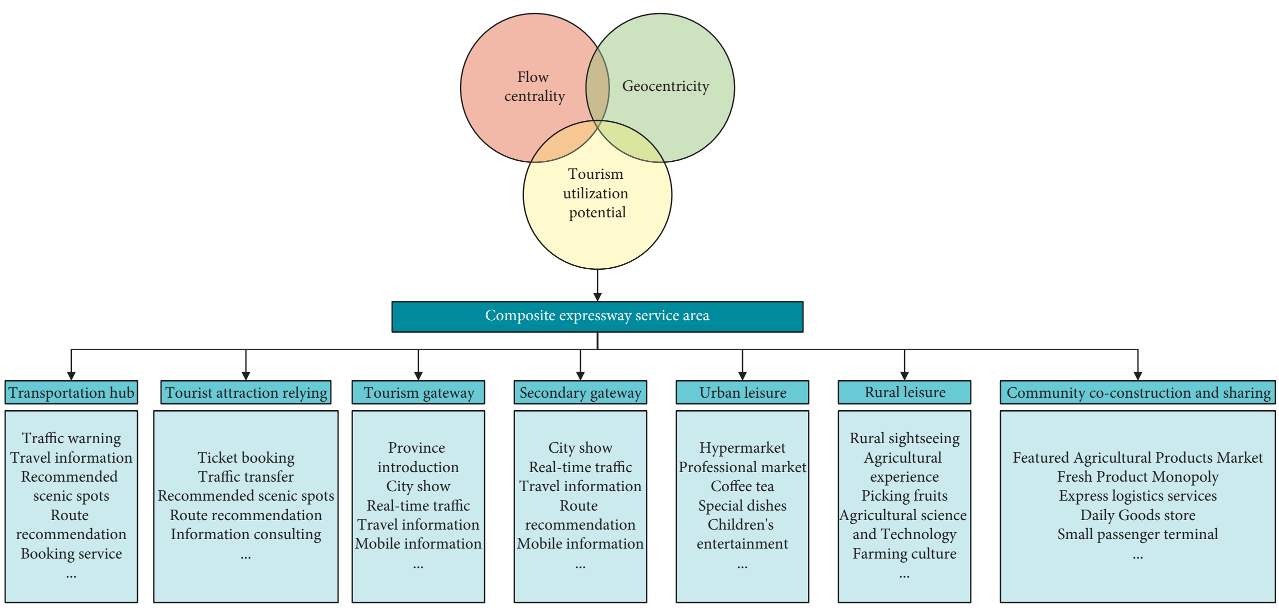


Figure 9: Seven types of development models for expressway service areas.

advantage and actual passenger flow advantage and allowed us to explore the tourism utilization potential of expressway service areas. Our main conclusions are as follows:

(1) The geographical centrality of the Guizhou expressway transportation network generally ranges between −1.28 and 3.33, and its distribution shows a single-core polyconcentric dispersed spatial structure. The core region is located in the south of Guiyang city, where the geographical centrality is concentrated between 1 and 3.33, and the area had the greatest advantage with respect to centrality. The central regions are distributed in Anshun and Bijie, where the geographical centrality is concentrated between 0.72 and 2.11, and the areas had superior transportation conditions and infrastructure. Other areas are located in the marginal zones of Guizhou province, where the geographical centrality is less than 0, and transportation conditions are poor.

(2) The passenger-car flow rate of the Guizhou expressway transportation network mainly ranges

between 15,000 and 3.66 million, and its distribution shows a dual-core, polycentric dispersed structure that is weakly concentric. Zunyi and Guiyang are the dual cores of the passenger flow network, with passenger-car flow rates of up to 2.37–3.66 million. Guiding, Xingyi, Sinan, and Bijie are the secondary centers, with an average passenger-car flow rate of about 800,000. The median-value regions had an average passenger-car flow rate of about 650,000, while the marginal regions had an average passenger-car flow rate of about 10,000.

(3) On the whole, the geographical centrality indicator and passenger flow indicator of the Guizhou expressway transportation network show a positive correlation of 0.22. This implies that expressway service areas tend to be constructed in areas with dense passenger flows, and core geographical locations have greater passenger flows. Based on the differences between the geographical advantage and actual passenger flow advantage in the expressway transportation network, the tourism utilization potential of the expressway service areas could be divided into seven types. Service areas in the "high-high" cluster type around Guiyang city should focus on their future development as transportation hub-type service areas, while those in the "moderately high-high" cluster type near Zunyi city should focus on their development as service areas relying on tourist attraction. Service areas in the "moderately low-high" and "low-high" cluster types should develop themselves as tourism gateways. Service areas in the "high-low" cluster type around Guiyang city should be developed as urban leisure-type service areas, while "moderately high-low" cluster-type areas should develop their rural leisure-type services. Finally, service areas in the "low-low" cluster type should design their development as community co-construction and sharing-type service areas.

4.2. Discussion. Expressways are an important part of the complex transportation network system. Due to the different geographic locations and passenger-car flow conditions of each node in an expressway network, the functions undertaken in the complex transportation network system are different, forming a complex network relationship with different divisions of labor. The complexity of expressway transportation networks is mainly reflected in the following three aspects: (1) the complexity of connectivity elements—expressways connect a variety of spatial elements such as cities, villages, and attractions; (2) the complexity of network structures, mainly including traffic connectivity, accessibility, intermediation, and other spatial complexity features; (3) the complexity of actual passenger flow—passenger flow trends will lead to expressway transportation network nodes having specific functions, increasing the complexity of expressway transportation networks.

Studies have been conducted to analyze the spatial structure characteristics of complex networks such as railways, airlines, and urban transportation using indicators such as degree centrality, closeness centrality, and betweenness centrality and to delineate the hierarchical structure and group structure of node centrality in transportation network systems [59]. In this study, from the less researched expressway perspective, the complex spatial features of the expressway transportation network were innovatively subsumed into two indicators of geographical centrality and passenger flow centrality, and coupled clustering was used to quantitatively analyze the difference between the geographic advantage and passenger flow advantage of the expressway transportation network. The study found that the most geographically advantaged nodes of the transportation network are often located at the center of the entire network, with important cities at the center, relying on expressway transportation corridors to expand into the surrounding central towns and core scenic areas. However, the large flow of tourists between the core city and the core scenic area has resulted in a severe polarization of passenger flows in the geographic center. The geographically disadvantaged nodes are often distributed in the peripheral areas of the overall network, relying on the input of other provincial passenger flows and radiation into the internal network to drive the surrounding towns, villages, and scenic areas where there are huge differences in passenger flow.

Finally, this study put forward seven types of expressway service area tourism utilization modes in the Guizhou expressway network (Figure 9), and suggestions are as follows:

(1) Transportation hub-type service areas: as a transportation hub, these should focus on promoting the construction of regional tourism distribution centers.

(2) Service areas relying on tourism attraction: these service areas should have close relationships with the surrounding tourist attractions, focusing on the core tourist attractions nearby so as to realize the integrated linkage development of the service area and those tourist attractions.

(3) Tourism gateway-type service areas: these service areas are location adjacent to service areas at the junction of provinces and cities and should focus on shaping the local tourism "image window" and providing information consulting services.

(4) Secondary gateway-type service areas: development of these service areas will mean taking tourism gateway-type service areas and connecting them with other service areas in the province internally, which should strengthen traffic utilization services and tourism information services, such as real-time transportation, urban display, and other tourism services.

(5) Urban leisure-type service areas: based on urban leisure needs, the construction of comprehensive service facilities such as large-scale stores and

professional markets should be promoted, and these should be developed into urban leisure areas.

(6) Rural leisure-type service areas: to develop these types of services areas, by relying on the characteristic agricultural resources around the service area, the surrounding villages should be linked, rural tourism activities should be carried out, and urban rural leisure tourism destinations should be built.

(7) Community co-construction and sharing-type service areas: the development of the service area in conjunction with the surrounding ethnic villages should be promoted, and the service area should be made a comprehensive service center for local communities, an exhibition center for the trade of agricultural products, and an exhibition center for the cultural heritage of ethnic minorities.

4.2.1. Significance. Research on complex transportation networks combines complexity science with transportation science, and expressways are a form of complex transportation networks. Therefore, this study is significant because

(1) Domestic and foreign studies on complex transportation networks have mostly been conducted from the perspective of railways [46], air transportation [33], and urban transportation [24] but seldom on expressway transportation networks. Hence, this study enriches the knowledge on complex transportation networks.

(2) This study broadens the scope for the practical application of complexity research on transportation networks by analyzing the spatial structural characteristics of a transportation network and innovatively performing the coupled clustering of geographical centrality and passenger flow centrality to quantitatively analyze the differences between geographical advantage and actual passenger flow advantage.

(3) A comprehensive indicator was calculated using factor analysis to uniformly characterize the transportation convenience, accessibility, and intermediation of expressway service areas using geographical centrality. This approach enabled us to avoid problems caused by scattered indicators' inability to holistically reflect the spatial structural characteristics of transportation networks.

(4) This study proposed seven development models that have practical significance in guiding the upgrade and transformation of service areas for optimizing the layout of the expressway transportation network and promoting the composite use of expressway service areas for tourism.

4.2.2. Limitations. In this study, complex network theory, social network analysis, kernel density analysis, and bivariate autocorrelation were employed to analyze the complexity of the Guizhou expressway transportation network and the tourism utilization potential of expressway service areas.

Due to limitations of the data, we cannot deduce the influence of the evolution of the Guizhou expressway traffic network in terms of its tourism utilization potential across time. We merely discuss its static structure characteristics. In the future, however, we will carry out dynamic evolution and simulation prediction research on the complex traffic network and its tourism utilization potential. In addition, this study still leaves room for additional improvement in the understanding of the complexity of transportation networks. It does not take into consideration the impact of aviation, railway, urban transportation, and other transportation networks on tourism utilization potential nor does it account for the impact of urban and rural self-attraction. In the future, we will focus on the impact of the interaction of multiple transportation elements and spatial elements on the tourism utilization potential, as well as complex transportation. The comprehensive influence of the communication network structure on the development orientation of the spatial structure of the tourism destination is the key issue to be explored in future research.

Acknowledgments

This study was supported by the National Natural Science Foundation of China, "Simulation Study on the Spatial Evolution Model and System Optimization of Tourism Urbanization" (no. 41671151).

References

[1] J. Xi and M. Liu, "Analysis of basic national conditions of China's tourism industry," *Journal of Natural Resources*, vol. 34, pp. 1569–1580, 2019.

[2] S. Porta, P. Crucitti, and V. Latora, "The network analysis of urban streets: a primal approach," *Environment and Planning B: Planning and Design*, vol. 33, no. 5, pp. 705–725, 2006.

[3] A. Sevtsuk and M. Mekonnen, "Urban network analysis: a new toolbox for measuring city form in ArcGIS," in *Proceedings of the 2012 Symposium on Simulation for Architecture and Urban Design*, pp. 114–126, Society for Computer Simulation International, San Diego, CA, USA, March 2012.

[4] C. Cooper, *Spatial Design Network Analysis (sDNA) Version 3.3 Manual*, Cardiff University, Cardiff, UK, 2016.

[5] Y. T. Mohmand and A. Wang, "Complex network analysis of Pakistan railways," *Discrete Dynamics in Nature and Society*, vol. 2014, Article ID 126261, 5 pages, 2014.
[6] A. Pagani, G. Mosquera, A. Alturki et al., "Resilience or robustness: identifying topological vulnerabilities in rail networks," *Royal Society Open Science*, vol. 6, no. 2, Article ID 181301, 2019.
[7] Z. Xu and R. Harriss, "Exploring the structure of the U.S. intercity passenger air transportation network: a weighted complex network approach," *GeoJournal*, vol. 73, pp. 87–102, 2014.
[8] D. Tsiotas and S. Polyzos, "Decomposing multilayer transportation networks using complex network analysis: a case study for the Greek aviation network," *Journal of Complex Networks*, vol. 3, no. 4, pp. 642–670, 2015.
[9] Q. H. A. Tran and A. Namatame, "Worldwide aviation network vulnerability analysis: a complex network approach," *Evolutionary and Institutional Economics Review*, vol. 12, no. 2, pp. 349–373, 2015.
[10] E. Tranos, "The topology and the emerging urban geographies of the internet backbone and aviation networks in Europe: a comparative study," *Environment and Planning A: Economy and Space*, vol. 43, no. 2, pp. 378–392, 2011.
[11] P. Crucitti, V. Latora, and S. Porta, "Centrality measures in spatial networks of urban streets," *Physical Review E: Covering Statistical, Nonlinear, Biological, and Soft Matter Physics*, vol. 73, Article ID 36125, 2006.
[12] S. Porta, V. Latora, F. Wang et al., "Street centrality and the location of economic activities in Barcelona," *Urban Studies*, vol. 49, no. 7, pp. 1471–1488, 2012.
[13] Z. Tian, L. Jia, H. Dong, F. Su, and Z. Zhang, "Analysis of urban road traffic network based on complex network," *Procedia Engineering*, vol. 137, pp. 537–546, 2016.
[14] S. Yang, X. Liu, Y.-J. Wu, J. Woolschlager, and S. L. Coffin, "Can freeway traffic volume information facilitate urban accessibility assessment?" *Journal of Transport Geography*, vol. 44, pp. 65–75, 2015.
[15] R. Ding, N. Ujang, H. B. Hamid et al., "Application of complex networks theory in urban traffic network researches," *Networks and Spatial Economics*, vol. 19, no. 4, pp. 1281–1317, 2019.
[16] F. Jin and Z. Chen, "Evolution of transportation in China since reform and opening up: patterns and principles," *Journal of Geographical Sciences*, vol. 29, no. 10, pp. 1731–1757, 2019.
[17] Y. Chen, F. Jin, Y. Lu, Z. Chen, and Y. Yang, "Development history and accessibility evolution of land transportation network in Beijing-Tianjin-Hebei region over the past century," *Journal of Geographical Sciences*, vol. 28, no. 10, pp. 1500–1518, 2018.
[18] J. Yang, J. Sun, H. Zhao, J. Xi, and X. Li, "Spatio-temporal differentiation of residential land for coastal town: a case study of dalian jinshitan," *Chinese Geographical Science*, vol. 26, no. 4, pp. 566–576, 2016.
[19] J. Yang, A. Guo, X. Li, and T. Huang, "Study of the impact of a high-speed railway opening on China's accessibility pattern and spatial equality," *Sustainability*, vol. 10, no. 8, p. 2943, 2018.
[20] J. Wang, H. Mo, and F. Jin, "Spatial structural characteristics of Chinese aviation network based on complex network theory," *Acta Geographica Sinica*, vol. 64, pp. 899–910, 2009.
[21] X. Wu and S. Man, "Air transportation in China: temporal and spatial evolution and development forecasts," *Journal of Geographical Sciences*, vol. 28, no. 10, pp. 1485–1499, 2018.
[22] Y. Xing, J. Lu, S. Chen, and S. Dissanayake, "Vulnerability analysis of urban rail transit based on complex network theory: a case study of Shanghai metro," *Public Transport*, vol. 9, no. 3, pp. 501–525, 2017.
[23] H. Cao, F. Zhao, H. Liu, and T. Yu, "The impact of subway on urban traffic network based on complex network theory," *MATEC Web of Conferences*, vol. 61, p. 4025, 2016.
[24] C. Du, J. Wang, B. Liu, and D. Huang, "Impacts of street and public transport network centralities on housing rent: a case study of Beijing," *Progress in Geography*, vol. 38, no. 12, pp. 1831–1842, 2019.
[25] Z. Xu and B. Chen, "Study on node importance evaluation of the high-speed passenger traffic complex network based on the structural hole theory," *Open Physics*, vol. 15, no. 1, pp. 1–11, 2017.
[26] R. Ding, "The complex network theory-based urban land-use and transport interaction studies," *Complexity*, vol. 2019, Article ID 4180890, 14 pages, 2019.
[27] W. Dougill, "Regional plan of New York and its environs: Highway traffic (book review)," *Town Planning Review*, vol. 12, no. 2, pp. 145–147, 1926.
[28] D. R. Judd, "Promoting tourism in US cities," *Tourism Management*, vol. 16, no. 3, pp. 175–187, 1995.
[29] G. I. Crouch, "Demand elasticities for short-haul versus long-haul tourism," *Journal of Travel Research*, vol. 33, no. 2, pp. 2–7, 1994.
[30] T. Bieger and A. Wittmer, "Air transport and tourism-perspectives and challenges for destinations, airlines and governments," *Journal of Air Transport Management*, vol. 12, no. 1, pp. 40–46, 2006.
[31] D. M. Spencer, "Airport stops and flights on small airplanes as inhibitors of tourism-related air travel: a case study," *Tourism Management*, vol. 30, no. 6, pp. 838–846, 2009.
[32] S. A. Rehman Khan, D. Qianli, W. SongBo, K. Zaman, and Y. Zhang, "Travel and tourism competitiveness index: the impact of air transportation, railways transportation, travel and transport services on international inbound and outbound tourism," *Journal of Air Transport Management*, vol. 58, pp. 125–134, 2017.
[33] A. Papatheodorou and P. Arvanitis, "Spatial evolution of airport traffic and air transport liberalisation: the case of Greece," *Journal of Transport Geography*, vol. 17, no. 5, pp. 402–412, 2009.
[34] C. A. Vogt, "Multi-destination trip patterns," *Annals of Tourism Research*, vol. 24, pp. 458–461, 1997.
[35] A. Lew and B. McKercher, "Modeling tourist movements," *Annals of Tourism Research*, vol. 33, no. 2, pp. 403–423, 2006.
[36] S. Page and J. Connell, "Exploring the spatial patterns of car-based tourist travel in loch lomond and trossachs national park, Scotland," *Tourism Management*, vol. 29, pp. 561–580, 2008.
[37] K. Thompson and P. Schofield, "An investigation of the relationship between public transport performance and destination satisfaction," *Journal of Transport Geography*, vol. 15, no. 2, pp. 136–144, 2007.
[38] P. Peeters, E. Szimba, and M. Duijnisveld, "Major environmental impacts of European tourist transport," *Journal of Transport Geography*, vol. 15, no. 2, pp. 83–93, 2007.
[39] M. Brtnický, V. Pecina, M. V. Galiová et al., "The impact of tourism on extremely visited volcanic island: link between environmental pollution and transportation modes," *Chemosphere*, vol. 249, p. 126118, 2020.
[40] F. Deng, Y. Fang, L. Xu, and Z. Li, "Tourism, transportation and low-carbon city system coupling coordination degree: a

case study in Chongqing municipality, China," *International Journal of Environmental Research and Public Health*, vol. 17, no. 3, p. 792, 2020.
[41] K. S. Bunds, J. M. Casper, J. A. Hipp, and J. Koenigstorfer, "Recreational walking decisions in urban away-from-home environments: the relevance of air quality, noise, traffic, and the natural environment," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 65, pp. 363–375, 2019.
[42] D. A. Jiménez-Uribe, D. Daniels, Á. González-Álvarez, and A. M. Vélez-Pereira, "Influence of vehicular traffic on environmental noise spectrum in the tourist route of santa marta city," *Energy Reports*, vol. 6, pp. 818–824, 2019.
[43] J. E. Dickinson, S. Calver, K. Watters, and K. Wilkes, "Journeys to heritage attractions in the UK: a case study of national trust property visitors in the south west," *Journal of Transport Geography*, vol. 12, no. 2, pp. 103–113, 2004.
[44] Z. Wang, "On several characteristics of tourism transportation in China and its development direction," *Tourism Tribune*, vol. 3, pp. 35–40, 1989.
[45] J. Bao and Y. Chu, *Tourism Geography*, Higher Education Press, Beijing, China, 1999.
[46] S. B. Wang, X. L. Luo, J. H. Guo, P. G. Zhang, and Z. N. Gu, "Dynamic evolution of tourism spatial structure under the improvement of the high speed rail network in northeast China," *Scientia Geographica Sinica*, vol. 39, pp. 568–577, 2019.
[47] S. Jin, J. Yang, E. Wang, and J. Liu, "The influence of high-speed rail on ice–snow tourism in northeastern China," *Tourism Management*, vol. 78, Article ID 104070, 2020.
[48] Y. T. Yang, R. K. Zhang, Y. R. An, and J. Z. Wu, "Steady vortex force theory and slender-wing flow diagnosis," *Acta Mechanica Sinica*, vol. 23, no. 6, pp. 609–619, 2007.
[49] Z. Yang, M. Yin, J. Xu, and W. Lin, "Spatial evolution model of tourist destinations based on complex adaptive system theory: a case study of southern Anhui, China," *Journal of Geographical Sciences*, vol. 29, no. 8, pp. 1411–1434, 2019.
[50] W. Pu and T. Mi, "On estimating transportation energy consumption and carbon dioxide emissions from off-shore island tourism-a case study of Haikou city, China," *Journal of Resources and Ecology*, vol. 7, no. 6, pp. 472–479, 2016.
[51] B. Wu and M. Li, "EDVAET: A linear landscape evaluation technique—a case study on the Xiaoxinganling scenery drive," *Acta Geographica Sinica*, vol. 2, pp. 214–222, 2001.
[52] L. C. Freeman, "Centrality in social networks conceptual clarification," *Social Networks*, vol. 1, no. 3, pp. 215–239, 1978.
[53] E. Kreyszig, *Advanced Engineering Mathematics*, Wiley, Hoboken, NJ, USA, 4th edition, 1979.
[54] M. Rosenblatt, "Remarks on some nonparametric estimates of a density function," *The Annals of Mathematical Statistics*, vol. 27, no. 3, pp. 832–837, 1956.
[55] E. Parzen, "On estimation of a probability density function and mode," *The Annals of Mathematical Statistics*, vol. 33, no. 3, pp. 1065–1076, 1962.
[56] K. Dehnad and B. Silverman, "Density estimation for statistics and data analysis," *Technometrics*, vol. 29, p. 495, 1986.
[57] M. F. Goodchild, *Spatial Autocorrelation*, Geo Books, Norwich, UK, 1986.
[58] L. Anselin, "Local indicators of spatial association—lisa," *Geographical Analysis*, vol. 27, pp. 93–115, 1995.
[59] H. H. Mo, F. J. Jun, Y. Liu, and J. E. Wang, "Network analysis on centrality of airport system," *Scientia Geographica Sinica*, vol. 30, pp. 204–212, 2010.

Safety Risk Assessment of Tourism Management System Based on PSO-BP Neural Network

Wenru Guo [1,2]

[1]School of Tourism and Urban-Rural Planning, Zhejiang Gongshang University, Hangzhou, Zhejiang 310018, China
[2]School of Tourism Management, Xinyang Agriculture and Forestry University, Xinyang, Henan 464000, China

Correspondence should be addressed to Wenru Guo; jiangshan89@xyafu.edu.cn

Academic Editor: Syed Hassan Ahmed

With the development of science and technology, system management is gradually applied to tourism management. How to correctly assess the security risks of the tourism management system has become an important means to maintain passenger information. The security risk index of the travel management system is input into the PSO-BP network as a sample, and the corresponding risk value of the index is used as the network output. The results show that the error results, accuracy (96.53%), training time (216 s), number of iterations (275 times), and convergence speed are all better than traditional BP network. The relative error of PSO-BP network (0.32%) is better than that of BP network, with 300 iterations, and the error is close to 10–5. The average evaluation accuracy of *S* based on PSO-BP network is 99.72%, and the average time consumed is 2.512 s. It is superior to the evaluation model based on fuzzy set and entropy weight theory and the evaluation model based on gray correlation analysis and radial basis function neural network. In conclusion, the security risk assessment of the tourism management system based on PSO-BP network can effectively assess the security risk of the tourism management system.

1. Introduction

With economic and technological developments and the continuous improvement of people's living standards, tourism has become a common leisure way for people to relieve pressure and enjoy their minds and bodies, and the tourism industry has brought about rapid development [1]. With the proliferation of tourism-related data and information, the traditional tourism management model has gradually replaced Internet technology, and the tourism management system has shifted to management [2]. While networks provide convenience to users, they also increase the security risks of travel management systems. Effective and scientific assessment of system security risks is an important way to ensure network information security [3]. A BP neural network (BPNN) is a multilayer forward network based on error backpropagation, consisting primarily of an input layer, several hidden layers, and an output layer. It has strong nonlinear fitting capabilities and has some practicality in classifying, identifying, and calculating risk values [4, 5]. BPNN can classify any complex pattern and has excellent multidimensional function mapping capabilities. This greatly improves network classification and network recognition capabilities and has powerful application effects in solving nonlinear problems [6]. However, in the BPNN network's self-learning process, changes in thresholds or weights make BPNN training more prone to the situation of local minimal solutions and reduce the accuracy of risk values in tourism management systems [7, 8]. At the same time, the BPNN network requires more training time, the corresponding slow convergence speed, and poor real-time control performance [9]. Particle swarm optimization (PSO) is used to improve BPNN to improve BPNN calculation accuracy. This speeds up BPNN training and reduces the chances of the latter going to the limit.

Ramesh et al. [10] verified the effectiveness of the back propagation neural network model in prediction of stock returns. Parwez et al. [11] trained a neural network prediction model with anomalous and nonanomalous data to highlight the influence of anomalies in data while constructing the intelligent model; this can greatly improve the accuracy of neural networks. Wang et al. [12] have used evolutionary algorithms to improve traditional BP neural network algorithms to prevent particles from falling into locally optimal solutions. Researchers such as Ai and Yang [13] have proposed a machine learning method based on a support vector machine optimized by a particle swarm optimization algorithm and applied it to cost prediction of environmental governance. Wen and Yuan [14] have introduced random forest algorithms and particle swarm optimization algorithms into the construction of commercial sector carbon dioxide emission prediction models to establish new network prediction models based on BP neural networks. The results show that the model can accurately predict carbon dioxide emissions in the commercial sector. Jiang et al. proposed [15] the particle swarm optimization algorithm in combination with the BP neural network algorithm to establish predictive models and predict the cost of product remanufacturing based on data-driven methods. The results show that the model has high prediction accuracy. Hao and Zhu [16] established a Levenberg Marquardt Backpropagation (LMBP) neural network and used it to predict the quality of polyamide 66 gears.

Particle swarm optimization algorithms such as be used for training neural networks and for co-designing PSO training neural network software and hardware [17]. Zhang et al. [18] obtained a global optimal parameter-optimized data-driven framework through the PSO algorithm and proposed a data-driven detection technology for laser welding defects based on real-time spectrometer signals. Dehghanbanadaki et al. [19] estimated the unconstrained compressive strength of natural fillers using two feed-forward artificial neural network models trained by particle swarm optimization algorithms and BP neural network algorithms. In the process of investigating safety risk assessments and early warning mechanisms in building engineering, researchers such as Ma et al. [20] have managed cloud security based on the scalable theory of distributed computing to quantitatively assess the safety status of construction sites. When studying the mechanism of security sharing strategies in information sharing systems, scholars such as Ss et al. [21] proposed a new corporate information sharing framework from the perspective of information system security and implemented the optimal level of information sharing strategies. Researchers such as Zhang et al. [22] have conducted 28 activities to conduct social ecosystem risk assessments and ecosystem service stress assessments at the mouths of subtropical coasts of Brazil to directly generate supplies and cultural ecosystem services for habitat risk assessments. Scholars such as Terzi used Bayesian networks, agent-based models, and system dynamic models to assess multiple risks in mountainous areas [23–25].

In summary, there have been many studies in recent years on artificial neural networks, BP neural networks, particle swarm optimization, and system security risk assessment, but there is a lack of relevant research on security risk assessment of tourism management systems. The BP neural network algorithm is optimized through the particle swarm. Therefore, this article proposes a security risk assessment technology for tourism management systems based on the PSO-BP neural network to help people quickly assess the security risks of tourism management systems.

2. Safety Risk Assessment of Tourism Management System Based on PSO-BP Neural Network

2.1. System Security Risk Assessment Based on PSO-BP Neural Network. BPNN has adaptive learning functions [26]. The feedback propagation mechanism constantly adjusts the weights of the network parameters, reducing the difference between the output vector and the expected vector.

First, the least squares method is used to plan the formula for the 3-layer BP neural network, and then the number of hidden layer neurons is determined by continuously adjusting the experimental parameters (Figure 1).

$$h = \left(0.43mn + 0.12m^2 + 2.54n + 0.77m + 0.35\right)^{1/2} + \alpha. \tag{1}$$

Formula (1) is the formula for calculating the number of neurons h in the hidden layer. The number of neurons in the input layer and the output layer is n and m, respectively; α is a constant, and $\alpha \in (0, 9)$. At the same time, BPNN uses limited accounting to calculate the error between the predicted result and the actual expected value.

$$E = \frac{1}{2}\sum_{j=1}^{J}\left(d_j - Y_j\right)^2. \tag{2}$$

Formula (2) is the error calculation formula of BPNN network, where the mean square error is E; the expected output value and the actual output value of the output layer j are expressed as d_j and Y_j in turn; J refers to the number of neurons in the output layer. BPNN network completes the input and output of the network mainly through neurons.

$$y_j = f\left(\sum \omega_{ji}x_i + \theta_i\right). \tag{3}$$

In formula (3), y_j and x_i refer to network output prediction results and network input sample data, respectively; the connection weight is ω_{ji}; the threshold value is θ_i, which reflected the connection strength between neurons; and the transfer function is f.

$$f(x) = \frac{1}{1 + e^{-x}}. \tag{4}$$

Equation (4) is the expression of the transfer function (log sigmoid function), e takes the natural constant 2.718. The connection weight ω_{ji} mainly reflects the connection strength between the layers of BPNN, and when ω_{ji} exceeds 0, the function is activated. In addition, when the sample data volume is large, the convergence speed of BPNN is reduced, and the real-time performance of inhibition is poor. Therefore, the particle swarm optimization (PSO)

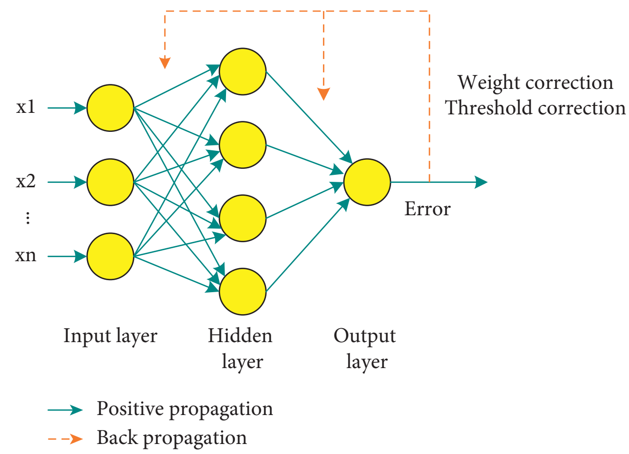


FIGURE 1: Schematic diagram of BP neural network.

algorithm with easy implementation and high convergence speed is studied to optimize BPNN [27].

If the particle swarm is composed of m particles, the different particles correspond to a feasible solution to the problem. The d-dimensional position vector of the i particle is expressed as $z_i = (z_{i1}, z_{i2}, \ldots, z_{iD})$, the flight speed of the particle is expressed as $v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$, the optimal position of the particle so far is expressed as $p\text{best}_i = (p_{i1}, z_{i2}, \ldots, p_{id}, \ldots, p_{iD})$, and the optimal position of the whole particle swarm so far is expressed as $g\text{best}_i = (g_{i1}, g_{i2}, \ldots, g_{id}, \ldots, g_{iD})$.

$$v_{id}^{k+1} = WV_{id}^{k} + c_1 r_1 \left(p_{id} - z_{id}^{k}\right) + c_2 r_2 \left(g_d - z_{id}^{k}\right), \quad (5)$$

$$z_{id}^{k+1} = z_{id}^{k} + v_{id}^{k+1}. \quad (6)$$

Equation (5) is the update expression of particle velocity, and equation (6) is the update expression of particle position where k and W represent iteration times and inertia weight in turn; r_1 and r_2 is a random number between [0, 1]; c_1 refers to learning factor; and c_2 is acceleration factor; usually, the empirical value is $c_1 = c_2 = 1$. The current position of particles in the population can be expressed as the set of BP weights and thresholds. The neural network weight matrix and neural network threshold are scanned, and the particle position is initialized.

$$v_{id}^{k+1} = \theta v_{id}^{k} + c_1 r_1 \left(p_{id} - z_{id}^{k}\right) + c_2 r_2 \left(g_d - z_{id}^{k}\right). \quad (7)$$

According to equations (6) and (7) to complete the iteration,

$$\theta = \theta_{\max} - \frac{\theta_{\max} - \theta_{\min}}{k_{\max}} \times k. \quad (8)$$

Formula (8) is the weight θ calculation formula of particle velocity iteration, where $\theta_{\max}$ is the initial weight, $\theta_{\min}$ is the final weight, $k_{\max}$ is the maximum number of iterations, and k is the current number of iterations. In the process of research, the PSO algorithm is used to train the weights and thresholds of BP neural network and then find out the optimal position of particle swarm optimization.

$$\omega_{i,j}^{k+1} = \omega_{i,j}^{k} + v_{id}^{k+1}. \quad (9)$$

Formula (9) is the learning formula of network weight and network threshold, where v_{id}^{k+1} is the corresponding speed of particles in the $k+1$ iteration and $\omega_{i,j}^{k}$ is the corresponding weight of particles in the k iteration.

$$y_{j,i}^{d} = \frac{1}{\left(1 + e^{-\sum_{i=1}^{N} \omega_{ij}}\right)}. \quad (10)$$

Equation (10) is the expression of the maximum fitness principle, where $y_{j,i}^{d}$ represents the ideal output value of the sample corresponding to the output node of the network, ω_{ji} represents the weight corresponding to the output node, and N is the number of network layers.

$$E(X_i) = g\text{best}_i \times \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{t} \left(y_{j,i}^{d} - y_{j,i}\right)^2. \quad (11)$$

Equation (11) is the minimum principle expression of mean square error, where t is the number of neurons output by the network and $y_{j,i}$ represents the actual value of the sample at the output node.

2.2. Construction of Safety Risk Evaluation Index System of Tourism Management System. With the improvement of science and technology, tourism practitioners gradually use the management system to manage tourism-related information, and the privacy information of tourism customers is recorded in the network. In order to ensure that the information of tourism customers is not infringed, it is very important to evaluate the security risk of the tourism management system. Based on PSO-BP neural network, according to the basic content of the tourism security management system, the system security risk evaluation index is determined.

As shown in Figure 2, according to the basic content of the tourism security management system, seven security risk indicators such as user personal information security risk index, information security risk index of scenic spot

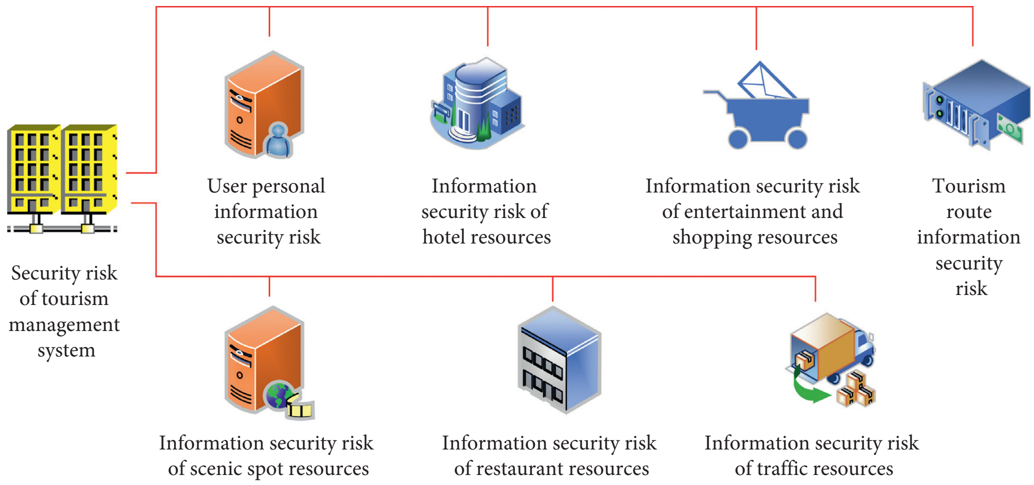


Figure 2: Security risk index system of the tourism management system.

resources, hotel resource information security risk index, restaurant resource information security risk index, information security risk indicators of entertainment and shopping resources, risk indicators of traffic resource information security in the process of tourism, and tourism route information security risk index are selected as the main indicators affecting the security risk of the tourism management system.

Suppose that the parameter of security risk influencing factors of the tourism management system is expressed as $x_i\,(i = 1, 2, \ldots, m)$, k experts are selected to score the corresponding security risk index, and the corresponding partition of the h expert is recorded as $[u_1^k, u_2^k]$, where $u_i \in [0, 1]$.

$$\overline{u} = \frac{\sum_{h=1}^{k}\left[\left(u_1^h\right)^2 - \left(u_2^h\right)^2\right]}{\sum_{h=1}^{k}\left[u_1^h, u_2^h\right]}. \tag{12}$$

Equation (12) can be used to evaluate the objectivity of safety risk index $\overline{u}$, where u_1^k and u_2^k, respectively, refer to the lowest score and the highest score given by the h expert and k is the total number of experts involved in the evaluation.

$$b_i = \sum_{j=1}^{n} \frac{b_{ji}}{n}. \tag{13}$$

Formula (13) is mainly used to calculate the reliability of the evaluation index. The total confidence of the safety risk index x_i is expressed as b_i, and $b_{ji} = 1/(1+g)$, where g is the safety risk identification index. When the evaluation risk is j, the confidence of x_i is expressed as b_{ji}. Quantitative treatment is applied to the safety risk related indicators of the tourism management system, and the specific quantitative method is shown in Figure 3.

$$\begin{cases} g_i = \dfrac{1}{3}\dfrac{\sum_{h=1}^{k}\left[\left(u_1^h - \overline{u}\right)^3 - \left(u_1^h - \overline{u}\right)^2\right]}{\sum_{h=1}^{k}\left[u_1^h, u_2^h\right]}, \\ x_i = \overline{u} b_i. \end{cases} \tag{14}$$

In formula (14), x_i is the safety risk index and k is the total number of experts participating in the evaluation.

Through the expert evaluation method, different experts evaluate the security risk of the tourism management system according to their own actual cognition, including the overall evaluation. Combined with the experts' own experience, the grading of the comment set is determined.

As shown in Figure 4, the security risk equivalence of tourism management systems can be divided into five levels: Level 1–5. The corresponding risk levels are low risk, low risk, medium risk, high risk, and high risk. The scores for the different risk levels are [0.0, 0.2], [0.2, 0.4], [0.4, 0.6], [0.6, 0.8.], and [0.8, 1.0]. Training the sample data should be performed according to different risk levels.

As shown in Figure 5, the PSO-BP neural network is used to train the sample data of the security related risks of the tourism management system. The risk factors affecting the security of the tourism management system are taken as the input layer, and the security risk level of the tourism management system is taken as the output layer.

3. Application Effect Analysis of Security Risk Assessment of Tourism Management System Based on PSO-BP Neural Network

3.1. Application Effect Analysis of PSO-BP Neural Network Model. In order to verify the practical operation effect of the PSO-BP neural network and the actual operational effect of the PSO-BP neural network model designed in this study, 10,000 data related to the safety risk evaluation index of the tourism management system were selected as samples and 3,000 were randomly tested. And the other 7,000 are used as training samples.

Although limited by the length of the article, Figure 6 shows only the test results for some test samples. It turns out that the actual risk value of sample 1 is 0.3049, the risk value detected by the proposed PSO-BP neural network model is 0.4550, the actual risk value of sample 2 is 0.7731, and the risk value of the proposed model is 0.9233. The actual risk value for sample 5 is 0.2492, and the risk value

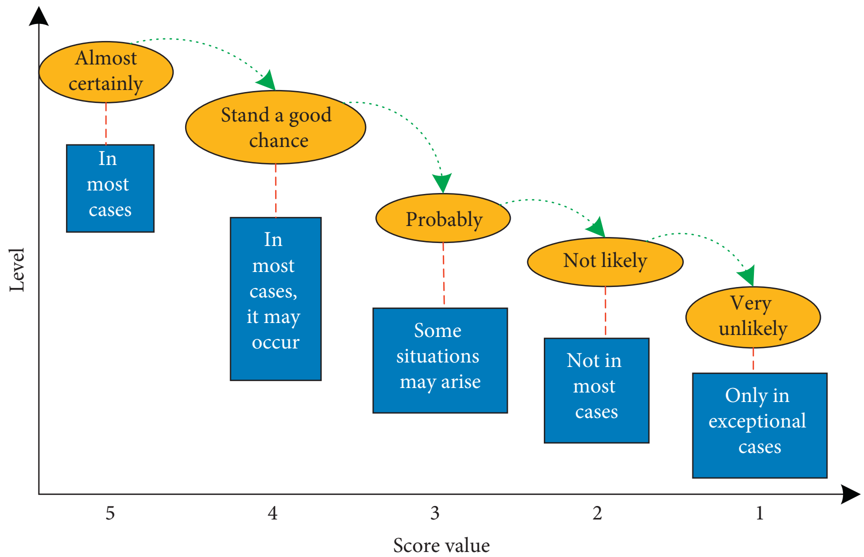


Figure 3: Quantification of security risk identification index of the tourism management system.

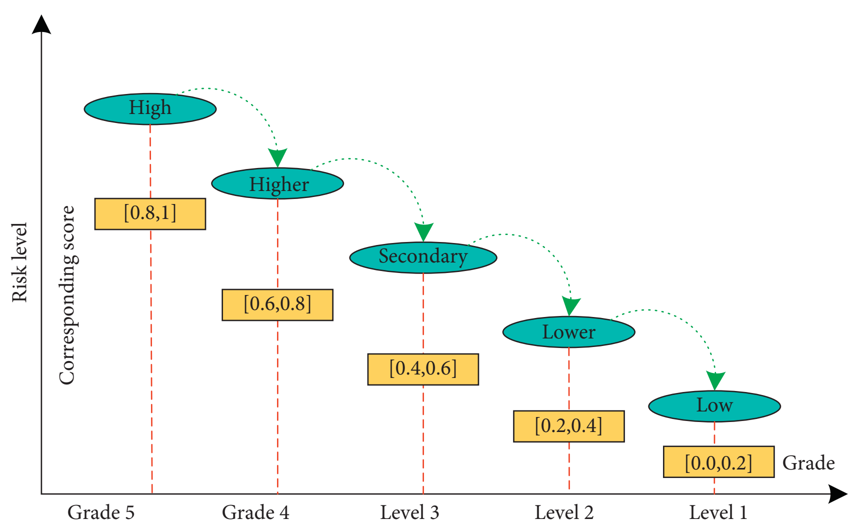


Figure 4: Security risk assessment level of the tourism management system.

detected in the proposed model is 0.2884. In summary, the risk values detected by the PSO-BP neural network model proposed in this paper are slightly higher than the actual risk values in the sample, but the difference between the two is not very large. In the experiment, the training sample and the test sample compare the error curve fitting graphs of the BP neural network algorithm and the PSO-BP neural network algorithm.

In Figure 7, the horizontal axis represents the number of sample iterations and the vertical axis represents the result of the curve error. It can be seen that when the number of iterations of the training sample reaches 600, the error result of the PSO-BP neural network algorithm tends to be 10–5, and the error result of the BP neural network algorithm is higher than 10–4. When the number of iterations of the test sample reaches 300, the error result of the PSO-BP neural network algorithm is close to 10–5, and the error result of the BP neural network algorithm is higher than 10–2. From the two error curves of the training sample and the test sample, we can see that under the same number of iterations, the error result of the BP neural network algorithm is always higher than the error result of the PSO-BP neural network algorithm.

From Figure 8, it can be seen that the average accuracy rate of the risk evaluation of the PSO-BP neural network algorithm proposed in this paper is 96.53% compared with the conventional BP neural network algorithm, which is significantly higher than that of the BP neural network. In terms of training time, the average training time of the PSO-BP neural network algorithm is 216 seconds, which is much shorter than the BP neural network algorithm (>10000 seconds). In terms of the number of iterations, the

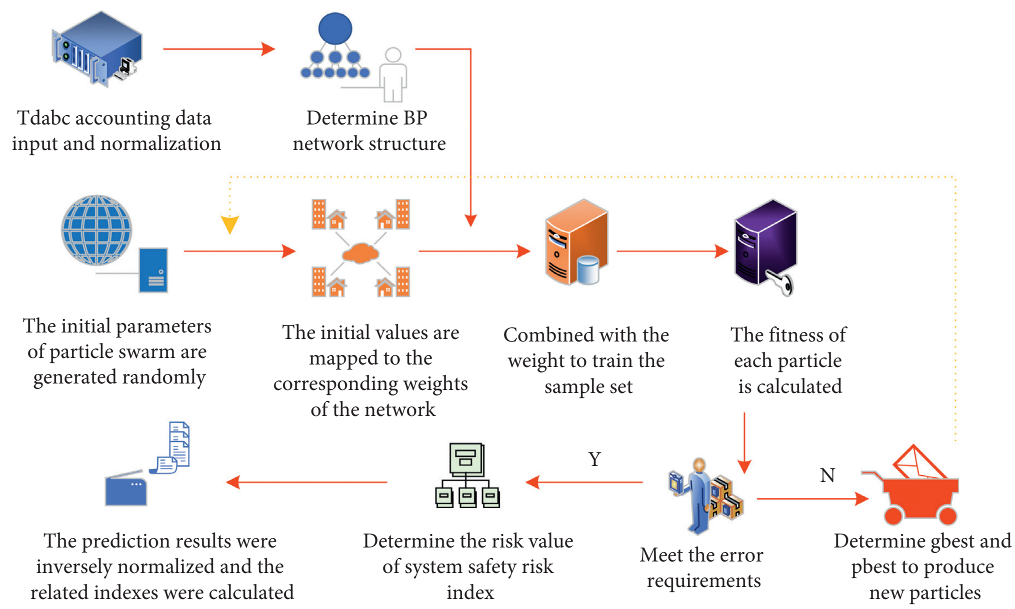


Figure 5: The steps of safety risk assessment of the tourism management system based on PSO-BP neural network.

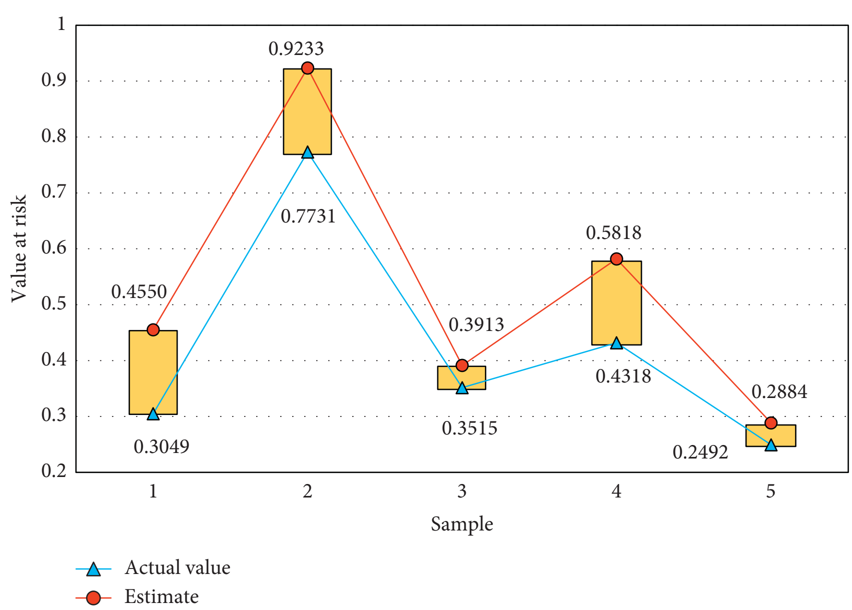
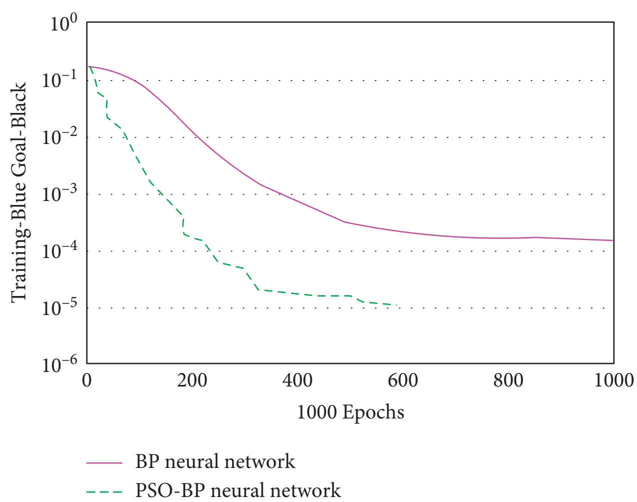


Figure 6: Value at risk prediction results of test samples (part).

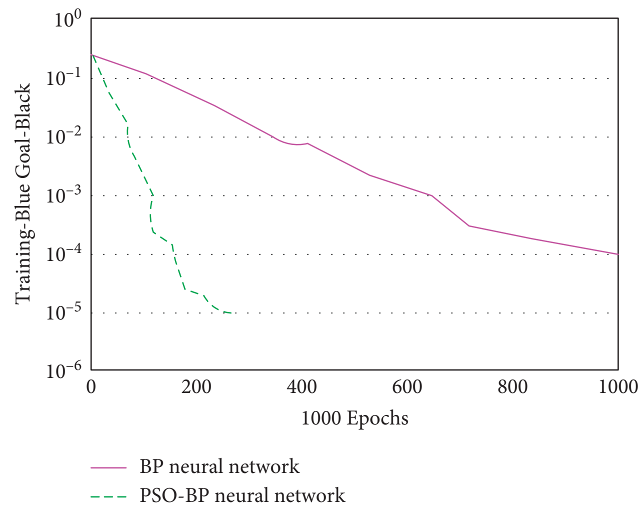
average PSO-BP neural network algorithm has 275 iterations, which is much less than the BP neural network. The average number of iterations (>18000) of the network algorithm is a relative error compared with the BP neural network algorithm. The PSO-BP neural network algorithm has a relative error of only 0.32%, and the BP neural network algorithm has a relative error of 0.45%. The above results show that the PSO algorithm can significantly reduce the convergence time and improve the convergence speed of conventional BP neural network algorithms. The final PSO-BP neural network algorithm has more powerful advantages than the traditional BP neural network algorithm.

3.2. Performance Analysis of Safety Risk Assessment Scheme. To compare the effectiveness of the proposed security risk assessment method for tourism management systems based on the PSO-BP neural network, the traditional security assessment technology for tourism management systems is compared with the proposed technology. The survey target is the security risk data set X of the tourism management system, and there are 200 samples in the survey target. In the experiment, 100 samples are randomly selected as test samples and the remaining 100 samples are used as training samples.

As shown in Figure 9, with the increase in the number of training samples, the training error of the proposed risk

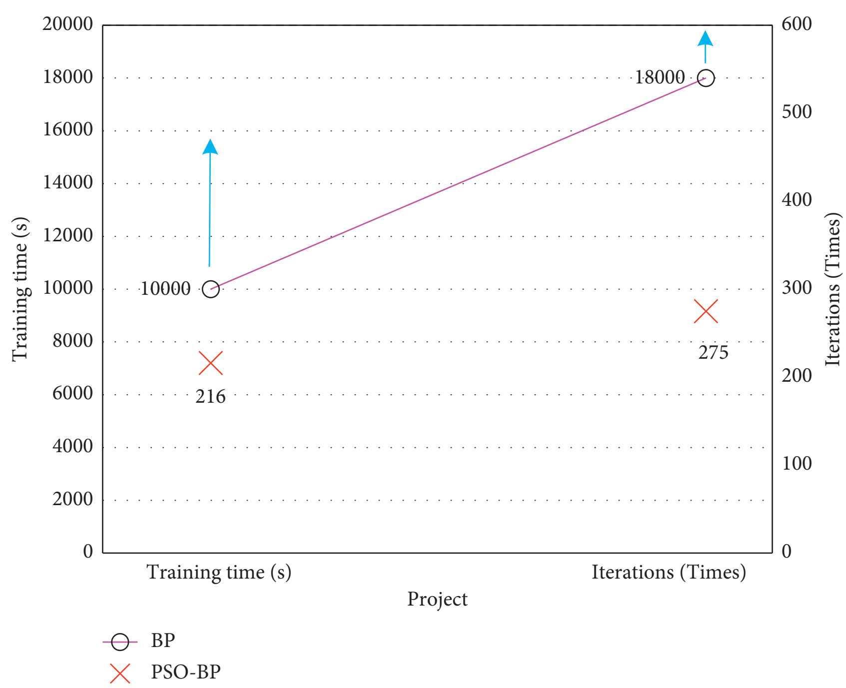


(a)



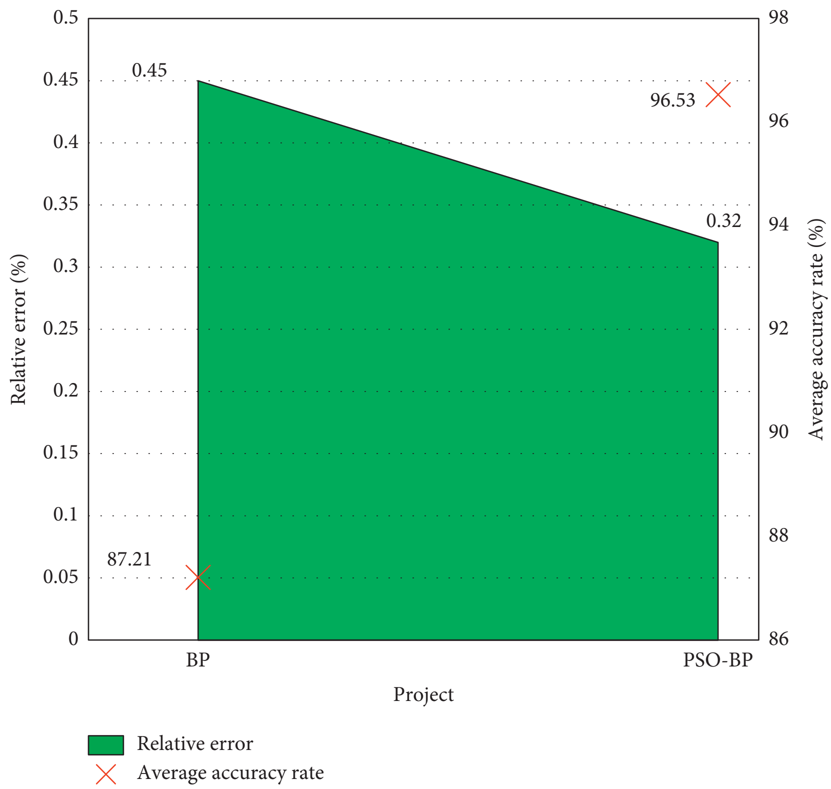
(b)

FIGURE 7: Comparison of error curves of two algorithms; (a) comparison of error curves of training samples; (b) comparison of error curves of test samples.



(a)

FIGURE 8: Continued.



(b)

Figure 8: Comparison of simulation results of test samples. (a) Training time and iteration times of the two algorithms. (b) The average accuracy and relative error of the two algorithms are compared.

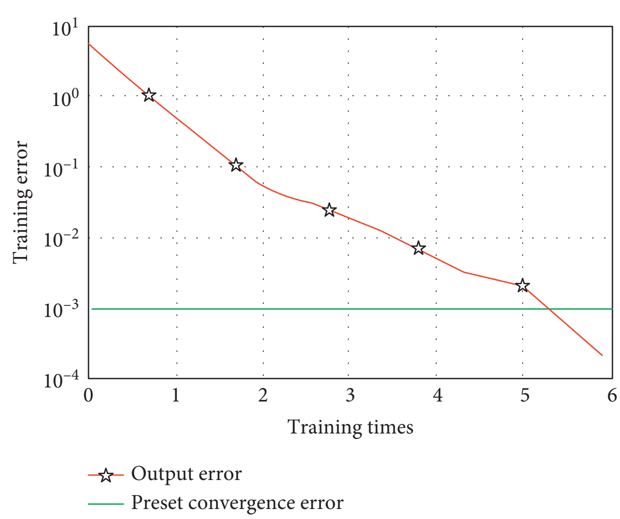


Figure 9: Training sample error.

assessment method presents a decreasing trend. When the number of training reaches 5, the corresponding output error of the proposed risk assessment scheme has been reduced to 10^{-3}, reaching the preset range of convergence error. After the training of sample data, the weight value of evaluation index is determined.

According to Figure 10, the corresponding weight values of user personal information security, tourism route information security, traffic resource information security, entertainment and shopping information security, restaurant resource information security, scenic spot resource information security, and hotel resource information security are 0.4, 0.15, 0.15, 0.15, 0.05, 0.05, and 0.05. According to the weight values corresponding to the above different safety risk indicators, the risk levels of different indicators are determined.

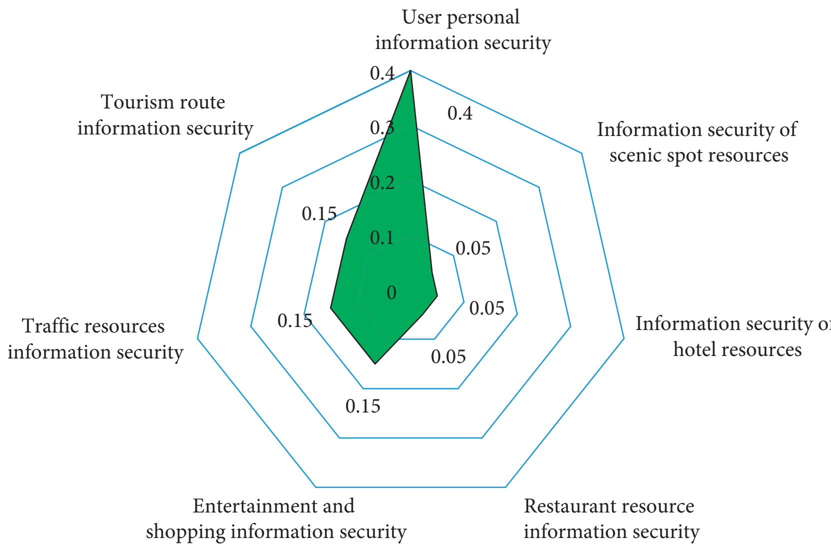


FIGURE 10: The weight of the safety risk evaluation index of the tourism management system.

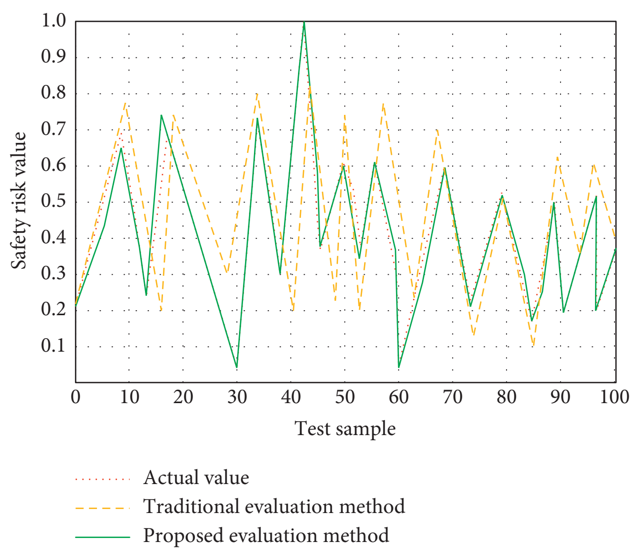


FIGURE 11: Comparison results of two methods in evaluating errors.

From Figure 11, the system safety risk value curve obtained by the risk evaluation method of the proposed PSO-BP neural network-based tourism management system is almost in agreement with the actual risk value curve and is in line with the conventional system. We can see that there is a big error in safety risk curve and actual risk curve. In other words, the risk assessment method of the tourism management system based on the PSO-BP neural network proposed in this study is more accurate and effective in the security risk assessment of the tourism management system. The security risk assessment of the tourism management system is mainly the system information risk assessment. Therefore, we selected a security risk evaluation model based on fuzzy sets and entropy weighting theory and an information system security risk evaluation model based on gray correlation analysis and radial basis function neural networks as comparison targets, and the effects of applying the three methods are as follows. Information system security risk assessment methods include the methods proposed in Dataset *X*. For each program, 20 experiments were performed and average values were taken.

As shown in Figure 12, the average evaluation accuracy of the security risk evaluation model based on the fuzzy set and entropy weighting theory is 96.90%. The average evaluation accuracy of the information system security risk evaluation model based on neural network is 96.90% and the average evaluation accuracy rate of the evaluation scheme based on the PSO-BP neural network is 99.72%. The average time for risk assessment based on fuzzy sets and entropy weighting theory is 2.593 seconds, and the average time for security risk assessment of information systems based on gray relation analysis and radial basis function neural networks is 3.081 seconds, based on only 2.512 seconds. The above results are compared with the security risk assessment

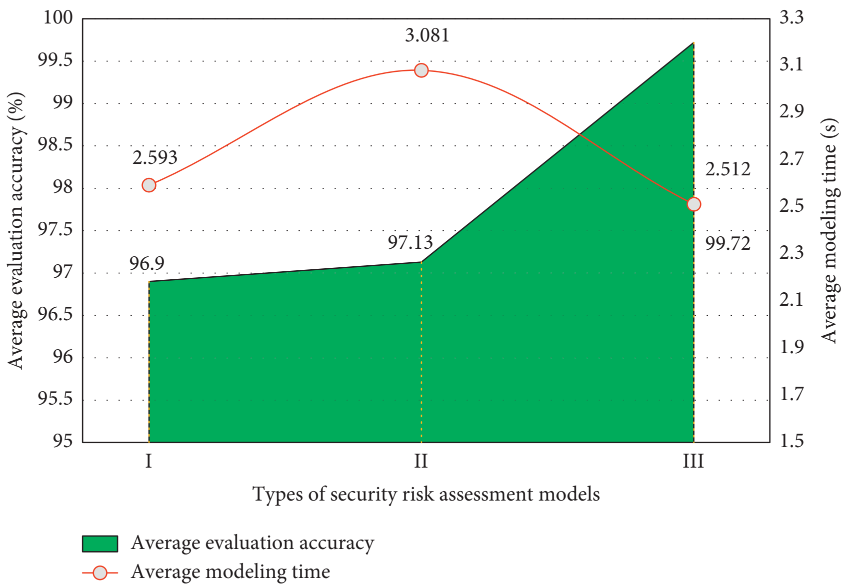


Figure 12: Comparison results of two methods in evaluating errors. Note: I refers to a security risk assessment model based on fuzzy sets and entropy weighting theory. II is an information system security risk assessment model based on gray correlation analysis and radial basis function neural networks. III represents the evaluation scheme based on PSO-BP neural network.

scheme based on fuzzy set and entropy weighting theory and the information system security risk assessment scheme based on gray relation analysis and radial basis function neural network, and the tourism security risk assessment proposed in this paper. The results show that the neural network management system based on PSO-BP has the advantages of high evaluation accuracy, short calculation time, and excellent safety risk evaluation performance.

4. Conclusion

Traditional tourism management system security risk assessment schemes have the disadvantage of causing large assessment errors when performing system security risk assessments. Therefore, this paper uses particle swarm optimization (PSO) to improve the slow convergence rate of traditional BP neural networks and is prone to local optimal solutions and the security risks of tourism management systems based on PSO-BP neural networks. We propose evaluation technology. The convergence time of the BP neural network algorithm, which can be shortened, improves the accuracy of risk value assessment. The results show that under the same number of iterations, the error results of the proposed PSO-BP neural network are always smaller than the error results of the traditional BP neural network. If the test sample is repeated 300 times, the error result is that the error in the PSO-BP network is close to 10–5. The error results for the BP network are still higher than 10–2, the average accuracy for the PSO-BP network is high (96.53%), and the average training time is short (216 seconds); the number of iterations required (275) is relatively small, the error is small (0.32%), 87.21%, >10000 seconds, >18000 times, 0.45% better than traditional BP networks, respectively. The user's personal information security risk value is highest at 0.4, followed by tourist route information security and traffic resource information security. The risk value curve of the proposed risk assessment scheme is similar to the actual risk value curve. In summary, the proposed security risk assessment scheme for tourism management systems based on PSO-BP neural networks can effectively assess the security risks of tourism management systems. While this study has some value in how to improve the effectiveness of security risk assessments in tourism management systems, this scheme can only assess the value of risks and will continue to resist network intrusions.

Acknowledgments

This work was supported by Zhejiang Gongshang University.

References

[1] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, 2017.
[2] P. I. Rahmawati, M. Jiang, A. Law, A. S. Wiranatha, and T. DeLacy, "Spirituality and corporate social responsibility: an empirical narrative from the Balinese tourism industry,"

Journal of Sustainable Tourism, vol. 27, no. 1–3, pp. 156–172, 2019.
[3] A. P. Tafti, J. Badger, E. LaRose et al., "Adverse drug event discovery using biomedical literature: a big data neural network adventure," *JMIR medical informatics*, vol. 5, no. 4, p. e51, 2017.
[4] W. Ahmed, K. Muhammad, and F. I. Siddiqui, "Predicting calorific value of thar lignite deposit: a comparison between back-propagation neural networks (BPNN), gradient boosting trees (gbt), and multiple linear regression (mlr)," *Applied Artificial Intelligence*, vol. 34, no. 5, pp. 1–13, 2020.
[5] W. Wang, S. Zhao, L. Jiao et al., "Estimation of PM2.5 concentrations in China using a spatial back propagation neural network," *Scientific Reports*, vol. 9, no. 1, pp. 13788–13810, 2019.
[6] L. Wang, B. Wu, Q. Zhu, and Y.-R. Zeng, "Forecasting monthly tourism demand using enhanced backpropagation neural network," *Neural Processing Letters*, vol. 52, no. 3, pp. 1–30, 2020.
[7] N. Bisoyi, H. Gupta, N. P. Padhy, and G. J. Chakrapani, "Prediction of daily sediment discharge using a back propagation neural network training algorithm: a case study of the Narmada River, India," *International Journal of Sediment Research*, vol. 34, no. 2, pp. 125–135, 2019.
[8] J. Feng, Q. Sun, Z. Li, Z. Sun, and K. Jia, "Back-propagation neural network-based reconstruction algorithm for diffuse optical tomography," *Journal of Biomedical Optics*, vol. 24, no. 5, 2019.
[9] J. Wu, J. She, Y. Wang, and C.-Y. Su, "Position and posture control of planar four-link underactuated manipulator based on neural network model," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 6, pp. 4721–4728, 2020.
[10] V. P. Ramesh, P. Baskaran, A. Krishnamoorthy, D. Damodaran, and P. Sadasivam, "Back propagation neural network based big data analytics for a stock market challenge," *Communications in Statistics - Theory and Methods*, vol. 48, no. 14, pp. 3622–3642, 2019.
[11] M. S. Parwez, D. B. Rawat, and M. Garuba, "Big data analytics for user-activity analysis and user-anomaly detection in mobile wireless network," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 4, pp. 2058–2065, 2017.
[12] Y. Wang, H. Liu, Z. X. Yu, and L. P. Tu, "An improved artificial neural network based on human-behaviour particle swarm optimization and cellular automata," *Expert Systems with Applications*, vol. 140, no. 1, Article ID 112862, 2019.
[13] D. Ai and J. Yang, "A machine learning approach for cost prediction analysis in environmental governance engineering," *Neural Computing & Applications*, vol. 31, no. 12, pp. 8195–8203, 2019.
[14] L. Wen and X. Yuan, "Forecasting CO_2 emissions in Chinas commercial department, through BP neural network based on random forest and PSO," *The Science of the Total Environment*, vol. 718, pp. 137194.1–137194.14, 2020.
[15] Z. Jiang, Z. Ding, Y. Liu, Y. Wang, X. Hu, and Y. Yang, "A data-driven based decomposition-integration method for remanufacturing cost prediction of end-of-life products," *Robotics and Computer-Integrated Manufacturing*, vol. 61, pp. 101838.1–101838.10, 2020.
[16] Y. Hao and Z. Zhu, "A quality prediction model of plastic gears based on an LMBP neural network and the PSO algorithm," *Journal of the Chinese Institute of Engineers*, vol. 43, no. 8, pp. 785–795, 2020.
[17] T. L. Dang and Y. Hoshino, "Hardware/software Co-design for a neural network trained by particle swarm optimization algorithm," *Neural Processing Letters*, vol. 49, no. 2, pp. 481–505, 2019.
[18] Y. Zhang, X. Gao, D. You, and N. Zhang, "Data-driven detection of laser welding defects based on real-time spectrometer signals," *IEEE Sensors Journal*, vol. 19, no. 99, pp. 9364–9373, 2019.
[19] A. Dehghanbanadaki, M. Khari, A. Arefnia, K. Ahmad, and S. Motamedi, "A study on UCS of stabilized peat with natural filler: a computational estimation approach," *KSCE Journal of Civil Engineering*, vol. 23, no. 4, pp. 1560–1572, 2019.
[20] Z. Ma, J. Xie, H. Li et al., "Deep neural network-based impacts analysis of multimodal factors on heat demand prediction," *IEEE Transactions on Big Data*, vol. 6, no. 3, pp. 594–605, 2019.
[21] A. Ss and B. Yza, "Optimal policies for information sharing in information system security," *European Journal of Operational Research*, vol. 284, no. 3, pp. 934–950, 2020.
[22] Y.-D. Zhang, Z. Dong, X. Chen et al., "Image based fruit category classification by 13-layer deep convolutional neural network and data augmentation," *Multimedia Tools and Applications*, vol. 78, no. 3, pp. 3613–3632, 2019.
[23] M. Chen, S. Lu, and Q. Liu, "Uniqueness of weak solutions to a Keller-Segel-Navier-Stokes system," *Applied Mathematics Letters*, vol. 121, Article ID 107417, 2021.
[24] M. Chen, S. Lu, and Q. Liu, "Uniqueness of weak solutions to a Keller-Segel-Navier-Stokes model with a logistic source," *Applications of Mathematics*, vol. 2021, Article ID 0069-20, 9 pages, 2021.
[25] S. S. Yadav and S. M. Jadhav, "Deep convolutional neural network based medical image classification for disease diagnosis," *Journal of Big Data*, vol. 6, no. 1, pp. 1–18, 2019.
[26] N. Li, D.-Q. Zhang, H.-T. Liu, and T.-J. Li, "Optimal design and strength reliability analysis of pressure shell with grid sandwich structure," *Ocean Engineering*, vol. 223, no. 10, Article ID 108657, 2021.
[27] Y. Gu, Z. Zhang, D. Zhang, Y. Zhu, Z. Bao, and D. Zhang, "Complex lithology prediction using mean impact value, particle swarm optimization, and probabilistic neural network techniques," *Acta Geophysica*, vol. 68, no. 6, pp. 1727–1752, 2020.

Predicting Thalasso Tourist Delight: A Hybrid SEM—Artificial Intelligence Analysis

Agustín J. Sánchez-Medina, [1] **Ylenia I. Naranjo-Barrera**, [2] **Jesús B. Alonso**, [3] **and Julio Francisco Rufo Torres** [3]

[1] *Instituto Universitario de Ciencias y Tecnologías Cibernéticas (IUCTC), University of Las Palmas de Gran Canaria, Despacho C-2.21, Ed. de Económicas y Empresariales, Campus de Tafira, 35017 Las Palmas de Gran Canaria, Spain*
[2] *Instituto Universitario de Ciencias y Tecnologías Cibernéticas (IUCTC), University of Las Palmas de Gran Canaria, Campus de Tafira, 35017 Las Palmas de Gran Canaria, Spain*
[3] *Instituto para el Desarrollo Tecnológico y la Innovación en Comunicaciones (IDeTIC), University of Las Palmas de Gran Canaria, Campus de Tafira, 35017 Las Palmas de Gran Canaria, Spain*

Correspondence should be addressed to Agustín J. Sánchez-Medina; agustin.sanchez@ulpgc.es and Ylenia I. Naranjo-Barrera; ynaranjobarrera@gmail.com

Academic Editor: Jorge Arenas-Gaitán

This study focuses on the influence of the quality of services received by thalassotherapy customers on their global satisfaction and the relationship between this and the word of mouth. This study uses a hybrid SEM—classification tree analysis. The empirical findings reveal a significant relationship between the quality of each offered service and global satisfaction. This study contributes to identify tourist's satisfaction or delight on received thalasso services through a proposed methodology. The main contribution of this work consists of the proposal of a methodology to identify objectively through the opinion of tourists if they were satisfied or had reached delight. This work demonstrates, confirming what has been found in previous literature, that global satisfaction is related to the different experiences provided by the service. Thus, all hypotheses are accepted, supporting the hypotheses that relate the pool, the staff, the treatments, and the environment to satisfaction. In addition, the hypotheses that link satisfaction with the word of mouth are also supported. This theoretical implication has important practical implications for managers of the type of facilities such as those studied in this paper, since it shows that it is not enough to do well in one of the services provided if the environment or the interaction with the staff is not right.

1. Introduction

The concept of well-being has its origin in the work of Halbert Dunn in 1959, in which he discusses a particular state that incorporates a general sense of well-being that is formed by the body, mind, spirit, and surrounding environment [1, 2]. Since old times, health has been known as a motivation to travel. We can mention examples like the Roman terms, the Turkish baths, the Japanese *onsens*, or nowadays the Alpine healing resorts [3]. However, in recent years, health tourism has reinvented itself and grown in popularity, becoming a tourist phenomenon worldwide with an upward trend that seems to be maintained [4]. Scholars like Goodarzi et al. [5] believe that this trend is due to the growing awareness of the importance of health in the middle and upper middle classes.

According to Dimitrovski and Todoroviic [6], definitions of health and wellness tourisms are inconsistent and vary significantly, which means that the concept can be understood in different ways. Moreover, this inconsistency is even found in the term itself, and according to the authors, "health tourism," "thermal tourism," and "wellness tourism" are used interchangeably.

Other authors like Mueller and Kaufmann [2] establish different categories for this type of tourism, dividing it into illness spa/convalescence tourism and prevention tourism, the latter being divided into specific illness prevention and wellness tourism. However, on many occasions, wellness centers offer all these services together, and thus, making distinctions between them is not easy.

Therefore, health and wellness tourisms include all the relationships and phenomena that result from a trip with a stay of at least one night, and in which the main motivation is to preserve or promote health and well-being [2, 5, 7].

Bennett et al. [8] believe that any type of tourism aimed at reducing stress can be considered as a type of health or wellness tourism. If we consider Wray et al. [9], we must note that they emphasize that this traditional way of contemplating health tourism has recently expanded itself to include other types such as yoga, spiritual pilgrimages, or holistic tourism. In this sense, [10] defines it as “the trip of at least one night in a facility that is specifically designed for physical, psychological, spiritual, and/or social welfare enhancement.”

This research focuses on the study of tourist’s satisfaction and delights in a particular wellness service: thalassotherapy. Etymologically, thalassotherapy comes from the Greek terms “thalassa” and “terapia,” these mean sea and therapy [11]. According to the Spanish Society of Thalassotherapy, this is a method of therapy that has been used since ancient times for therapeutic purposes. The most important aspects are the properties that have the chemical elements of sea water, seaweed, mud, and other elements extracted from the sea for health and physical appearance.

Ortiz [11] defines thalassotherapy as “a treatment technique that combines seawater baths (hydrotherapy), marine climate (atherapy), and solar radiation (heliotherapy) bringing benefits to healthy and sick individuals.” Since the Greek-Roman period, there is knowledge of these types of treatments. During the Middle Ages, their use decay, but from the eighteenth century onwards, they recover their interest. We find the first traces of thalassotherapy in the tourism sector in the 19th century with the development of large health villas [12].

On one hand, consumer satisfaction is a matter of interest for academic research [13]. The study of the satisfaction of tourists has gained great relevance and topicality in the last years. In this sense, according to Google Scholar, of the 841 researches that have been published with the topic “tourist satisfaction” in the title, 90% of them have been put forth in the last decade (data obtained the first week of July 2016). If we carry out the same operation in Web of Science, the results are quite similar. It is important to highlight the fact that of the total of 151 investigations that appear in the search, 92% have been written in the last ten years. Scholars like Choi and Chu [13] confirmed that research on customer satisfaction in the service industry had increased significantly in recent years. On the other hand, if we focus on *wellness* and *tourism*, the results obtained show that their study has lately grown. However, the number of documents is considerably lower, 151 researches in Google Scholar (88% published in the last decade) and 32 studies in Web of Science (96% published in the last decade).

The importance of this research is based on the different topics we mention below. It is framed in tourism, an economic sector that has developed a great importance in the last decades. It is focused on a specific touristic service, the wellness area. This field has not been studied in depth. Studies about thalassotherapy centers do not abound, so the literature about it is limited.

Therefore, this document has as main purpose to determine how the services offered in thalassotherapy, its personnel, and its facilities influence the satisfaction of the client and how the satisfaction is related to the *word of mouth* (wom) recommendation. Another important aspect of this work is how to predict the delight through artificial intelligence starting from the variables that influenced satisfaction. It was assumed that there was happiness when people gave the highest score to each item on the overall satisfaction scale, and in addition, they also did it on all of the *word of mouth* scale.

The results obtained in this study have helped to develop an objective methodology which identifies and evaluates tourist’s conditions after receiving thalassotherapy treatments. This way, we have a tool to know if they have felt satisfaction or if they have reached delight. This last status is related by scholars with the highest rate of repetition and with the *word of mouth*.

The present essay is divided in four chapters. In the first chapter, we make a presentation of the state of the art and of the hypothesis of this research. In the second chapter, the development of the methodology applied during the essay is dealt with. In the third chapter, obtained results are shown, and a short discussion is presented. Finally, in the last chapter, the main conclusions of the research are offered.

2. Theoretical Background

In large service industries, customer satisfaction is seen as a key element [14, 15]. Thus, customer satisfaction or the lack of it could serve as a control mechanism for companies to identify which attributes should improve to achieve this satisfaction [15]. Rajaguru and Hassanli [16] affirm that the quality of the service is considered an important predictor of success in the tourism industry. In addition, it must be considered that, in order to have good results, continuous customer feedback must be made on this variable [17, 18].

Although quality of service and satisfaction are related concepts [16, 19, 20], they are different. Thus, Parasuraman et al. [21] define the quality of services as a judgment related to the superiority of the service. Ryan [22] asserts that quality in the tourism industry is the features and characteristics of services and products that meet the needs of tourists, whether they are declared or implied. Finally, Prayag [23] adds that the quality of the service is an enduring construct that encompasses quality performance in all activities carried out by management and employees.

Satisfaction can be defined as the general assessment that the client makes of the service once it has been consumed [15], being a consequence of the quality of the service [24]. On the other hand, Anderson et al. [25] assert that satisfaction is the result of the general evaluation that derives from the total experience of consumption with a good or service. Cong [26] and Ramamoorthy et al. [27] affirm that this concept is related to the difference between the expectations that were held before the consumption of the service and the perceived performance once it was consumed. Thus, in the tourism sector, if the expectations are exceeded, the tourist will be satisfied [24]. In addition, it must be taken into account that the relationships between companies and customers have changed and they must strive to achieve customer satisfaction. To do so, companies must compete in order to provide higher quality services that lead them to achieve the tourist satisfaction [27].

Satisfaction is a very important aspect in the tourism area [28], and it is also a matter of interest for scholars [13, 29]. Thus, in a changing and dynamic environment, providing quality services to their customers becomes an important tool for suppliers to maintain the competitive advantage [30]. In this way, increasing satisfaction allows to improve the retention and, with that, to increase the profits, to generate a word of mouth, and to expend less in marketing [31]. Thus, it has been related, among other positive aspects, with the fidelity and intention to repeat of the tourist [32–35], with the word of mouth [30, 36, 37] or with paying *premium prices* [33, 38].

For Ifie et al. [39], one of the most important sources of new customers for companies is the recommendations of current customers. This form of promotion is interesting, for companies, because of the low cost it has. In this way, wom is an effective way to promote products and services [40, 41]. Thus, marketing professionals have not been oblivious to this issue and the implications it has on the results of the company [42]. For Sivadas and Jindal [15], the wom can be defined as the transmission of experiences from person to person that does not originate commercially with respect to a brand or service, being perceived as more credible than advertising; for its part, Saleem et al. [43] state that the wom refers to communications between clients, talking about their experiences and evaluating a service.

Determining what causes a positive wom is of great interest and has been analyzed from different perspectives [39, 44]. In the tourism industry, due to its fragmented structure, it is of special interest since the acquisition of new clients depends on the references of existing satisfied consumers, generated in the form of a positive wom [15]. According to Ifie et al. [39] or Sivadas and Jindal [15], some of these antecedents of the wom have been issues such as the characteristics of the product and the organization, the relations with the client, the brand image, or the quality of the service which is the most analyzed in the literature [15].

3. Research Hypothesis

Satisfaction can be defined as the positive reaction of customers to a specific experience with a product or service [45]. Other authors go further by asserting that it is the reaction to a set of experiences and not just a single one [33, 35]. As expressed by McDougall and Levesque [31], customer satisfaction has to do with a global evaluation of the service provider. Besides, Hu et al. [30] consider it as the affective reaction that occurs as a result of one or several services received, which would cover the two previous points of view. In this sense, the overall satisfaction of the tourist in the thalassotherapy centers can come from the satisfaction with the main activities: water treatments in the swimming pools, the personal treatments (body or facial treatments), the environment, and the interaction with the staff. For this reason, the following four hypotheses are formulated:

H1: Satisfaction with swimming pool treatments is positively related to overall satisfaction with the thalassotherapy center

H2: Satisfaction with body treatments is positively related to overall satisfaction with the thalassotherapy center

H3: Satisfaction with the thalassotherapy environment is positively related to overall satisfaction with the thalassotherapy center

H4: Satisfaction with thalassotherapy staff is positively related to overall satisfaction with the thalassotherapy center

According to Saleem et al. [43], the intentions of wom list several factors, among which is the quality of service as one of the most important [39]. In this way, in the tourism industry, there is a link between customer satisfaction and their tendency to share their experiences with positive recommendations [15, 16, 34, 35, 46–50]. So, according to Lai and Hitchcock [51], the relationship between quality of service and the wom is well confirmed in previous studies. In the same line, Meng and Han [24] assert that wom is a direct result of satisfaction and that this relationship is well supported in the literature. First of all, we propose that the satisfied customers can contribute positively to a positive word of mouth (wom) promotion.

Therefore, the fifth hypothesis of this work is formulated.

H5: Overall satisfaction with the thalassotherapy center is positively related to a favourable word of mouth (wom)

According to Liu and Keh [29], in the last decades, the interest in the emotional states of the consumers has increased. Among these emotional states, delight stands out [29, 52, 53]. It is important to note that delight and satisfaction are not the same [54, 55]. Thus, mere customer satisfaction is not enough to achieve their delight [56]. Following Finn [57], satisfaction and delight do not have exactly the same effects on behavioral intentions, and he suggests that existing research on satisfaction cannot be applied in full to delight. Thus, it can be considered that there are three levels along the continuum of satisfaction: the area of no satisfaction, mere satisfaction, and delight [29]. There must be high satisfaction and an emotional response for delight to exist [58]. Liu and Keh [29] believe that delight is defined by managers in a pragmatic way as what goes beyond satisfaction. However, academics define it as a pleasant surprise. Following this argumentation, Chandler [59] states that it occurs when the customer experiences an unexpected level of value or satisfaction. Likewise, Berman [60] considers that delight requires an extraordinary service or performance of the product. Arnold et al. [61] and Rust and Oliver [62] argue that it is a positive emotional state resulting from the positive improvement of the consumer's expectations and the existence of a degree of surprise. Delight can be defined as a positive effect with a high level of activation in which there is a combination of satisfaction with excitement and pleasure [63, 64]. Thus, delight is generated by a combination of positive disconfirmation and surprise to some previous expectations [55]. It means that it happens when the expectations are positively exceeded with a degree of surprise, so consumers do not expect the product or service to be so good [65].

As believed by Liu and Keh [29] and Berman [60], moving consumers from the satisfaction zone to the delight area is very positive for the company in terms of getting better results in customer retention and sales, word of mouth, and market share. In addition, it increases the value of the brand and the ability to resist the entry of new bidders [60].

To sum up, it should be noted that the tourism sector has not been excluded from research on delights, as has been studied, for example, in hotels [66], restaurants [67], or theme parks [55, 68]. In the second part of this paper, a proposal is to study the importance of satisfaction with the environment of the establishment, the interaction with the staff, and the main offered activities. Thus, a methodology will be provided that, through classification trees, allows to identify and evaluate objectively the importance that the aforementioned variables have to achieve.

4. Methodology

In the elaboration of the present research, both primary and secondary sources of information were used. Secondary ones were used to elaborate the theoretical framework and formulate the hypotheses. The primaries, to validate the hypotheses mentioned above.

Table 1: Demographic profile of the respondents.

Variables	Frequency	Percentage
Age		
≤30	78	31.7%
31–40	67	27.2%
41–50	30	12.2%
51–60	56	22.8%
≥61	15	6.1%
Gender		
Male	149	60.6%
Female	97	39.4%
Nationality		
German	35	14.2%
Argentinian	4	1.6%
Austrian	2	0.8%
Brazilian	4	1.6%
British	48	19.5%
Czech	4	1.6%
Spanish	104	42.3%
French	15	6.1%
Hungarian	2	0.8%
Irish	5	2.0%
Mexican	2	0.8%
Portuguese	2	0.8%
Russian	7	2.8%
Swedish	4	1.6%
Swiss	4	1.6%
Indian	2	0.8%
Polish	2	0.8%
Total	246	

4.1. Sample. The sample used to carry out this study was tourists using a well-known Thalasso Hotel located in the south of Gran Canaria, one of the main tourist areas of the Canary Islands, Spain. This 4-star hotel has one of the largest thalassotherapy centers in Europe. It has an area of approximately 7000 m^2 focused on health with sea water. The thalassotherapy center offers health and wellness treatments, including massage techniques, body treatments (peeling and wrapping), facials, wellness cures, and hydrotherapy [69].

Questionnaires were used to collect information from the Thalasso visitors. Tourists were informed of the purpose of this work. Data was collected as tourists had just finished their treatment. Surveys were conducted in June 2016.

In total and after eliminating several of them because they were poorly completed, 246 valid questionnaires were obtained. The description of the main characteristics of this sample is reflected in Table 1. Thus, the majority of the respondents, more than 75%, were Spanish, British, or German nationalities which are the main visitors of the hotel. As for sex, approximately 60% were men, and the remaining 40% were women. Finally, it should be mentioned that the majority of respondents were less than 50 years old.

4.2. Measurements. In the present study, the method used to obtain the necessary information to cover the objectives was the survey, in which the basic observation instrument is the questionnaire [70]. Except for age, sex, nationality, level of education, and place of residence, all items in this study are scored on a 7-point Likert scale ranging from (1) "strongly disagree" to (7) "totally agree." The survey questions were written in Spanish, English, and German.

Besides, the scales to evaluate the services offered by the Thalasso, i.e., the hydrotherapy circuit, the individual treatments (body or face), and the general environment, in addition to the satisfaction with the staff and global satisfaction were elaborated based on the proposal by Huang et al. [71]. To this, we have to add that the word of mouth scale was elaborated based on the work of Riquelme et al. [72].

4.3. Data Analysis. Data analysis has been divided into two parts. The first part has been used to test the hypotheses that related the quality of the services with global satisfaction. For this purpose, structural equations based on covariance were used. This is done using the lavaan R package [73]. Once the proposed model was validated, a methodology was

Table 2: Reliability, convergent validity, and discriminant validity: correlation coefficients and chi-square difference test.

Cronbach's alpha	Composite reliability	AVE	Construct	Body treatment	Human resources	Pool treatment	Environment	Satisfaction	*wom*
0.915	0.916	0.785	Treatment	**0.886**					
0.868	0.871	0.693	Staff	0.222*** (9.831**) #0.220#	**0.833**				
0.944	0.944	0.809	Pool	0.698*** (153.53***) #0.702#	0.259*** (13.913***) #0.268#	**0.900**			
0.950	0.950	0.825	Environment	0.615*** (99.324***) #0.614#	0.352*** (26.953***) #0.338#	0.749*** (174.52***) #0.750#	**0.908**		
0.955	0.954	0.874	Satisfaction	0.760*** (166.61***) #0.756#	0.396*** (31.651***) #0.376#	0.762*** (173.62***) #0.754#	0.793*** (204.76***) #0.778#	**0.935**	
0.963	0.963	0.897	wom	0.601*** (126.75***) #0.668#	0.313*** (43.728***) #0.434#	0.602*** (158.66***) #0.722#	0.627*** (137.08***) #0.671#	0.791*** (194.38***) #0.774#	**0.947**

Note: $n = 246$; $^{***}p \leq 0.001$; $^{**}p \leq 0.01$; square root of AVE (in bold) is shown on the diagonal; off-diagonal elements are the correlation coefficients; values in brackets show the chi-square difference statistics with $df = 1$; values in # show the ratio of heterotrait–monotrait correlations.

developed to objectively identify and evaluate whether the clients were satisfied or had reached delight (second part). To do this, we used as input data the opinion of the tourists about the different services, the environment of the facilities, and the interaction with the staff. It should be mentioned that there was delight when people gave the highest score to each item on the overall satisfaction scale and, in addition, they also did it on all of the word of mouth scale. All this was implemented with the assembly of classification trees, specifically using the techniques of bagging and boosting. For this purpose, adabag software was used [74].

5. Results

5.1. Contrast of Hypotheses. As it can be seen in Table 2, there is no occurrence of multicollinearity [75, 76] because all the correlation coefficients are below 0.8 and also the largest variance inflation factor (VIF) is 3.366 (<10). As recommended by Hair et al. [77], Leong et al. [78], and Wang et al. [79], a two-step technique was used to examine the causal relationship between the constructs. First, an exploratory factorial analysis, which was useful for filtering and defining the dimensional character of the scale [80], was used. The second stage was a confirmatory factor analysis to evaluate the validity of constructs [81, 82].

To evaluate the convergent validity, the estimated load of each indicator in its construct was examined. For such validity, the load must be high, and the values of t statistically must be significant [83]. In the planned model, the above is confirmed with an acceptable convergent validity. Thus, the AFC results indicate that the relationship between each item and its respective construct is statistically significant with loads that exceed 0.790 (all p value $\leq$ 0.001). With these results, the existence of convergent validity is assumed (see Table 3). It is also necessary to determine the convergent validity of the constructs. According to Hair et al. [84] and Roldán and Sánchez-Franco [85], this validity must be evaluated by analyzing *Cronbach's alpha*, the composite reliability index by Fornell and Larcker [86], and the average extracted variance (AVE). The reference point, for the first two cases, is 0.7 and for the third case is 0.5 [84, 85]. In the model we considered and as shown in Table 2, all these criteria are well met. Thus, the minimum *Cronbach's alpha* value obtained is 0.868, the composite reliability is 0.871, and the AVE, 0.693. Therefore, it can be concluded that the reflective constructs are consistent.

To obtain the discriminant validity, the square root of the AVE (located on the diagonal of the matrix in Table 2) is compared to the correlations between the constructs (the elements located outside the diagonal) [85, 87]. On average, it can be observed that each construct is stronger related to its own means than to the other constructs. Also, the chi-square difference test [88] is also achieved, and the result shows that all constructs are different. In addition, it was used on the evaluation of the heterotrait–monotrait ratio (HTMT) [89]. This criterion is more demanding than the previous criteria. This measure establishes the ratio of heterotrait–monotrait correlations, with discriminant validity confirmed when the values are less than 0.90 [90]. The highest value obtained in our sample is 0.778. Consequently, there are no discriminant validity problems even though the correlations between the constructs are high.

5.2. Test of Hypotheses. The structural model was verified with some measures of goodness. To adjust the measurement model, robust maximum likelihood estimators were used [91, 92]. As it can be seen in Table 4, all of them exceeded the recommended thresholds (CFI = 0.940, TLI = 0.929, RMSEA = 0.056, and SRMR = 0.044). Hence, the structural model fits with the collected data.

In the path analysis, the significance of a path is determined based on its *p value*. The results implied that 77.5%

Table 3: Confirmatory analyses.

Construct/indicator	Standardized loading	*Z value*	*p value*
Body treatments			
The Thalasso has an adequate number of body care treatments	0.906		
The Thalasso offers a wide variety of body care treatments	0.890	23.324	≤0.001
I am satisfied with the body care treatments provided by the Thalasso	0.858	21.036	≤0.001
Pool treatments			
The "Get in Shape" pool treatments are adequate	0.911		
I am satisfied with the "Get in Shape" pool treatments	0.914	23.949	≤0.001
The pool programmes are satisfactory	0.911	20.579	≤0.001
I am satisfied with the guidance that I was given for the "Get in Shape" pool services	0.866	16.329	≤0.001
Human resources			
The staff gives an adequate service to the clients	0.866		
The staff gives personal attention to the clients	0.836	13.514	≤0.001
The staff is polite to the clients	0.790	8.764	≤0.001
Environment			
I think the Thalasso has a comfortable atmosphere	0.863		
I am satisfied with the cleanness of the facilities of the Thalasso	0.887	23.028	≤0.001
I am satisfied with the decoration, conditions, and style of the Thalasso	0.955	24.839	≤0.001
I am satisfied with the security conditions of the Thalasso	0.925	26.676	≤0.001
Satisfaction			
The Thalasso has met my expectations	0.930		
I am willing to return to the Thalasso	0.936	41.619	≤0.001
In general, I am satisfied with the service given at the Thalasso	0.940	24.767	≤0.001
Word of mouth			
I would be willing to recommend the Thalasso to someone who sought my advice	0.944		
I would be willing to encourage friends and family to use Thalasso	0.960	29.624	≤0.001
I would have no problem in saying positive things about the Thalasso	0.936	25.543	≤0.001

Table 4: Measures of the model fit.

Number of observations: 246		
Estimator	Maximum likelihood	Robust
Minimum function test statistic	301.741	279.968
Degrees of freedom	159	159
p value (chi-square)	≤0.001	≤0.001
Scaling correction factor or the Satorra-Bentler correction		1.081
Model test baseline model		
Minimum function test statistic	5648.416	2212.795
Degrees of freedom	190	190
p value	≤0.001	≤0.001
	Maximum likelihood	Robust
User model versus baseline model		
Comparative fit index (CFI)[a]	0.974	0.940
Tucker-Lewis index (TLI)[b]	0.969	0.929
RMSEA[c]	0.061	0.056
SRMR[d]	0.044	0.044

[a]Recommended value ≥ 0.90 [77]. [b]Recommended value ≥ 0.90 [77]. [c]Recommended value ≤ 0.08 [78]. [d]Recommended value ≤ 0.1 [78].

Table 5: Results of path analysis.

Hypothesis	Path	Estimate	Std. error	Z value	p value	Remarks
H1	Pool→satisfaction	0.186**	0.071	2.624	0.009	Supported
H2	Staff→satisfaction	0.132*	0.078	2.448	0.014	Supported
H3	Treatment→satisfaction	0.366***	0.067	5.739	≤0.001	Supported
H4	Environment→satisfaction	0.383***	0.075	5.093	≤0.001	Supported
H5	Satisfaction→wom	0.791***	0.086	13.745	≤0.001	Supported

Significance level: $^{***}p \le 0.001$; $^{**}p \le 0.01$; $^{*}p \le 0.05$; ^{ns} not significant

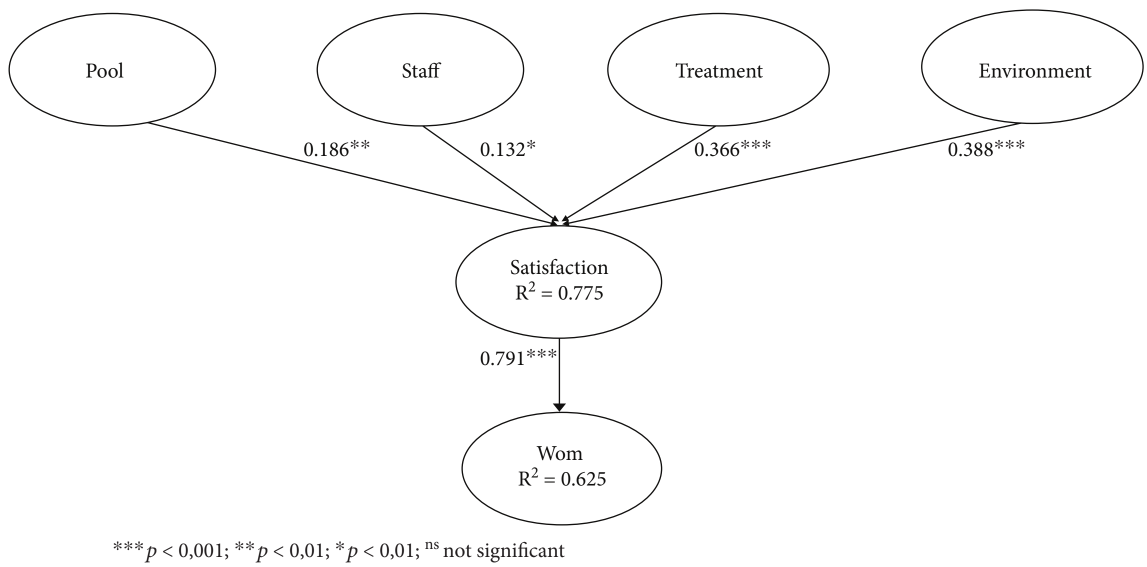


Figure 1: Structural model.

of the variance in satisfaction is explained by the model variables while satisfaction is able to explain 62.5% of the variance in wom.

As shown in Table 5, the findings further reveal that pool treatments ($\beta = 0.186^{**}$), human resources ($\beta = 0.132^{*}$), body treatments ($\beta = 0.366^{***}$), and environment ($\beta = 0.383^{***}$) have significant and positive impacts on satisfaction while satisfaction ($\beta = 0.791^{***}$) positively impacted on wom. Therefore, all hypotheses were supported (see Figure 1 and Table 5).

5.3. Proposal of a Model to Establish the Importance of the Determinants of Delight in the Services of Thalassotherapy. Based on the previous results, it was decided to include as input variables of the delight classifier the four variables that were significant in the previous model, that is to say, the environment, the service of body treatments, the service of the swimming pool, and the interaction with the staff.

To analyze the data, an artificial intelligence method was used, classification trees were assembled with boosting and bagging [93–96]. Bagging and boosting [74] can generate a diverse set of classifiers through the manipulation of training data with a learning algorithm [97]. The bagging method produces multiple versions of a predictor so that an aggregate predictor can be obtained. These multiple versions are generated by making bootstrap replicates of the learning set [98].

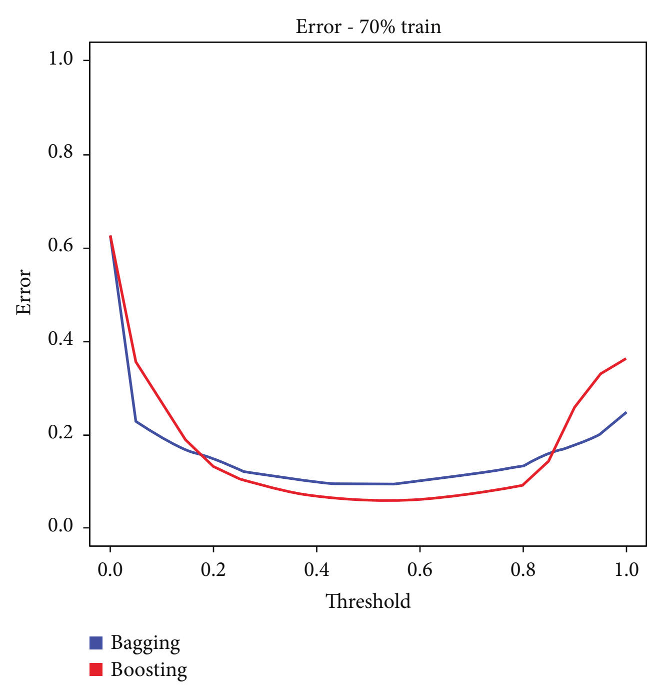


Figure 2: Total error of the models used.

Table 6: Total error of the models used.

Threshold	**0.000**	**0.050**	**0.100**	**0.150**	**0.200**	**0.250**	**0.300**	**0.350**	**0.400**	**0.450**
Bagging	0.627	0.228	0.191	0.166	0.148	0.122	0.113	0.105	0.099	0.093
Boosting	0.627	0.356	0.270	0.182	0.131	0.106	0.088	0.076	0.069	0.063
Threshold	**0.500**	**0.550**	**0.600**	**0.650**	**0.700**	**0.750**	**0.800**	**0.850**	**0.900**	**0.950**
Bagging	0.093	0.094	0.101	0.106	0.114	0.122	0.132	0.160	0.176	0.201
Boosting	0.060	0.060	0.062	0.065	0.071	0.079	0.092	0.144	0.260	0.329

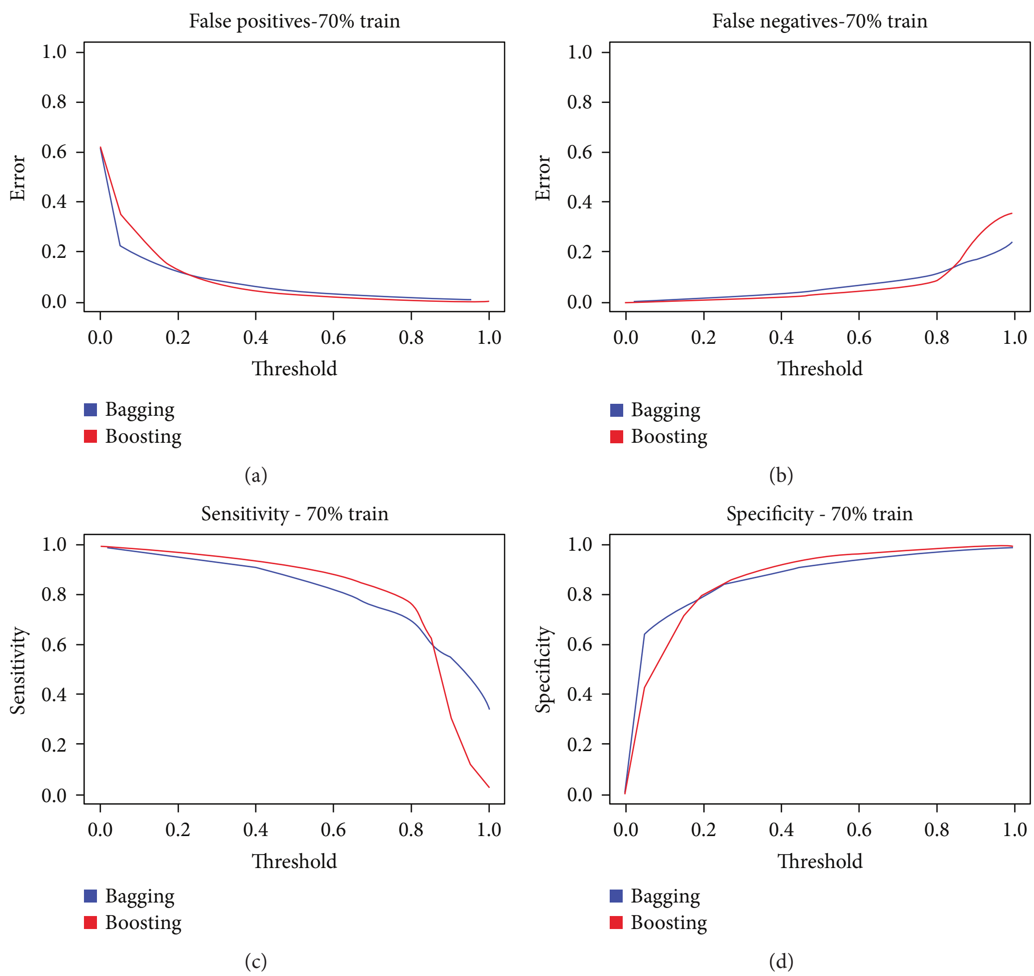


Figure 3: False positives, false negatives, specificity, and sensitivity.

Thus, starting from a training set with m cases, other sets are created (with replacements) [97]. A series of classifiers can be obtained with the boosting technique. The training set for each member of the series is chosen according to the performance of the previous classifier. Thus, the cases are extracted with replacement with probability proportional to their weights [97].

Classification and regression trees are, compared to other learning techniques, one of the most intuitive and transparent classification algorithms [99], representing a powerful alternative to the more traditional statistical models [98]. According to Homaie-Shandizi et al. [100], they were presented during the ‘60s by Morgan and Sonquist [101], and two decades later, Breiman et al. [102] develop the first exhaustive and modern algorithm. In the tree structure, the leaves represent the classifications and the branches the conjunctions of characteristics that lead to the mentioned categories [98, 103]. Its purpose is to perform a recursive partition of the training data into homogeneous subsets so that each new partition will minimize the number of members [104]. The technique of the decision trees is attractive for a lot of business applications [99] since a minimum of parameters and no domain knowledge is required. They have the advantage, too, of being able to detect nonlinear relationships and to show a good performance when there is qualitative information [98].

As already mentioned in Methodology, the adabag package of R, which allows the use of bagging and boosting for the assembly of classification trees, was used. For its application, 70% of the sample for training and the remaining 30% for testing was established. It is worth mentioning that different thresholds for classification were implemented. Thus, values ranging from 0 to 1 were used for this threshold with increments of 0.05. In all, 1000 iterations were performed. In each one of them, which elements of the database would be in the training group and which were in the test group were chosen in a random way. For each of these training and test groups, bagging and boosting were applied, obtaining the results that will be shown below. Once all the results were available, the average value and the standard deviation obtained with the aforementioned 1000 iterations were calculated, for each level of threshold. The t value was also calculated to compare it with a two-tailed Student's t with 998 degrees of freedom.

The results obtained from applying the cited methods will be presented below. The "rough data" produced by a classification system are the counts of the correct and incorrect classifications of each class. A matrix of confusion, which is a contingency table form that shows the differences between the actual and predicted classes for a set of labeled examples [105], is used to analyze the obtained information. Referring to the total error obtained, it can be observed that the smaller errors, which are around 9% with bagging and 6% with boosting, occur in both methods with thresholds close to 0.5 (see Figure 2). Table 6 show that the minimum error is obtained using bagging. Errors occurring with the first method are always lower when the threshold is less than 0.20 or higher than 0.85, that is, in extreme cases.

In addition, Figure 3 shows that for the false positives, that is, cases classified as "delight" that in reality were not "delight," both methods behave similarly. As for specificity, it is worth mentioning that for very low thresholds, the bagging behaves better, occurring otherwise when it exceeds the heat of 0.1. As far as sensitivity is concerned, boosting for all thresholds below 0.85 behaves better. Moreover, an analysis is presented of sensitivity, "the proportion of true positives correctly identified by the test," and specificity, "the proportion of true negatives correctly identified by the test" [106]. (Sensitivity = true positive/(true positive + false negative); specificity = true negative/(true negative + false positive)). In relation to sensitivity, boosting always behaves slightly better except when the thresholds are very high; in that case, the bagging provides a better performance. For thresholds higher than 0.15, boosting presents a better specificity.

In order to show the performance of both methods, the ROC curves obtained for both are presented below. These curves are a good way to visualize the performance of the classifiers [105]. Figure 4 shows that the area under the curve when using boosting is greater than when using bagging.

Regarding the importance given by bagging and boosting to the variables used to classify the companies in the categories "delight" and "nondelight" (see Figure 5), the bootstrapping technique (1000 subsamples) was used to generate the Student t statistics and the standard errors. Thus, the statistical significance of the mean values for importance was obtained. In both methods, it considered as the least important variable the pool treatments and as the most important the staff. However, there is a slight difference in the situation of those in the second and third positions. Thus, in the boosting, the second in relevance is that of treatment followed by environment, whereas in the bagging, these positions are interchanged (see Table 7).

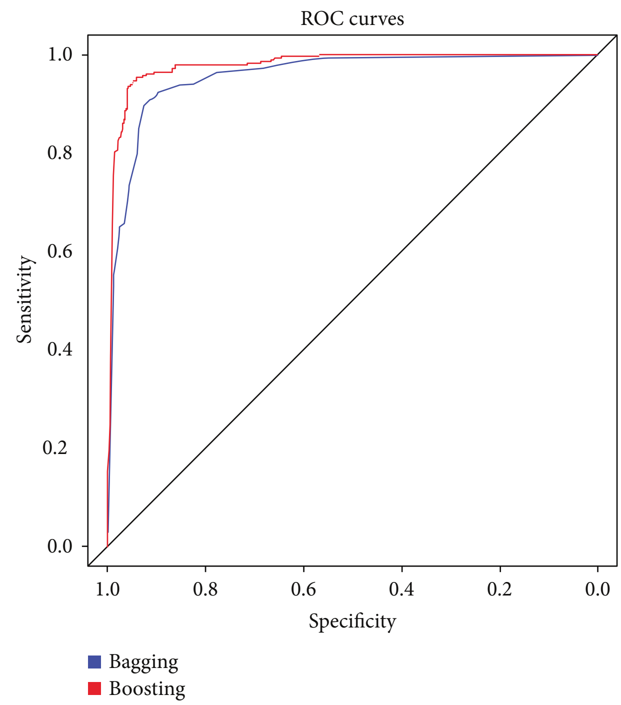


Figure 4: ROC curves.

5.4. Discussion. According to the results, the presented hypotheses are confirmed. The overall satisfaction of the tourist in the thalassotherapy centers comes from the satisfaction with the main activities: water treatments in the swimming pools, the personal treatments (body or facial treatments), the environment, and the interaction with the staff. The results tell us, as well, that the satisfied customers can contribute positively to the word of mouth promotion. This theoretical implication has important practical implications for managers of facilities, such as those studied in this work, since it shows that it is not enough to do well in one of the services provided if the environment or the interaction with the staff is not right. In this case, all the thalasso facilities and the staff interaction must be taken into account by managers to increase the tourist delight. Today's business is characterized by tough competition; consequently, the delivery of a quality service becomes a fundamental element to attract and retain customers [27].

It is a contribution of the present work the proposal of a methodology to identify and evaluate objectively and through the opinion about the different services offered by thalassotherapy if the tourists' status was of satisfaction or had arrived at delight. This is a matter of great importance if we take into account that, as it has been indicated throughout this work, when a customer moves from satisfaction to delight, he

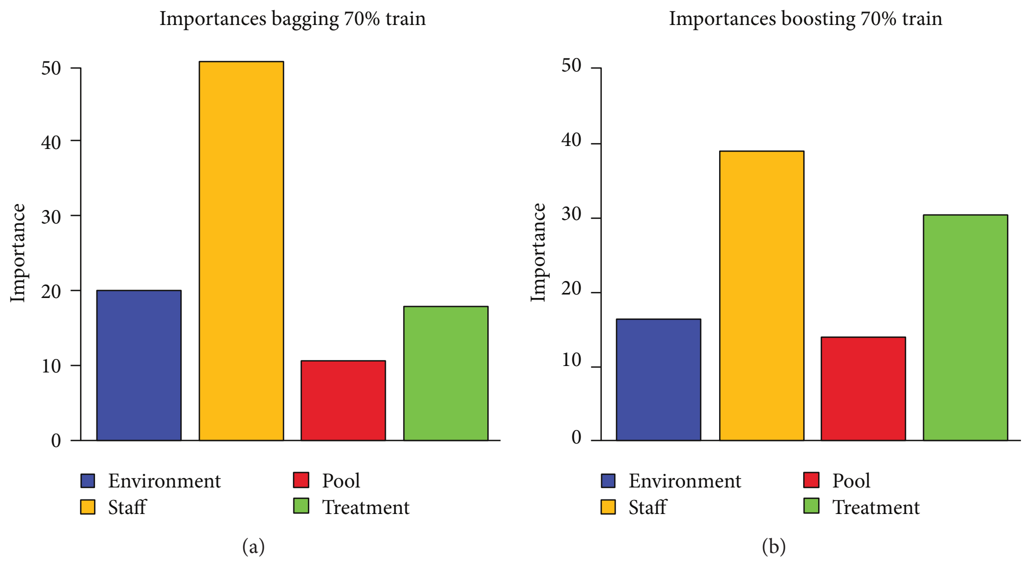


Figure 5: Importance of each of the variables studied for classification.

Table 7: Means of the importance, standard deviations, and Student t for bagging and boosting.

	Bagging			
	Environment	Staff	Pool	Treatment
Mean importances	20.272**	50.865***	10.778*	18.085**
SD importances	7.765	9.501	4.207	6.504
t	2.611	5.354	2.562	2.780
	Boosting			
Boosting	Environment	Staff	Pool	Treatment
Mean importances	16.499***	39.071***	14.129***	30.302***
SD importances	3.360	4.513	2.732	4.467
t	4.910	8.657	5.172	6.783

Bootstrap-t (based on $t(998)$ two-tailed test); $t(0.001;998) = 3.300$; $t(0.01;998) = 2.581$; $t(0.05;998) = 1.962$; $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; ^{ns} nonsignificant.

contributes to greater profitability to the company, increases its fidelity, and improves its word of mouth [53, 60].

The methodology developed is based on the use of assembled classification trees, specifically with the methods of bagging and boosting. Also, from the comparison of the results obtained with both methods, it was observed that the assembly with boosting provided better results. The great use of machine learning is in situations where the variables are related in a highly nonlinear way. Besides, it is also an academic contribution of this work that the proposed model, if it is frequently fed, can maintain the classifications updated with the tastes of the clients and the conditions of the service provided. So, this kind of artificial intelligence (AI) can make continuous evaluations as we mentioned in the theoretical background of this paper.

Regarding the main weaknesses of the present study, it is worth mentioning that a cross-sectional methodology was used, thus increasing the probability of the study being biased due to the use of a single method/data source. Another limitation is determined by the technique used, structural equations, which assumes a linearity of the relationships between latent variables [77].

6. Conclusions

This work demonstrates, confirming what has been found in previous literature [55, 59, 68], that global satisfaction is related to the different experiences provided by the service. Thus, all hypotheses are accepted, supporting the hypotheses that relate the pool, the staff, the treatments, and the environment to satisfaction. In addition, the hypotheses that link satisfaction with the wom are also supported. This theoretical implication has important practical implications for managers of the type of facilities such as those studied in this paper, since it shows that it is not enough to do well in one of the services provided if the environment or the interaction with the staff is not right. In this way, managers could have a tool that could inform them about which aspects of the business are contributing to a better satisfaction and delight of the clients. In this sense, they can establish corrective actions to improve these variables. In addition, the system can be fed with new data so that managers could always have up-to-date information on which of the services provided contributes more, at each moment, to the satisfaction of customers. This is in line with the constant feedback that authors like Lu et al. [17] and Mohsin and Lockyer [18] consider necessary in business nowadays. This issue is relevant because in this type of business, the pleasures of customers can change quickly for various issues such as the emergence of new treatments both in the cabin and in the pool or the appearance of new competitors with modern facilities. The conditions in which the service is provided may change, due to deterioration of the facilities, personnel changes or behavior, etc. All this is of great importance since the service companies have become increasingly clear that they must focus on the client side and that the quality of the service is a differentiator on the road to success [27]. In this way, Sivadas and Jindal [15] state that those responsible for marketing in the tourism sector must understand better the factors that drive the intention of wom if they wish to develop effective marketing strategies. Moreover, this is even more important taking into account that the growth of the power of wom comes from the increasing use of social networks [107].

Finally, as far as possible future lines of research are concerned, it has been considered that it would be interesting to go deeper into the search for a shorter scale to measure satisfaction with the different services provided by the hotel, as well as to study if there are cultural differences between the various nationalities in order to reach delight for the service received.

References

[1] K. H. Chen, F. H. Chang, and F. Y. Liu, "Wellness tourism among seniors in Taiwan: previous experience, service encounter expectations, organizational characteristics, employee characteristics, and customer satisfaction," *Sustainability*, vol. 7, no. 8, pp. 10576–10601, 2015.

[2] H. Mueller and E. L. Kaufmann, "Wellness tourism: market analysis of a special health tourism segment and implications for the hotel industry," *Journal of Vacation Marketing*, vol. 7, no. 1, pp. 5–17, 2001.

[3] L. Puczkó and M. Bachvarov, "Spa, bath, thermae: what's behind the labels?," *Tourism Recreation Research*, vol. 31, no. 1, pp. 83–91, 2006.

[4] E. Alén, P. De Carlos, and T. Domínguez, "An analysis of differentiation strategies for Galician thermal centres," *Current Issues in Tourism*, vol. 17, no. 6, pp. 499–517, 2014.

[5] M. Goodarzi, N. Haghtalab, and E. Shamshiry, "Wellness tourism in Sareyn, Iran: resources, planning and development," *Current Issues in Tourism*, vol. 19, no. 11, pp. 1071–1076, 2016.

[6] D. Dimitrovski and A. Todorović, "Clustering wellness tourists in spa environment," *Tourism Management Perspectives*, vol. 16, pp. 259–265, 2015.

[7] P. Erfurt-Cooper and M. Cooper, *Health and Wellness Tourism*, Channel View Publications, Bristol, 2009.

[8] M. Bennett, B. King, and L. Milner, "The health resort sector in Australia: a positioning study," *Journal of Vacation Marketing*, vol. 10, no. 2, pp. 122–137, 2004.

[9] M. Wray, J. Laing, and C. Voigt, "Byron Bay: an alternate health and wellness destination," *Journal of Hospitality and Tourism Management*, vol. 17, no. 1, pp. 158–166, 2010.

[10] N. A. Valentine, "Wellness tourism: using tourists' preferences to evaluate the wellness tourism market in Jamaica," *Review of Social Sciences*, vol. 1, no. 3, 2016.

[11] M. R. Ortiz, "Orígenes y fundamentos de la talasoterapia," *Revista de La Facultad de Ciencias*, vol. 2, p. 12, 2004, http://www.uax.es/publicacion/origenes-y-fundamentos-de-la-talasoterapia.pdf.

[12] Abalnearios, "Abalnearios," 2016, July 2016, http://www.abalnearios.com/talasoterapia/.

[13] T. Y. Choi and R. Chu, "Determinants of hotel guests' satisfaction and repeat patronage in the Hong Kong hotel industry," *International Journal of Hospitality Management*, vol. 20, no. 3, pp. 277–297, 2001.

[14] Z. Zhang, M. Jiang, and X. Li, "Refining the relationship between attribute performance and customer satisfaction in the Chinese hospitality industry," *Total Quality Management and Business Excellence*, vol. 24, no. 11-12, pp. 1364–1375, 2013.

[15] E. Sivadas and R. P. Jindal, "Alternative measures of satisfaction and word of mouth," *Journal of Services Marketing*, vol. 31, no. 2, pp. 119–130, 2017.

[16] R. Rajaguru and N. Hassanli, "The role of trip purpose and hotel star rating on guests' satisfaction and WOM," *International Journal of Contemporary Hospitality Management*, vol. 30, no. 5, pp. 2268–2286, 2018.

[17] C. Lu, C. Berchoux, M. W. Marek, and B. Chen, "Service quality and customer satisfaction: qualitative research implications for luxury hotels," *International Journal of Culture, Tourism, and Hospitality Research*, vol. 9, no. 2, pp. 168–182, 2015.

[18] A. Mohsin and T. Lockyer, "Customer perceptions of service quality in luxury hotels in New Delhi, India: an exploratory study," *International Journal of Contemporary Hospitality Management*, vol. 22, no. 2, pp. 160–173, 2010.

[19] E. N. Torres, "Deconstructing service quality and customer satisfaction: challenges and directions for future research," *Journal of Hospitality Marketing and Management*, vol. 23, no. 6, pp. 652–677, 2014.

[20] R. Hallak, G. Assaker, and R. El-Haddad, "Re-examining the relationships among perceived quality, value, satisfaction, and destination loyalty: a higher-order structural model," *Journal of Vacation Marketing*, vol. 24, no. 2, pp. 118–135, 2018.

[21] A. Parasuraman, V. Zeithaml, and L. Berry, "SERVQUAL—a multiple-item scale for measuring consumer perceptions of service quality," *Journal of Retailing*, vol. 64, no. 1, pp. 12–37, 1988.

[22] C. Ryan, "Seeking quality in Pacific tourism," in *Tourism in the Pacific: Issues and Cases*, C. M. Hall and S. J. Page, Eds., pp. 146–160, International Thomson Business Press, London, England, 1996.

[23] G. Prayag, "Tourists' evaluations of destination image, satisfaction, and future behavioral intentions—the case of

Mauritius," *Journal of Travel & Tourism Marketing*, vol. 26, no. 8, pp. 836–853, 2009.

[24] B. Meng and H. Han, "Working-holiday tourism attributes and satisfaction in forming word-of-mouth and revisit intentions: impact of quantity and quality of intergroup contact," *Journal of Destination Marketing & Management*, vol. 9, pp. 347–357, 2018.

[25] E. W. Anderson, C. Fornell, and D. R. Lehmann, "Customer satisfaction, market share, and profitability: findings from Sweden," *Journal of Marketing*, vol. 58, no. 3, p. 53, 1994.

[26] L. C. Cong, "A formative model of the relationship between destination quality, tourist satisfaction and intentional loyalty: an empirical test in Vietnam," *Journal of Hospitality and Tourism Management*, vol. 26, pp. 50–62, 2016.

[27] R. Ramamoorthy, A. Gunasekaran, M. Roy, B. K. Rai, and S. A. Senthilkumar, "Service quality and its impact on customers' behavioural intentions and satisfaction: an empirical study of the Indian life insurance sector," *Total Quality Management & Business Excellence*, vol. 29, no. 7-8, pp. 834–847, 2016.

[28] E. F. Mathis, H. L. Kim, M. Uysal, J. M. Sirgy, and N. K. Prebensen, "The effect of co-creation experience on outcome variable," *Annals of Tourism Research*, vol. 57, pp. 62–75, 2016.

[29] M. W. Liu and H. T. Keh, "Consumer delight and outrage: scale development and validation," *Journal of Service Theory and Practice*, vol. 25, no. 6, pp. 680–699, 2015.

[30] H.-H. S. Hu, J. Kandampully, and T. D. Juwaheer, "Relationships and impacts of service quality, perceived value, customer satisfaction, and image: an empirical study," *The Service Industries Journal*, vol. 29, no. 2, pp. 111–125, 2009.

[31] G. H. G. McDougall and T. Levesque, "Customer satisfaction with services: putting perceived value into the equation," *Journal of Services Marketing*, vol. 14, no. 5, pp. 392–410, 2000.

[32] J. Alegre and J. Garau, "Tourist satisfaction and dissatisfaction," *Annals of Tourism Research*, vol. 37, no. 1, pp. 52–73, 2010.

[33] F. Ali, "Service quality as a determinant of customer satisfaction and resulting behavioural intentions: a SEM approach towards Malaysian resort hotels," *Tourism*, vol. 63, no. 1, pp. 37–52, 2015.

[34] Y. Kim and J. Lee, "Relationship between corporate image and customer loyalty in mobile communications service markets," *Africa Journal of Business Management*, vol. 4, no. 18, pp. 4035–4041, 2010.

[35] K. Ryu, H.-R. Lee, and W. G. Kim, "The influence of the quality of the physical environment, food, and service on restaurant image, customer perceived value, customer satisfaction, and behavioral intentions," *International Journal of Contemporary Hospitality Management*, vol. 24, no. 2, pp. 200–223, 2012.

[36] I. R. del Bosque and H. San Martín, "Tourist satisfaction a cognitive-affective model," *Annals of Tourism Research*, vol. 35, no. 2, pp. 551–573, 2008.

[37] Y. Yoon and M. Uysal, "An examination of the effects of motivation and satisfaction on destination loyalty: a structural model," *Tourism Management*, vol. 26, no. 1, pp. 45–56, 2005.

[38] R. A. Ganiyu, I. I. Uche, and A. O. Elizabeth, "Is customer satisfaction an indicator of customer loyalty?," *Australian Journal of Business and Management Research*, vol. 2, no. 7, pp. 14–20, 2012.

[39] K. Ifie, A. C. Simintiras, Y. Dwivedi, and V. Mavridou, "How service quality and outcome confidence drive pre-outcome word-of-mouth," *Journal of Retailing and Consumer Services*, vol. 44, pp. 214–221, 2018.

[40] M. Hultman, D. Skarmeas, P. Oghazi, and H. M. Beheshti, "Achieving tourist loyalty through destination personality, satisfaction, and identification," *Journal of Business Research*, vol. 68, no. 11, pp. 2227–2231, 2015.

[41] Y. Wardi, A. Abror, and O. Trinanda, "Halal tourism: antecedent of tourist's satisfaction and word of mouth (WOM)," *Asia Pacific Journal of Tourism Research*, vol. 23, no. 5, pp. 463–472, 2018.

[42] A. Marchand, T. Hennig-Thurau, and C. Wiertz, "Not all digital word of mouth is created equal: understanding the respective impact of consumer reviews and microblogs on new product success," *International Journal of Research in Marketing*, vol. 34, no. 2, pp. 336–354, 2017.

[43] M. A. Saleem, A. Yaseen, and A. Wasaya, "Drivers of customer loyalty and word of mouth intentions: moderating role of interactional justice," *Journal of Hospitality Marketing and Management*, vol. 27, no. 8, pp. 877–904, 2018.

[44] A. M. Baker, N. Donthu, and V. Kumar, "Investigating how word-of-mouth conversations about brands influence purchase and retransmission intentions," *Journal of Marketing Research*, vol. 53, no. 2, pp. 225–239, 2016.

[45] R. Oliver, "Measurement and evaluation of satisfaction processes in retail settings," *Journal of Retailing*, vol. 57, no. 3, pp. 25–48, 1981.

[46] A. Pizam, V. Shapoval, and T. Ellis, "Customer satisfaction and its measurement in hospitality enterprises: a revisit and update," *International Journal of Contemporary Hospitality Management*, vol. 28, no. 1, pp. 2–35, 2017.

[47] S. R. Swanson and M. K. Hsu, "The effect of recovery locus attributions and service failure severity on word-of-mouth and repurchase behaviors in the hospitality industry," *Journal of Hospitality & Tourism Research*, vol. 35, no. 4, pp. 511–529, 2011.

[48] G. Tripathi, "Customer satisfaction and word of mouth intentions: testing the mediating effect of customer loyalty," *Journal of Services Research*, vol. 17, no. 2, pp. 1–16, 2018.

[49] M. Amin, Z. Yahya, W. F. A. Ismayatim, S. Z. Nasharuddin, and E. Kassim, "Service quality dimension and customer satisfaction: an empirical study in the Malaysian hotel industry," *Services Marketing Quarterly*, vol. 34, no. 2, pp. 115–125, 2013.

[50] G. Dominici and R. Guzzo, "Customer satisfaction in the hotel industry: a case study from Sicily," *International Journal of Marketing Studies*, vol. 2, no. 2, pp. 3–12, 2010.

[51] I. K. W. Lai and M. Hitchcock, "Local reactions to mass tourism and community tourism development in Macau," *Journal of Sustainable Tourism*, vol. 25, no. 4, pp. 451–470, 2016.

[52] E. N. Torres, X. Fu, and X. Lehto, "Are there gender differences in what drives customer delight?," *Tourism Review*, vol. 69, no. 4, pp. 297–309, 2014.

[53] E. N. Torres and S. Kline, "From customer satisfaction to customer delight: creating a new standard of service for the hotel industry," *International Journal of Contemporary Hospitality Management*, vol. 25, no. 5, pp. 642–659, 2013.

[54] J. C. Crotts and V. P. Magnini, "Is Surprise Essential?," *Annals of Tourism Research*, vol. 38, no. 2, pp. 719–722, 2011.

[55] J. Ma, J. Gao, N. Scott, and P. Ding, "Customer delight from theme park experiences," *Annals of Tourism Research*, vol. 42, pp. 359–381, 2013.

[56] S. M. C. Loureiro, F. J. Miranda, and M. Breazeale, "Who needs delight?," *Journal of Service Management*, vol. 25, no. 1, pp. 101–124, 2014.

[57] A. Finn, "Customer delight: distinct construct or zone of nonlinear response to customer satisfaction?," *Journal of Service Research*, vol. 15, no. 1, pp. 99–110, 2012.

[58] J. Füller and K. Matzler, "Customer delight and market segmentation: an application of the three-factor theory of customer satisfaction on life style groups," *Tourism Management*, vol. 29, no. 1, pp. 116–126, 2008.

[59] C. H. Chandler, "Quality: beyond customer satisfaction," *Quality Progress*, vol. 22, no. 30–32, 1989.

[60] B. Berman, "How to delight your customers," *California Management Review*, vol. 48, no. 1, pp. 129–151, 2005.

[61] M. J. Arnold, K. E. Reynolds, N. Ponder, and J. E. Lueg, "Customer delight in a retail context: investigating delightful and terrible shopping experiences," *Journal of Business Research*, vol. 58, no. 8, pp. 1132–1145, 2005.

[62] R. T. Rust and R. L. Oliver, "Should we delight the customer?," *Journal of the Academy of Marketing Science*, vol. 28, no. 1, pp. 86–94, 2000.

[63] M. W. Alexander, "Customer delight: a review," *Academy of Marketing Studies Journal*, vol. 50, no. 5, pp. 535–545, 2010.

[64] S. Denning, "The essential metric of customer capitalism is customer outcomes," *Strategy & Leadership*, vol. 39, no. 4, pp. 12–18, 2011.

[65] R. Oliver and W. S. DeSarbo, "Processing of the satisfaction response in consumption: a suggested framework and research propositions," *Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior*, vol. 2, no. 1, pp. 1–16, 1989.

[66] E. N. Torres and S. Kline, "From satisfaction to delight: a model for the hotel industry," *International Journal of Contemporary Hospitality Management*, vol. 18, no. 4, pp. 290–301, 2006.

[67] J. L. H. Bowden and T. S. Dagger, "To delight or not to delight? An investigation of loyalty formation in the restaurant industry," *Journal of Hospitality Marketing & Management*, vol. 20, no. 5, pp. 501–524, 2011.

[68] F. Ali, W. G. Kim, J. Li, and H.-M. Jeon, "Make it delightful: customers' experience, satisfaction and loyalty in Malaysian theme parks," *Journal of Destination Marketing & Management*, vol. 7, pp. 1–11, 2018.

[69] Gloria Thalasso & Hotels, *Thalasso Gloria—San Agustín*, 2016, July 2016, http://www.gloriapalaceth.com/hoteles/gloria-palace-san-agustin-thalasso-hotel/thalasso/.

[70] R. Sierra Bravo, *Técnicas de investigación social. Teoría y ejercicios*, Paraninfo, Madrid, 1991.

[71] HuangSongshan (Sam), A. Afsharifar, and R. van der Veen, "Examining the moderating role of prior knowledge in the relationship between destination experiences and tourist satisfaction," *Journal of Vacation Marketing*, vol. 22, no. 4, pp. 320–334, 2016.

[72] I. P. Riquelme, S. Román, and D. Iacobucci, "Consumers' perceptions of online and offline retailer deception: a moderated mediation analysis," *Journal of Interactive Marketing*, vol. 35, pp. 16–26, 2016.

[73] Y. Rosseel, "Lavaan: an R package for structural equation modeling," *Journal of Statistical Software*, vol. 48, no. 2, pp. 1–36, 2012.

[74] E. Alfaro, M. Gamez, and N. García, "Adabag: an R package for classification with boosting and bagging," *Journal of Statistical Software*, vol. 54, no. 2, pp. 1–35, 2013.

[75] L. Y. Leong, T. S. Hew, V. H. Lee, and K. B. Ooi, "An SEM-artificial-neural-network analysis of the relationships between SERVPERF, customer satisfaction and loyalty among low-cost and full-service airline," *Expert Systems with Applications*, vol. 42, no. 19, pp. 6620–6634, 2015.

[76] A.-C. Teo, G. W.-H. Tan, K.-B. Ooi, T.-S. Hew, and K.-T. Yew, "The effects of convenience and speed in m-payment," *Industrial Management & Data Systems*, vol. 115, no. 2, pp. 311–331, 2015.

[77] J. F. Hair, W. Black, and B. Balbin, *Multivariate Data Analysis: A Global Perspective*, Prentice Hall, Upper Saddle River, NJ, USA, 7th ed. edition, 2010.

[78] L. Y. Leong, T. S. Hew, G. W. H. Tan, and K. B. Ooi, "Predicting the determinants of the NFC-enabled mobile credit card acceptance: a neural networks approach," *Expert Systems with Applications*, vol. 40, no. 14, pp. 5604–5620, 2013.

[79] C.-J. Wang, H.-T. Tsai, and M.-T. Tsai, "Linking transformational leadership and employee creativity in the hospitality industry: the influences of creative role identity, creative self-efficacy, and job complexity," *Tourism Management*, vol. 40, pp. 79–89, 2014.

[80] M. K. Cabrera-Suárez, M. D. L. C. Déniz-Déniz, and J. D. Martín-Santana, "The setting of non-financial goals in the family firm: the influence of family climate and identification," *Journal of Family Business Strategy*, vol. 5, no. 3, pp. 289–299, 2014.

[81] F. T. S. Chan and A. Y. L. Chong, "A SEM-neural network approach for understanding determinants of interorganizational system standard adoption and performances," *Decision Support Systems*, vol. 54, no. 1, pp. 621–630, 2012.

[82] K. K. F. So, C. King, B. A. Sparks, and Y. Wang, "The role of customer engagement in building consumer loyalty to tourism brands," *Journal of Travel Research*, vol. 55, no. 1, pp. 64–78, 2015.

[83] J. C. Anderson and D. W. Gerbing, "Structural equation modeling in practice: a review and recommended two-step approach," *Psychological Bulletin*, vol. 103, no. 3, pp. 411–423, 1988.

[84] J. F. Hair, G. T. Hult, C. M. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, SAGE, Thousand Oaks CA, USA, 2014.

[85] J. L. Roldán and M. J. Sánchez-Franco, "Variance-based structural equation modeling: guidelines for using partial least squares in information systems research," in *Research Methodologies, Innovations and Philosophies in Software Systems Engineering and Information Systems*, M. Mora, A. Steenkamp, L. Johnston, and J. Gamon, Eds., pp. 193–221, Information Science Reference, Hershey, PA, USA, 2012.

[86] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, vol. 18, no. 1, pp. 39–50, 1981.

[87] W. W. Chin, "Issues and opinion on structural equation modeling," *MIS Quarterly*, vol. 22, no. 1, pp. 7–16, 1998.

[88] P. Bertea and A. Zait, "Methods for testing discriminant validity," *Management & Marketing Journal*, vol. 9, no. 2, pp. 217–224, 2011.

[89] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *Journal of the Academy of Marketing Science*, vol. 43, no. 1, pp. 115–135, 2015.

[90] J. F. Hair, G. T. M. Hult, C. Ringle, and M. Sarstedt, *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, SAGE Publications, Thousand Oaks, CA, USA, 2016.

[91] A. Satorra, "Power of χ^2 goodness-of-fit test in structural equation models: the case of non-normal data," in *New Developments of Psychometrics*, H. Yanai, A. Okada, K. Shigemasu, Y. Kano, and J. Meulman, Eds., pp. 57–68, Springer, Tokyo, 2003.

[92] A. Satorra and P. M. Bentler, "A scaled difference chi-square test statistic for moment structure analysis," *Psychometrika*, vol. 66, no. 4, pp. 507–514, 2001.

[93] E. Bauer and R. Kohavi, "An empirical comparison of voting classification algorithms: bagging, boosting, and variants," *Machine Learning*, vol. 36, no. 1/2, pp. 105–139, 1999.

[94] T. G. Dietterich, "Ensemble methods in machine learning," in *Multiple Classifier Systems*, pp. 1–15, Springer, Berlin, Heidelberg, 2000.

[95] M. Galar, A. Fernandez, E. Barrenechea, H. Bustince, and F. Herrera, "A review on ensembles for the class imbalance problem: bagging-, boosting-, and hybrid-based approaches," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 42, no. 4, pp. 463–484, 2012.

[96] S. B. Kotsiantis, "Supervised machine learning: a review of classification techniques," *Informatica*, vol. 31, pp. 249–268, 2007.

[97] T. G. Dietterich, "An experimental comparison of three methods for constructing ensembles of decision trees," *Machine Learning*, vol. 40, no. 2, pp. 139–157, 2000.

[98] M. Chrzanowska, E. Alfaro, and D. Witkowska, "The individual borrowers recognition: single and ensemble trees," *Expert Systems with Applications*, vol. 36, no. 3, pp. 6409–6414, 2009.

[99] M. A. King, A. S. Abrahams, and C. T. Ragsdale, "Ensemble learning methods for pay-per-click campaign management," *Expert Systems with Applications*, vol. 42, no. 10, pp. 4818–4829, 2015.

[100] A.-H. Homaie-Shandizi, V. P. Nia, M. Gamache, and B. Agard, "Flight deck crew reserve: from data to forecasting," *Engineering Applications of Artificial Intelligence*, vol. 50, pp. 106–114, 2016.

[101] J. N. Morgan and J. A. Sonquist, "Problems in the analysis of survey data, and a proposal," *Journal of the American Statistical Association*, vol. 58, no. 302, pp. 415–434, 1963.

[102] L. Breiman, J. Friedman, R. Olshen, and C. Stone, *Classification and Regression Trees*, Wadsworth & Brooks, Wadsworth International Group, Monterey, CA, USA, 1984.

[103] C. F. Tsai and Y. J. Chiou, "Earnings management prediction: a pilot study of combining neural networks and decision trees," *Expert Systems with Applications*, vol. 36, no. 3, pp. 7183–7191, 2009.

[104] G. Shmueli, N. Patel, and P. Bruce, *Data Mining for Business Intelligence: Concepts, Techniques, and Applications in Microsoft Office Excel with XLMiner*, Wiley, Hoboken, N.J, USA, 2010.

[105] A. P. Bradley, "The use of the area under the ROC curve in the evaluation of machine learning algorithms," *Pattern Recognition*, vol. 30, no. 7, pp. 1145–1159, 1997.

[106] D. G. Altman and J. M. Bland, "Statistics notes: diagnostic tests 1: sensitivity and specificity," *BMJ*, vol. 308, no. 6943, article 1552, 1994.

[107] S. Gopinath, P. K. Chintagunta, and S. Venkataraman, "Blogs, advertising, and local-market movie box office performance," *Management Science*, vol. 59, no. 12, pp. 2635–2654, 2013.